# Technological change in the production of new scientific knowledge: a second look

By: Albert N. Link and John T. Scott

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**Abstract:**

This paper presents and explains an approach for measuring technological change in the production of new scientific knowledge. The paper expands our previous work on this topic. Our approach is illustrated by using as an example new scientific journal publications from the U.S. National Institute of Standards and Technology. The empirical findings are consistent with the expectation that resource constraints will cause a breakdown in the process of creating new scientific knowledge and with the evidence that scientific research has been less productive in recent decades.

**Keywords:** scientific publications | technological change | R&D | knowledge production function

**Article:**

## 1. Introduction

In a previous issue of this journal (Link and Scott 2019), we used a version of the Solow (1957) method of functional decomposition to study the production of new scientific knowledge as proxied by new scientific publications from the U.S. National Institute of Standards and Technology (NIST).[1] We found that 79 percent of the increase in scientific publications per unit of scientific personnel from 1973 through 2008 is explained by an increase in federal R&D capital expenditures per unit of scientific personnel. What is also interesting is that 21 percent of the increase in scientific publications per index unit of scientific personnel is not explained by the flows of new investments in R&D-based research capital per index unit of scientific personnel. We called the unexplained, or residual, 21 percent a measure of creativity-enhancing technological change.

[1] Others who have studied scientific publications are, for example as discussed in Link and Scott (2019), Adams and Griliches (1996) and Shelton (2008).

Our previous approach to the production of new scientific knowledge (i.e. new scientific publications) considered the knowledge output for each period as being the product of a shift factor for the period multiplied by a function of each period's expenditures for research capital and the research labor services. Our method was to first to sweep out the effect, on each period's knowledge output, of the period's new expenditures for research capital and for research labor services. That swept-out effect was assumed to be the relation between the inputs and outputs that is the part of the production function that would remain the same from period to period if there were no technological change in the process of creating new scientific knowledge. Then, second, we measured technological change as a shift factor from one period to another. Thus, measured technological change in the production of new knowledge included the effect of using the extant research capital stock – the use of it is itself necessarily creating technological change, unlike the use of the capital stock to produce ordinary goods and services.[2] In this paper, we take a second look at technological change in the production of new scientific knowledge using the same data as before.

The approach for this second look isolates shifts in the knowledge production function after sweeping out the effects on knowledge production of *all* inputs of research capital (including the extant capital stock before the new capital expenditures for a period) and scientific personnel as we explain in Section 2. In Section 3, we briefly describe the data used to illustrate our method, and then in Section 4 we present the results of applying our method in which overall research expenditures are disaggregated into expenditures for research capital and for the services of scientific personnel. Section 5 presents a more parsimonious production function with knowledge output as a function of a single argument – namely, the stock of scientific knowledge, and then uses our data to estimate the function and the findings for the rate of technological change in the process of creating new science. Finally, in Section 6, we conclude the paper by emphasizing the importance of measuring the technological change for the production of new knowledge.

## 2. Technological change in the production of new scientific knowledge

Let new scientific knowledge output, $Q$, be a function of the inputs of research capital stock, $K$, and scientific labor services, $L$, with the function, given neutral technological change, being $Q = A(t)f(K, L)$.[3] In this context, technological change is measured as a shift in the production function, with the shift factor $A(t)$ increasing with technological change that increases

[2] In the production of new science, scientific physical capital – the equipment, instruments and facilities – is used to innovate, to create new science, or more generally new knowledge, and hence the existing stock of physical capital is used to create technological change in science and technology. For example, a microscope in a laboratory that is engaged in producing new science is part of the stock of scientific physical capital. In Link and Scott (2019), the output, new knowledge, from the microscope's use in the process of scientific discovery is itself a measure of technological change for the knowledge production function after sweeping out the relationship between output and the new inputs of research capital and scientific labor services in each period. In contrast, in the production of ordinary goods and services, the use of the stock of physical production capital to produce output need not be accompanied by technological change. Applying labor services with the physical production capital may simply give us more of the goods and services associated with the production process and do so just as it has done in the preceding period, yielding more automobiles or more rubbish removal for example, with the inputs providing more of the same goods or services and without any technological change.

[3] We follow Solow's (1957) assumption of neutral technological change, although other scholars have shown instances in which technological change is in fact biased (e.g., Antonelli and Quatraro 2010, 2014).

the output from the inputs. This formulation is analogous to the one in the seminal use of the aggregate production function to measure technological change in Solow (1957). Research expenditures, $R^+$, in the current period, are in part for new scientific research capital, $K^+$, and in part for the scientific labor services, $L$.

Using the 'dot' notation for time derivatives, observe that

$$\frac{\dot{Q}}{Q} = \frac{\dot{A}}{A} + s_K \frac{\dot{K}}{K} + s_L \frac{\dot{L}}{L}, \tag{1}$$

where $s_K$ and $s_L$ are respectively the elasticity of research output with respect to research capital stock and the elasticity of research output with respect to scientific labor services.[4] Thus,

$$s_K = \frac{\partial Q}{\partial K} \frac{K}{Q}, \tag{2}$$

and

$$s_L = \frac{\partial Q}{\partial L} \frac{L}{Q}, \tag{3}$$

Rearranging (1), we have

$$\frac{\dot{Q}}{Q} - s_L \frac{\dot{L}}{L} = \frac{\dot{A}}{A} + s_K \frac{\dot{K}}{K}. \tag{4}$$

Then, following Terleckyj (1974), substitute for $s_K$ using (2), to have

$$\frac{\dot{Q}}{Q} - s_L \frac{\dot{L}}{L} = \frac{\dot{A}}{A} + \frac{\partial Q}{\partial K} \frac{K}{Q} \frac{\dot{K}}{K} = \frac{\dot{A}}{A} + \frac{\partial Q}{\partial K} \frac{\dot{K}}{Q}. \tag{5}$$

Finally, assuming that for a good approximation we can ignore the depreciation in the research capital stock, we can use the observed flow of new research capital expenditures, $K^+$, as the value for $\dot{K}$. To estimate the rate, $\dot{A}/A$, of technological change in the production function for new knowledge, we use the estimated intercept from the estimation of the equation

$$\frac{\dot{Q}}{Q} - s_L \frac{\dot{L}}{L} = \frac{\dot{A}}{A} + \frac{\partial Q}{\partial K} \frac{K^+}{Q}. \tag{6}$$

### 3. Description of the data

[4] The elasticities would also be shares in the value of output assuming that the factors' prices equaled their marginal products.

To estimate Equation (6), we use the NIST data published in Link and Scott (2019) in order to be able to compare the results for the two different approaches to measuring technological change in the production of new scientific knowledge.[5, 6] We continue to view new scientific publications as a measure of the laboratory's new scientific knowledge output. See column (1) in Table 1.[7]

**Table 1.** Data for Estimation of Equation (6) for Scientific Publications.

| **Year** | **(1) Number NIST Scientific Publications** $Q$ | **(2)** $\dot{Q}/Q$ | **(3) Intramural R&D ($2015, 000s)** | **(4) Scientific Personnel Costs ($2015, 000s)** $L$ | **(5) Research Capital Costs ($2015, 000s)** $K^{+}$ | **(6)** $K^{+}/Q$ | **(7) Scientific Personnel's Relative Share** $s_L$ | **(8)** $\dot{L}/L$ | **(9)** $dNIST$ |
|---|---|---|---|---|---|---|---|---|---|
| 1973 | 417 | .2398082 | 147267 | 104306 | 42961 | 103.024 | .7083 | .0257799 | 0 |
| 1974 | 517 | −.098646 | 148257 | 106995 | 41263 | 79.81238 | .7217 | −.0100659 | 0 |
| 1975 | 466 | −.0193133 | 146277 | 105918 | 40359 | 86.6073 | .7241 | .106337 | 0 |
| 1976 | 457 | .0787746 | 154474 | 117181 | 37293 | 81.60394 | .7586 | .0013227 | 0 |
| 1977 | 493 | .020284 | 161743 | 117336 | 44407 | 90.07505 | .7254 | −.0056419 | 0 |
| 1978 | 503 | −.0218688 | 159157 | 116674 | 42483 | 84.45924 | .7331 | .0343178 | 0 |
| 1979 | 492 | .1300813 | 167397 | 120678 | 46719 | 94.95731 | .7209 | .0506638 | 0 |
| 1980 | 556 | .1672662 | 176443 | 126792 | 49652 | 89.30215 | .7186 | .0050398 | 0 |
| 1981 | 649 | .0616333 | 175590 | 127431 | 48159 | 74.20493 | .7257 | −.0170367 | 0 |
| 1982 | 689 | .1044993 | 177380 | 125260 | 52120 | 75.64587 | .7062 | .0094603 | 0 |
| 1983 | 761 | −.4086728 | 182639 | 126445 | 56194 | 73.84232 | .6923 | −.0018111 | 0 |
| 1984 | 450 | .6733333 | 178873 | 126216 | 52657 | 117.0156 | .7056 | −.0198073 | 0 |
| 1985 | 753 | .0584329 | 181975 | 123716 | 58259 | 77.36919 | .6799 | −.0064745 | 0 |
| 1986 | 797 | .0803011 | 179033 | 122915 | 56118 | 70.41154 | .6866 | −.0257902 | 0 |
| 1987 | 861 | −.0162602 | 170463 | 119745 | 50718 | 58.90592 | .7025 | .0218715 | 0 |
| 1988 | 847 | .0011806 | 182056 | 122364 | 59692 | 70.47462 | .6721 | .0021248 | 1 |
| 1989 | 848 | −.067217 | 183611 | 122624 | 60987 | 71.91863 | .6678 | .0302388 | 1 |
| 1990 | 791 | .1340076 | 187114 | 126332 | 60782 | 76.84197 | .6752 | .0765048 | 1 |
| 1991 | 897 | −.1204013 | 197142 | 135997 | 61145 | 68.16611 | .6898 | .0486481 | 1 |
| 1992 | 789 | .1064639 | 207196 | 142613 | 64583 | 81.85425 | .6883 | .1141972 | 1 |
| 1993 | 873 | .0687285 | 229642 | 158899 | 70743 | 81.03436 | .6919 | .1279555 | 1 |
| 1994 | 933 | .0203644 | 271415 | 179231 | 92184 | 98.80386 | .6604 | .0304579 | 1 |

[5] The National Institute of Standards and Technology (NIST) is the U.S. federal laboratory responsible for the advancement of measurement science, standards, and new technology in order to promote innovation and industrial competitiveness in ways that enhance economic security and improve our quality of life. See, https://www.nist.gov/about-nist/our-organization/mission-vision-values. For an historical overview of NIST, see Link (2019) and Link and Scott (2019).

[6] The Technology Partnerships Office at NIST is responsible for the summary report to the President and the Congress on annual technology transfers from federal laboratories. Although the information is not part of the official reports, NIST has collected data on scientific publications that have appeared as articles in peer-reviewed journals. The Office provided those data by fiscal year of publication. We thank Dr. Gary Anderson, then Senior Economist within the Technology Partnerships Office, for graciously sharing these data.

[7] Data on scientific publications were provided from 1973 through 2015. As in Link and Scott (2019), we use the data through 2008. In 2009 and 2010, NIST received funding through the American Recovery and Reinvestment Act of 2009 (ARRA). Thus, post-2008 R&D data and perhaps post-2008 scientific publication data might not be comparable to pre-Great Recession measures.

| Year | (1) Number NIST Scientific Publications $Q$ | (2) $\dot{Q}/Q$ | (3) Intramural R&D ($2015, 000s) | (4) Scientific Personnel Costs ($2015, 000s) $L$ | (5) Research Capital Costs ($2015, 000s) $K^{+}$ | (6) $K^{+}/Q$ | (7) Scientific Personnel's Relative Share $s_L$ | (8) $\dot{L}/L$ | (9) *dNIST* |
|---|---|---|---|---|---|---|---|---|---|
| 1995 | 952 | .0231092 | 307575 | 184690 | 122886 | 129.0819 | .6005 | .0564676 | 1 |
| 1996 | 974 | .0020534 | 304320 | 195119 | 109201 | 112.116 | .6412 | .0166821 | 1 |
| 1997 | 976 | .0522541 | 312584 | 198374 | 114210 | 117.0184 | .6346 | .0280228 | 1 |
| 1998 | 1027 | .0632911 | 314619 | 203933 | 110687 | 107.777 | .6482 | .0343152 | 1 |
| 1999 | 1092 | .0815018 | 317905 | 210931 | 106974 | 97.96154 | .6635 | −.0353481 | 1 |
| 2000 | 1181 | −.1168501 | 309428 | 203475 | 105953 | 89.71465 | .6576 | .0255068 | 1 |
| 2001 | 1043 | .029722 | 343094 | 208665 | 134429 | 128.8869 | .6082 | .0411521 | 1 |
| 2002 | 1074 | −.0083799 | 352096 | 217252 | 134844 | 125.5531 | .617 | −.0135097 | 1 |
| 2003 | 1065 | .1370892 | 369088 | 214317 | 154771 | 145.3249 | .5807 | .073312 | 1 |
| 2004 | 1211 | −.0495458 | 328160 | 230029 | 98131 | 81.03303 | .701 | −.0237101 | 1 |
| 2005 | 1151 | .0451781 | 354188 | 224575 | 129612 | 112.6082 | .6341 | −.0316776 | 1 |
| 2006 | 1203 | −.0074813 | 351564 | 217461 | 134103 | 111.4738 | .6186 | .0443206 | 1 |
| 2007 | 1194 | .0343384 | 388379 | 227099 | 161280 | 135.0754 | .5847 | .0313167 | 1 |
| 2008 | 1235 | 0 | 380177 | 234211 | 145966 | 118.1911 | .6161 | .0700223 | 1 |
| 2009 | 1235 | | | 250611 | | | | | |

Notes: All data pertain to fiscal years.
Nominal data for (3), (4), and (5) are from NIST; data are converted to $2015 using the GDP deflator.

The R&D data provided by NIST separates the total intramural R&D into scientific personal costs and the remaining non-scientific personnel or research capital costs (see columns (3), (4), and (5) of Table 1). As shown in Table 1, on average for the years we observe, about two-thirds of total intramural R&D has been allocated to scientific personnel each year. In our most parsimonious model, we use labor's share of intramural R&D as an approximation for $s_L$, the elasticity of output with respect to scientific labor services, although we can and do estimate the unconstrained model and obtain similar results.[8] The variable *dNIST* is a qualitative variable that is 0 during the years before 1988 when the federal laboratory that became NIST in 1988 was organized as the National Bureau of Standards (NBS); starting in 1988 when the Bureau was reorganized and renamed as NIST, *dNIST* = 1.

[8] Note that our approach does not require an estimate of the research capital stock or an assumption about the elasticity of output with respect to that stock. In contrast, the approach in Link and Scott (2019), while not requiring an estimate of the research capital stock, uses the shares of capital and labor in current research expenditures as an approximation of the elasticity of output with respect to those expenditures. One anonymous referee observes that while for the formulation in Equation (6) we have assumed that labor's share equals the elasticity of output with respect to labor, in principle the elasticity could be estimated as a part of the model. That approach would have the advantage of not imposing constant returns to scale on the production function. With our small sample size (an issue other researchers may also confront) in order to conserve degrees of freedom, we estimate Equation (6) and avoid estimating the extra parameter. In the Appendix, we also present the unconstrained model, with the rate of growth in labor on the right-hand side and with the elasticity of output with respect to labor estimated rather than assumed to equal labor's share. As shown in the Appendix, despite the small sample, we are able to estimate the unconstrained version of the model.

Table 2 provides the descriptive statistics for the variables used in Section 4 to estimate, with new scientific publications as the measure of new scientific knowledge output, the model provided by Equation (6).

**Table 2.** Descriptive Statistics for the Variables ($n = 36$) Used in the Model of Scientific Publications.

| Variable | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| $\dot{Q}/Q$ | 0.04108 | 0.1522 | −0.4087 | 0.6733 |
| $dNIST$ | 0.5833 | .50 | 0 | 1 |
| $K^{+}/Q$ | 94.95 | 21.98 | 58.91 | 145.3 |
| $s_L$ | 0.6739 | 0.04554 | 0.5807 | 0.7586 |
| $\dot{L}/L$ | 0.02542 | 0.04072 | −0.03535 | 0.1280 |

**4. Estimation of technological change in the production function for new scientific knowledge**

To estimate the annual rate of technological change for the production function for new scientific knowledge, we estimate the model in Equation (6), assuming that the regressors are uncorrelated with the error in the equation. As shown in Link and Scott (2019), the time series for the production function for new knowledge behaves differently in the periods before and after the institutional reorganization in 1988 when NBS became NIST. We therefore estimate different parameters for the model during the period of the NBS and for the later period after the reorganization. Table 3 shows the ordinary least squares (OLS) results from estimating Equation (6).[9] The Durbin-Watson statistic and Durbin's alternative test statistic show that first-order autocorrelation is not an issue. However, the test for autoregressive conditional heteroscedasticity (ARCH) suggests that such heteroscedasticity is present in the estimated

[9] Looking at the first column of Table 1, the time series of NIST's publications behaves oddly from 1983 through 1985. As a referee observed, the steady upward trend during the NBS era suddenly plunges from 1983 to 1984, and then it just as suddenly jumps in 1985 and resumes to its upward trend. We have no *a priori* information about why this happened (and the data for the publication series are correct) apart from the random error modeled, but we investigated the matter by including a qualitative variable that is 1 during the three years from 1983 through 1985, and is zero otherwise. In the Appendix, we show the model with the addition of the qualitative variable gives essentially the same results.

model.[10] Table 4 uses a generalized autoregressive conditional heteroscedasticity (GARCH) model to control for the heteroscedasticy in the model's errors.[11, 12]

**Table 3.** Ordinary Least Squares (OLS) Regression Estimation of Equation (6) for New Scientific Publications: Dependent Variable $\dot{Q}/Q - s_L(\dot{L}/L)$, $n = 36$.

| Variable | Coefficient (standard error) [probability > \|t\|] |
|---|---|
| *dNIST* | 0.740 (0.227) [0.003] |
| $K^+/Q$ | 0.0110 (0.00227) [0.000] |
| (*dNIST*) × ($K^+/Q$) | −0.00985 (0.00254) [0.000] |
| Constant | −0.859 (0.193) [0.000] |
| $F(3, 32)$<br>(probability > $F$) | 8.99<br>(0.0002) |
| $R^2$ | 0.457 |
| Durbin-Watson d-statistic (4, 36) | 2.19 |
| Durbin's alternative test for autocorrelation:<br>Chi-squared (1)<br>(probability > chi-squared) | 0.662<br>(0.416) |
| LM test for ARCH:<br>Chi-squared (1)<br>(probability > chi-squared) | 5.36<br>(0.0206) |

**Table 4.** Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Estimation of Equation (6) for New Scientific Publications: Dependent Variable $\dot{Q}/Q - s_L(\dot{L}/L)$, $n = 36$.

| Variable | Coefficient (standard error) [probability > \|t\|] |
|---|---|
| *dNIST* | 0.666 (0.179) [0.000] |
| $K^+/Q$ | 0.00929 (0.00186) [0.000] |
| (*dNIST*) × ($K^+/Q$) | −0.00838 (0.00199) [0.000] |
| Constant | −0.760 (0.161) [0.000] |

[10] See Greene (2012, 930–937) for a description and detailed discussion of autoregressive conditional heteroscedasticity.

[11] Greene (2012, 934) discusses an example where fitting a GARCH (1, 1) model as we have done accounts for a complicated pattern of autoregressive conditional heteroscedasticity. StataCorp (2011, 26) describes the GARCH model that we have estimated using *Stata: Release 12*, and observes, 'Empirically, many series with conditionally heteroskedastic disturbances have been adequately modeled with a GARCH (1, 1) specification.' As a practical matter, the effectiveness of the simple GARCH (1, 1) specification is important because it is often difficult to achieve convergence in the estimation of the parameters for specifications with additional lags (beyond a single lagged squared innovation and a single lagged variance). One anonymous referee observes that if we had a longer time series, we could explore longer differences (i.e., longer lags), and the other referee observes that examining the residuals across various specifications could uncover misspecification of the model that arguably causes the need for the GARCH model. With longer time series, those thoughts will be implementable. However, note in our short time series, the simple lag structure appears to be appropriate; and for the errors, it is appropriate not because of first-order serial autocorrelation, but instead for the autoregressive heteroscedasticity where variance in the error at any time depends on the square of the single-period lagged random error in the equation and the variance in that preceding period's error.

[12] We believe that our knowledge production function approach, with knowledge as the output from research inputs in the direct and simple way modeled, is an appropriate way to model the 'output' that we are examining in our model, although surely one could instead as an alternative model the output as a function of past output in a dynamic adjustment model. For the knowledge-production function as we have modeled it, we have examined the residuals in the models closely, plotting them through time and finding them consistent with the random errors as we have modeled them.

| Variable | Coefficient (standard error) [probability > \|t\|] |
| --- | --- |
| Wald chi-squared (3)<br>(probability > chi-squared) | 31.4<br>(0.0000) |

Notes: The standard errors for the estimated coefficients are derived from the outer product of gradients (OPG) and reported as OPG standard errors. See discussion in StataCorp (2011, pp. 82–83). The autoregressive conditional heteroscedasticity is controlled with the GARCH (1, 1) model; it estimates the error variance to be $\sigma_t^2 = 0.00173 + 0.959\varepsilon_{t-1}^2 + 0.0652\sigma_{t-1}^2$. The lagged squared innovation is the most important term; its two-tailed $p$-value is 0.122.

The estimated coefficient for the flow of new research capital per unit of output is the estimate for ∂Q/∂K, the annual rate of return to research capital. Using the estimates in Table 4, the annual rate of return to research capital is estimated to be 0.009 or 9 publications from the addition of $1,000,000 in research capital stock in the NBS era and 0.001 or 1 publication for $1,000,000 increase in the research capital stock in the NIST era. The finding of greater marginal productivity in the NBS era is consistent with the estimate of the rate of technological change using the approach in Link and Scott (2019) that incorporates returns to the extant capital stock in the measure of technological change. However, excluding those returns to the capital stock, with the approach in this paper we see just how important those returns are to the advance of scientific knowledge. With the approach in this paper, the estimated annual rate of change in the shift factor – the measure of technological change – is the estimate of $\dot{A}/A$, and that estimate is −0.76 or −76 percent in the NBS era, and −0.10 or −10 percent in the NIST era. The returns to research capital in the NBS era were higher, and so using the approach in this paper and removing those returns from the impact of technological change as it is measured with the approach in Link and Scott (2019) reduces the measured technological change by much more in the NBS era than in the NIST era.

In the approach of Link and Scott (2019), measured technological change includes the effects from the use of the extant research capital stock to recognize the fact that those effects are necessarily technological change, as in the example of the use of a microscope in scientific research in note 2. Including in the production function's annual shift factor the effects of using the research capital stock existing prior to the new expenditures for additions to that stock, in the earlier paper the annual rate of change in the shift factor was 0.0105 or 1.05 percent on average over the 36 years observed, averaging 0.056 or 5.6 percent in the first 15 years of the sample in the NBS era and −0.022 or −2.2 percent in the last 21 years covering the NIST era. In contrast, the present paper's approach isolates the shift factor in the relationship between all inputs and their effect on the knowledge output (rather than the relationship between just the new flows of inputs and their effect on the output as in the earlier paper), and the result is that the annual rate of change in the shift factor is strongly negative. The earlier approach emphasizes that technological change in the creation of new science comes from using extant research capital; the current approach emphasizes that the process of creating new science from the research capital stock has required increasing amounts of scarce resources.

## 5. New scientific knowledge as the output of a parsimonious production function of the stock of scientific knowledge

As a check on our basic finding that there has been a strong negative shift in the knowledge production function, we estimate one more model. Rather than breaking down NIST's total research expenditures into the expenditures for new research capital and the expenditures for scientific labor services, we consider the total of those expenditures in each year as adding to the stock of scientific knowledge and denote that stock of knowledge as $R$. The knowledge production function is $Q = A(t)f(R)$.

Using the 'dot' notation for time derivatives, observe that

$$\frac{\dot{Q}}{Q} = \frac{\dot{A}}{A} + s_R \frac{\dot{R}}{R}, \tag{7}$$

where $s_R$ is the elasticity of research output with respect to the stock of scientific knowledge. Thus,

$$s_R = \frac{\partial Q}{\partial R}\frac{R}{Q}. \tag{8}$$

Then, again following Terleckyj (1974), substitute for $s_R$ using (8), to have

$$\frac{\dot{Q}}{Q} = \frac{\dot{A}}{A} + \frac{\partial Q}{\partial R}\frac{\dot{R}}{Q}. \tag{9}$$

Assuming that for a good approximation we can ignore the depreciation in the scientific knowledge stock, we can use the observed flow of new research expenditures, $R^+$, as the value for $\dot{R}$. To estimate the rate of technological change in the knowledge production function, $\dot{A}/A$, we use the estimated intercept for the estimation of the equation

$$\frac{\dot{Q}}{Q} = \frac{\dot{A}}{A} + \frac{\partial Q}{\partial R}\frac{R^+}{Q}. \tag{10}$$

Table 5 provides the OLS estimates for Equation (10) using the NIST new scientific publications data for 1973 through 2008 as provided in Table 1. The test statistics show that there is no first order autocorrelation, but that there is autoregressive conditional heteroscedasticity. To address the ARCH effects a GARCH model is fitted in Table 6.

**Table 5.** Ordinary Least Squares (OLS) Regression Estimation of Equation (10) for New Scientific Publications: Dependent Variable $\dot{Q}/Q$, $n = 36$.

| **Variable** | **Coefficient (standard error) [probability > \|t\|]** |
|---|---|
| *dNIST* | .502 (0.274)[0.076] |
| $R^+/Q$ | .00251 (0.000611) [0.000] |
| $(dNIST) \times (R^+/Q)$ | −0.00185 (0.000932) [0.055] |
| Constant | −0.669 (0.183) [0.001] |
| F(3, 32)<br>(probability > $F$) | 6.35<br>(0.0017) |
| $R^2$ | 0.373 |
| Durbin-Watson d-statistic (4, 36) | 2.08 |

| Variable | Coefficient (standard error) [probability > \|t\|] |
|---|---|
| Durbin's alternative test for autocorrelation:<br>Chi-squared (1)<br>(probability > chi-squared) | <br>0.172<br>(0.678) |
| LM test for ARCH:<br>Chi-squared (1)<br>(probability > chi-squared) | <br>9.70<br>(0.0018) |

**Table 6.** Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Estimation of Equation (10) for New Scientific Publications: Dependent Variable $\dot{Q}/Q$, $n = 36$.

| Variable | Coefficient (standard error) [probability > \|t\|] |
|---|---|
| *dNIST* | 0.588 (0.245) [0.016] |
| $R^+/Q$ | 0.00272 (0.000715) [0.000] |
| $(dNIST) \times (R^+/Q)$ | −0.00199 (0.000798) [0.013] |
| Constant | −0.789 (0.221) [0.000] |
| Wald chi-squared (3)<br>(probability > chi-squared) | 19.0<br>(0.0003) |

Notes: The standard errors for the estimated coefficients are derived from the outer product of gradients (OPG) and reported as OPG standard errors. See discussion in StataCorp (2011, pp. 82–83). The autoregressive conditional heteroscedasticity is controlled with the GARCH (1, 1) model; it estimates the error variance to be $\sigma_t^2 = 0.000289 + 0.771\varepsilon_{t-1}^2 + 0.311\sigma_{t-1}^2$. The lagged squared innovation term has the biggest effect; its two-tailed *p*-value is 0.137. The lagged variance term is also important; its two-tailed *p*-value is 0.090.

The estimated coefficient for the flow of new research expenditures per unit of output is the estimate for $\partial Q/\partial R$, the annual rate of return to the stock of scientific knowledge. Using the estimates in Table 6, the annual rate of return to the knowledge stock is estimated to be 0.00272 or 27 publications from the addition of $10,000,000 in knowledge stock in the NBS era and 0.000734 or 7.3 publications for $10,000,000 increase in the knowledge stock in the NIST era. The estimated annual rate of change in the shift factor – the measure of technological change – is the estimate of $\dot{A}/A$, and that estimate is −0.789 or −78.9 percent in the NBS era, and −0.201 or −20.1 percent in the NIST era. The results are consistent for what we observe in the earlier model (6) that decomposes the research inputs into research capital and scientific labor services.

## 6. Concluding observations

The estimate of a strongly negative rate of change in the shift factor that captures technological change in the knowledge production function is consistent with the prediction of de Solla Price (1963) that there would be a breakdown in the overall process of creating new science as science inevitably ceases its exponential growth.[13] The estimate is also consistent with the evidence, such as in Bloom et al. (2017), that the productivity of scientific research in the United States has declined in recent decades.

Gordon (2016) has placed the slowdown in economic growth in the context of a richly detailed history that describes the growth of knowledge and implications for the growth of the U.S. economy from the second half of the nineteenth century into the twenty-first century. Jones

[13] The prediction of de Solla Price (1963) and its relation to the estimation of technological change in the knowledge production function are discussed in detail in Link and Scott (2019).

(2009) observes that as knowledge has grown it takes longer for potential inventors to learn about the discoveries that have already been made and reach the frontier of knowledge. Consequently, those working with science and technology specialize and must combine their knowledge with the knowledge of other specialists to create new knowledge by means of resource-devouring teamwork. Other things being the same, the growth of knowledge and economic growth become more costly. To Gordon's (2016) insightful history and Jones' (2009) thoughtful analysis of the productivity-reducing implications of the burden of knowledge, we add cliometric evidence by estimating a knowledge generation function to provide case study evidence of the decline in productivity in the production of scientific and technological knowledge.[14]

While productivity in the process of creating new science has declined when measured in terms of the increasing resource costs to achieve given amounts of output when that output is measured with metrics such as the number of publications, observing the outstanding examples – such as the CRISPR story – of progress in science, one can argue that current progress in science is very rapid.[15] Nonetheless, although one can reasonably say that we are in a period of rapid progress in science even as the conventional productivity measures show a pronounced downturn, the productivity decline is a concern, because with the right policies substantial amounts of scarce resources could potentially be saved with no diminishing of the progress of science. That is extraordinarily important because continued exponential growth in the scarce resources devoted to science is clearly not possible.

We have examined the evidence about the shifts in the knowledge production function for a federal laboratory. However, using our 'second look' methodology, technological change in the production of new knowledge could be documented for the research conducted by many different types of research institutions, whether federal laboratories, universities, private for-profit firms, or various types of nonprofit research institutions. Also, the methodology could be applied to different measures of knowledge – for example, citation-weighted counts of publications, or altogether different measures such as invention disclosures. Documenting the changing shift factor and hence technological change in the production of new science, and then developing understanding of the circumstances for progress in the process of creating new science, could lead to new policies to strengthen the performance of research to develop science and technology.[16] The need for such policies would seem to be urgent given this paper's strongly negative estimate for the rate of change in the shift factor for the knowledge production function

[14] One referee observed that our knowledge production function approach clearly delineates relationships among measures of knowledge output, inputs of research capital and scientific labor, and the total factor productivity in the production of new knowledge. The referee contrasted our approach with the approach in Bloom et al. (2017) that, for a variety of areas of knowledge, directly compares the growth rate in knowledge output over time with the research effort over time. The approaches differ, but both indicate a dramatic increase in the resources used to achieve gains in knowledge.
[15] For the CRISPR story, see Lander (2016) and Doudna and Sternberg (2017). For the view that science is not slowing down, see Guzey (2019). In the context of this paper, perhaps at the same time that more scarce resources are needed per publication, the quality of the publications, or at least a critical set of them, is increasing.
[16] Critiques of current policy are numerous and vary greatly in their perspectives and recommendations; for example, see Kealey (1996) and Firestein (2016).

– a finding that supports the view that the process of creating new scientific knowledge is in crisis.[17]

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[17] Taking the findings about publications at face value suggests a productivity crisis. However, there are other types of scientific output that result because of NIST's R&D budget – invention disclosures, patents, conferences and seminars and workshops, calibration services, standard reference data and materials, participation in documentary standards committees, and so forth. Of course, all of these other outputs will, to various extents, be associated with academic publications, but the approach of using scientific publications as the measure of output will be less good if there is variance in the mix of types of scientific output over time.

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## Appendix 1

In this appendix, we show that the essential results of our estimation of Equation (6) also obtain with alternative specifications (1) to control for the unusual behavior of the NIST publications time series as publications plunged from 1983 to 1984 and then rebounded to trend in 1985, and then (2) to estimate the elasticity of output with respect to labor rather than imposing the restriction that it equals labor's share.

Table A1 corresponds to Table 3; the specification in Table A1 adds a qualitative variable, *d838485*, that equals 1 in each of the years 1983, 1984, and 1985, and is zero otherwise. The variable controls for the years with the unexplained plunge in publications and the rebound to trend. The estimates and their significance change only very slightly from the estimates in Table 3.

**Table A1.** Ordinary Least Squares (OLS) Regression Estimation of Equation (6) for New Scientific Publications, with *d838485*: Dependent Variable $\dot{Q}/Q - s_L(\dot{L}/L)$, $n = 36$.

| **Variable** | **Coefficient (standard error) [probability > \|t\|]** |
|---|---|
| *dNIST* | 0.743 (0.232) [0.003] |
| $K^{+}/Q$ | 0.0111 (0.00235) [0.000] |
| $(dNIST) \times (K^{+}/Q)$ | −0.00992 (0.00262) [0.001] |
| *d838485* | −0.0117 (0.0803) [0.885] |
| Constant | −0.862 (0.197) [0.000] |
| $F(4, 31)$<br>(probability > $F$) | 6.54<br>(0.0006) |
| $R^2$ | 0.458 |
| Durbin-Watson d-statistic (5, 36) | 2.15 |
| Durbin's alternative test for autocorrelation:<br>Chi-squared (1)<br>(probability > chi-squared) | <br>0.460<br>(0.498) |
| LM test for ARCH:<br>Chi-squared (1)<br>(probability > chi-squared) | <br>6.06<br>(0.0139) |

Table A2 corresponds to Table 4. Given the significance of the test for autoregressive conditional heteroscedasticity as shown in Table A1, Table A2 shows the GARCH model for the new specification in Table A1. There are only slight changes in the coefficients and their significance.

**Table A2.** Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Estimation of Equation (6) for New Scientific Publications, with *d838485*: Dependent Variable $\dot{Q}/Q - s_L(\dot{L}/L)$, $n = 36$.

| **Variable** | **Coefficient (standard error) [probability > \|t\|]** |
|---|---|
| *dNIST* | 0.588 (0.206) [0.004] |
| $K^{+}/Q$ | 0.00849 (0.00219) [0.000] |
| $(dNIST) \times (K^{+}/Q)$ | −0.00754 (0.00228) [0.001] |
| *d838485* | −0.0682 (0.0670) [0.309] |
| Constant | −0.686 (0.194) [0.000] |

| Variable | Coefficient (standard error) [probability > \|t\|] |
|---|---|
| Wald chi-squared (4)<br>(probability > chi-squared) | 30.4<br>(0.0000) |

Notes: The standard errors for the estimated coefficients are derived from the outer product of gradients (OPG) and reported as OPG standard errors. See discussion in StataCorp (2011, pp. 82–83). The autoregressive conditional heteroscedasticity is controlled with the GARCH (1, 1) model; it estimates the error variance to be $\sigma_t^2 = 0.00204 + 0.974\varepsilon_{t-1}^2 + 0.00397\sigma_{t-1}^2$. The lagged squared innovation is the most important term; its two-tailed $p$-value is 0.112.

Table A3 changes the basic specification. Instead of assuming that the elasticity of output with respect to labor is approximated by labor's share and estimating Equation (6), the specification in Table A3 estimates the elasticity by including the labor growth rate on the right-hand side of the estimating equation. In other words, the product of labor's share and labor's growth rate is added to both sides of Equation (6) to have a new estimating equation that regresses the rate of growth in output on the variables used in Table A1 plus additionally the growth rate in labor. Constant returns to scale is not assumed, and the elasticity of output with respect to labor is estimated by the unconstrained model. As before, we allow the coefficients to vary across the NBS era and the NIST era. The results for the previously estimated coefficients and their significance are very similar to what we see in the constrained model. The estimated elasticity of output with respect to labor is strongly negative during the NBS era when the rate of growth in the shift factor for the knowledge production function was strongly negative; the estimated elasticity is 0.57 during the NIST era (almost as large as labor's share during that era).

**Table A3.** Ordinary Least Squares (OLS) Regression Estimation Unconstrained Model for New Scientific Publications: Dependent Variable $\dot{Q}/Q$, $n = 36$.

| Variable | Coefficient (standard error) [probability > \|t\|] |
|---|---|
| *dNIST* | 0.801 (0.218) [0.001] |
| $K^+/Q$ | 0.0121 (0.00222) [0.000] |
| $(dNIST) \times (K^+/Q)$ | −0.0111 (0.00247) [0.000] |
| $\dot{L}/L$ | −1.83 (0.958) [0.067] |
| $(dNIST) \times (\dot{L}/L)$ | 2.40 (1.12) [0.042] |
| *d838485* | −0.0846 (0.0794) [0.295] |
| Constant | −0.909 (0.184) [0.000] |
| $F(6, 29)$<br>(probability > $F$) | 5.76<br>(0.0005) |
| $R^2$ | 0.544 |
| Durbin-Watson d-statistic (7, 36) | 2.29 |
| Durbin's alternative test for autocorrelation:<br>Chi-squared (1)<br>(probability > chi-squared) | 1.460<br>(0.227) |
| LM test for ARCH:<br>Chi-squared (1)<br>(probability > chi-squared) | 2.63<br>(0.105) |

Notes: The LM test for autoregressive conditional heteroscedasticity is not significant at the 10% level, although it is almost so. Moreover, and probably because the ARCH test is not significant, the GARCH model cannot be fitted in any case; the estimation of the model will not converge, and so after many iterations and alternative algorithms, Stata reports 'flat log likelihood encountered, cannot find uphill direction'.