

Are Ideas Getting Harder to Find?

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Abstract

In many growth models, economic growth arises from people creating ideas, and the long-run growth rate is the product of two terms: the effective number of researchers and the research productivity of these people. We present a wide range of evidence from various industries, products, and firms showing that research effort is rising substantially while research productivity is declining sharply. A good example is Moore's Law. The number of researchers required today to achieve the famous doubling every two years of the density of computer chips is more than 75 times larger than the number required in the early 1970s. Across a broad range of case studies at various levels of (dis)aggregation, we find that ideas — and in particular the exponential growth they imply — are getting harder and harder to find. Exponential growth results from the large increases in research effort that offset its declining productivity.

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1. Introduction

The basic insight of this paper can be explained with a simple equation, highlighting a stylized view of economic growth that emerges from idea-based growth models:

$$\begin{array}{rcccl}
 \text{Economic} & & & & \\
 \text{growth} & = & \text{Idea TFP} & \times & \text{Number of} \\
 \text{e.g. 2\% or 5\%} & & \downarrow(\text{falling}) & & \text{researchers} \\
 & & & & \uparrow(\text{rising})
 \end{array}$$

Economic growth arises from people creating ideas, and the long-run growth rate is the product of two terms: the effective number of researchers and the research productivity of these people (“idea TFP”). We present a wide range of empirical evidence showing that in many different contexts and at various levels of disaggregation, research effort is rising substantially, while research productivity is declining sharply. Steady growth, when it occurs, results from the offsetting of these two trends.

Perhaps the best example of this finding comes from studying Moore’s Law, one of the key drivers of economic growth in recent decades. This “law” refers to the empirical regularity that the number of transistors packed onto a computer chip doubles approximately every two years. Such doubling corresponds to a constant exponential growth rate of around 35% per year, a rate that has been remarkably steady for nearly half a century. As we show in detail below, this growth has been achieved by putting an ever-growing number of researchers to work on pushing Moore’s Law forward. In particular, the number of researchers required to achieve the doubling of chip density today is more than 75 times larger than the number required in the early 1970s. At least as far as semiconductors are concerned, ideas are getting harder and harder to find. Idea TFP in this case is declining sharply, at a rate that averages about 10% per year.

We document qualitatively similar results essentially no matter where we look in the U.S. economy. We consider detailed microeconomic evidence on idea production functions, focusing on places where we can get the best measures of both the output of ideas and the inputs used to produce them. In addition to Moore’s Law, our case studies include agricultural productivity (corn, soybeans, cotton, and wheat) and medical innovations. Idea TFP for seed yields declines at about 5% per year. We find a similar rate of decline when studying the mortality improvements associated with cancer and heart disease. Finally, we examine firm-level data from Compustat to provide another

perspective on idea TFP. While the data quality from this sample is not as good as for our industry case studies, the latter suffer from possibly not being representative. We find substantial heterogeneity across firms, but idea TFP is declining in more than 85% of the firms in our sample. Averaging across firms, idea TFP declines at a rate of around 10% per year.

Perhaps idea TFP is declining sharply within every particular case that we look at and yet not declining for the economy as a whole. While existing varieties run into diminishing returns, perhaps new varieties are always being invented to stave this off. We consider this possibility by taking it to the extreme. Suppose each variety has a productivity that cannot be improved at all, and instead aggregate growth proceeds entirely by inventing new varieties. To examine this case, we consider idea TFP for the economy as a whole. We once again find that it is declining sharply: aggregate growth rates are relatively stable over time,¹ while the number of researchers has risen enormously. In fact, this is simply another way of looking at the original point of Jones (1995), and for this reason, we present this application first to illustrate our methodology. We find that idea TFP for the aggregate U.S. economy has declined by a factor of 41 since the 1930s, an average decrease of more than 5% per year.

Despite these large declines in idea TFP, relatively stable exponential growth is common in the cases we study (and in the aggregate U.S. economy). How is this possible? Looking back at the equation that began the introduction, declines in idea TFP must be offset by increased research effort, and this is indeed what we find. Moreover, we suggest at the end of the paper that the rapid declines in idea TFP that we see in semiconductors, for example, might be precisely due to the fact that research effort is rising so sharply. Because it gets harder to find new ideas as research progresses, a sustained and massive expansion of research like we see in semiconductors (for example, because of the “general purpose technology” nature of information technology), may lead to a substantial downward trend in idea TFP.

Others have also provided evidence suggesting that ideas may be getting harder to

¹There is a debate over whether the slower rates of growth over the last decade are a temporary phenomenon due to the global financial crisis, or a sign of slowing technological progress. Gordon (2016) argues that the strong US productivity growth between 1996 and 2004 was a temporary blip and that productivity growth will, at best, return to the lower growth rates of 1973–1996. Although we do not need to take a stance on this, note that if frontier TFP growth really has slowed down, this only strengthens our argument.

find over time. Griliches (1994) provides a summary of the earlier literature exploring the decline in patents per dollar of research spending. Gordon (2016) reports extensive new historical evidence from throughout the 19th and 20th centuries. Cowen (2011) synthesizes earlier work to explicitly make the case. (Ben) Jones (2009) documents a rise in the age at which inventors first patent and a general increase in the size of research teams, arguing that over time more and more learning is required just to get to the point where researchers are capable of pushing the frontier forward. We see our evidence as complementary to these earlier studies but more focused on drawing out the tight connections to growth theory.

The remainder of the paper is organized as follows. Section 2 lays out our conceptual framework and presents the aggregate evidence on idea TFP to illustrate our methodology. Section 3 places this framework in the context of growth theory and suggests that applying the framework to micro data is crucial for understanding the nature of economic growth. Sections 4 through 7 consider our applications to Moore’s Law, agricultural yields, medical technologies, and Compustat firms. Section 8 then revisits the implications of our findings for growth theory, and Section 9 concludes.

2. Idea TFP and Aggregate Evidence

2.1. The Conceptual Framework

An equation at the heart of many growth models is an idea production function taking a particular form:

$$\frac{\dot{A}_t}{A_t} = \alpha S_t. \tag{1}$$

Classic examples include Romer (1990) and Aghion and Howitt (1992), but many recent papers follow this approach, including Aghion, Akcigit and Howitt (2014), Acemoglu and Restrepo (2016), Akcigit, Celik and Greenwood (2016), and Jones and Kim (2014). In the equation above, \dot{A}_t/A_t is total factor productivity growth in the economy. The variable S_t (think “scientists”) is some measure of research input, such as the number of researchers. This equation then says that the growth rate of the economy — through the production of new ideas — is proportional to the number of researchers.

Relating \dot{A}_t/A_t to ideas runs into the familiar problem that ideas are hard to mea-

sure. Even as simple a question as “What are the units of ideas?” is troublesome. We follow much of the literature — including Aghion and Howitt (1992), Grossman and Helpman (1991), and Kortum (1997) — and define ideas to be in units so that a constant flow of new ideas leads to constant exponential growth in A . For example, each new idea raises incomes by a constant percentage (on average), rather than by a certain number of dollars. This is the standard approach in the quality ladder literature on growth: ideas are proportional improvements in productivity. The patent statistics for most of the 20th century are consistent with this view; indeed, this was a key piece of evidence motivating Kortum (1997). This definition means that the left hand side of equation (1) corresponds to the flow of new ideas.

We can now define the productivity of the idea production function, which we call “idea TFP,” as the ratio of the output of ideas to the inputs used to make them:

$$\text{Idea TFP} := \frac{\dot{A}_t/A_t}{S_t} = \frac{\# \text{ of new ideas}}{\# \text{ of researchers}}. \quad (2)$$

The null hypothesis tested in this paper comes from the relationship assumed in (1). Substituting this equation into the definition of idea TFP, we see that (1) implies that idea TFP equals α — that is, idea TFP is constant over time. This is the standard hypothesis in much of the growth literature. Under this null, a constant number of researchers can generate constant exponential growth.

The reason this is such a common assumption is also easy to see in equation (1). With constant idea TFP, a research subsidy that increases the number of researchers permanently will permanently raise the growth rate of the economy. In other words “constant idea TFP” and the fact that sustained research subsidies produce “permanent growth effects” are equivalent statements.² This clarifies a claim in the introduction: testing the null hypothesis of constant idea TFP is interesting in its own right but also because it is informative about the kind of models that we use to study economic growth. The finding that idea TFP is declining virtually everywhere we look poses problems for a large class of endogenous growth models. Moreover, the way we

²The careful reader may wonder about this statement in richer models — for example, lab equipment models where research is measured in goods rather than in bodies or models with both horizontal and vertical dimensions to growth. These extensions will be incorporated below in such a way as to maintain the equivalence between “constant idea TFP” and “permanent growth effects.”

have defined ideas gives this concept economic relevance: exponential growth (e.g. in semiconductor density or seed yields or living standards) is getting harder to find.

2.2. Aggregate Evidence

The bulk of the evidence presented in this paper concerns the extent to which a constant level of research effort can generate constant exponential growth within a relatively narrow category, such as a firm or a seed type or Moore's Law or a health condition. We provide consistent evidence that the historical answer to this question is no: idea TFP is declining at a substantial rate in virtually every place we look.

This finding raises a natural question, however. What if there is sharply declining idea TFP *within* each product line, but the main way that growth proceeds is by developing ever-better new product lines? First there was steam power, then electric power, then the internal combustion engine, then the semiconductor, then gene editing, and so on. Maybe there is limited opportunity within each area for productivity improvement and long-run growth occurs through the invention of entirely new areas. Maybe idea TFP is declining within every product line, but still not declining for the economy as a whole because we keep inventing new products. An analysis focused on microeconomic case studies would never reveal this to be the case.

The answer to this concern turns out to be straightforward and is an excellent place to begin. First, consider the extreme case where there is no possibility at all for productivity improvement in a product line and all productivity growth comes from adding new product lines. Of course, this is just the original Romer (1990) model itself, and to generate constant idea TFP in that case requires the equation we started the paper with:

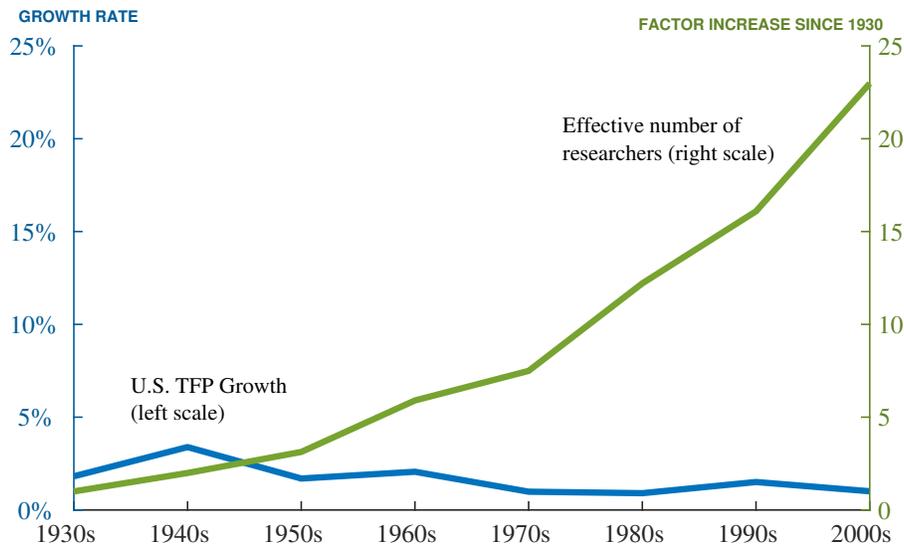
$$\frac{\dot{A}_t}{A_t} = \alpha S_t. \quad (3)$$

In this interpretation, A_t represents the number of product varieties and S_t is the aggregate number of researchers. Even with no ability to improve productivity within each variety, a constant number of researchers can sustain exponential growth if the variety-discovery function exhibits constant idea TFP.

This hypothesis, however, runs into an important well-known problem.³ For the U.S. economy as a whole, exponential growth rates in GDP per person since 1870 or in

³For example, see Jones (1995).

Figure 1: Aggregate Data on Growth and Research Effort

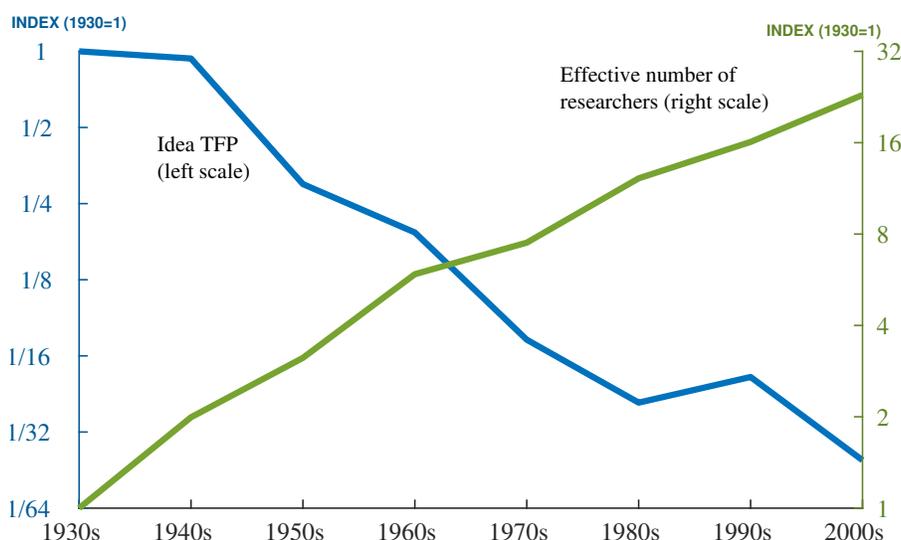


Note: The idea output measure is TFP growth, by decade (and for 2000-2014 for the latest observation). For the years since 1950, this measure is the BLS Private Business Sector multifactor productivity growth series, adding back in the contributions from R&D and IPP. For the 1930s and 1940s, we use the measure from Robert Gordon (2016). The idea input measure is gross domestic investment in intellectual property products from the National Income and Product Accounts, deflated by a measure of the nominal wage for high-skilled workers.

total factor productivity since the 1930s — which are related to the left side of equation (3) — are relatively stable or even declining. But measures of research effort — the right side of the equation — have grown tremendously. When applied to the aggregate data, our approach of looking at “idea TFP” is just another way of making this same point.

To illustrate the approach, we use the decadal averages of TFP growth to measure the “output” of the idea production function. For the input, we use the NIPA measure of investment in “intellectual property products,” a number that is primarily made up of research and development spending but also includes expenditures on creating other nonrival goods like computer software, music, books, and movies. As explained further below, we deflate this input by a measure of the average annual earnings for people with 4 or more years of college so that it measures the “effective” number of researchers that the economy’s R&D spending could purchase. These basic data are shown in Figure 1.

Figure 2: Aggregate Evidence on Idea TFP



Note: Idea TFP is the ratio of Idea Output, measured as TFP growth, to research effort. See notes to Figure 1. Both idea TFP and research effort are normalized to the value of 1 in the 1930s.

Figure 2 shows idea TFP and this measure of research effort by decade. Since the 1930s, research effort has risen by a factor of 23 — an average growth rate of 4.3 percent per year. Idea TFP has fallen by an even larger amount — by a factor of 41 (or at an average growth rate of -5.1 percent per year). By construction, a factor of 23 of this decline is due to the rise in research effort and so less than a factor of 2 is due to the well-known decline in TFP growth.

The “new economy” of the 1990s exhibited a bounceback of TFP growth that was even larger than the increase in research in that decade, resulting in a slight increase in idea TFP between the 1980s and 1990s. But the overall trend is clear. For example, between the 1960s and the 2000s, idea TFP fell by a factor of 8.0. And between the 1980s and the 2000s, it fell by a factor of 1.7, with the entire amount due to rising research effort.

This aggregate evidence could be improved on in many ways. One might question the TFP growth numbers — how much of TFP growth is due to innovation versus reallocation or declines in misallocation? One might seek to include international research in the input measure. But reasonable variations along these lines would not change the

basic point of Figure 2: a model in which economic growth arises from the discovery of newer and better varieties with limited possibilities for productivity growth *within* each variety exhibits sharply-declining idea TFP. If one wishes to maintain the hypothesis of constant idea TFP, one must look elsewhere. It is for this reason that the literature — and this paper — turns to the micro side of economic growth.

3. Refining the Conceptual Framework

In this section, we further develop the conceptual framework introduced in the previous section. First, we explain why the aggregate evidence just presented can be misleading, motivating our focus on micro data. Second, we consider the measurement of idea TFP when the input to research is R&D expenditures (i.e. “goods”) rather than just bodies or researchers (i.e. “time”). Finally, we discuss various extensions to our calculation of idea TFP.

3.1. The Importance of Micro Data

The null hypothesis that idea TFP is constant over time is attractive conceptually in that it leads to models in which changes in policies related to research can permanently affect the growth rate of the economy. Several papers, then, have proposed alternative models in which the calculations using aggregate data can be misleading about idea TFP. The insight of Dinopoulos and Thompson (1998), Peretto (1998), Young (1998), and Howitt (1999) is that the aggregate evidence may be masking important heterogeneity, and that idea TFP may nevertheless be constant for a significant portion of the economy. Perhaps the idea production function *for individual products* shows constant idea TFP. The aggregate numbers may simply capture the fact that every time the economy gets larger we add *more products*, so the aggregate calculation mismeasures idea TFP.⁴

To see the essence of the argument, suppose that the economy produces N_t different products, and each of these products is associated with some quality level A_{it} . Innovation can lead the quality of each product to rise over time according to an idea

⁴This line of research has been further explored by Aghion and Howitt (1998), Li (2000), Laincz and Peretto (2006), Dinopoulos and Syropoulos (2007), Ha and Howitt (2007), Kruse-Andersen (2016), and Peretto (2016a; 2016b).

production function,

$$\frac{\dot{A}_{it}}{A_{it}} = \alpha S_{it}. \quad (4)$$

Here, S_{it} is the number of scientists devoted to improving the quality of good i , and in a symmetric case, we might have $S_{it} = \frac{S_t}{N_t}$. The key is that the aggregate number of scientists S_t can be growing, but perhaps the number per product S_t/N_t is not growing. This can occur in equilibrium if the number of products itself grows endogenously at the right rate. In this case, the aggregate evidence discussed earlier would not tell us anything about the idea production functions associated with the quality improvements of each variety. Instead, aggregation masks the true constancy of idea TFP at the micro level.

This insight provides one of the key motivations for the present paper: to study the idea production function at the micro level. That is, we study equation (4) directly and consider idea TFP for individual products:

$$\text{Idea TFP: } iTFP_{it} := \frac{\dot{A}_{it}/A_{it}}{S_{it}}. \quad (5)$$

By considering micro evidence, we can directly test the key hypothesis underlying a large portion of endogenous growth theory.

3.2. “Lab Equipment” Specifications

In many applications, the input that we measure is R&D expenditures rather than the number of researchers. In fact, one could make the case that this is a more desirable measure, in that it weights the various research inputs according to their relative prices: if expanding research involves employing people of lower talent, this will be properly measured by R&D spending. When the only input into ideas is researchers, then deflating R&D expenditures by an average wage will appropriately recover the effective quantity of researchers. In practice, R&D expenditures also typically involve spending on capital goods and materials. As explained next, deflating by the nominal wage to get an “effective number of researchers” that this research spending could purchase remains a good way to proceed.

In the growth literature, these specifications are called “lab equipment” models, because implicitly both capital and labor are used as inputs to produce ideas. In lab

equipment models, the endogenous growth case occurs when the idea production function takes the form

$$\dot{A}_t = \alpha R_t, \quad (6)$$

where R_t is measured in units of a final output good. For the moment, we discuss this issue in the context of a single-good economy; in the next section, we explain how the analysis extends to the case of multiple products.

To see why equation (6) delivers endogenous growth, it is necessary to specify the economic environment more fully. First, suppose there is a final output good that is produced with a standard Cobb-Douglas production function:

$$Y_t = K_t^\theta (A_t L)^{1-\theta}. \quad (7)$$

Next, the resource constraint for this economy is

$$Y_t = C_t + I_t + R_t \quad (8)$$

That is, final output is used for consumption, investment in physical capital, or research.

We can now combine these three equations to get the endogenous growth result. First, notice that dividing both sides of the production function for final output by Y_t^θ and rearranging yields

$$Y_t = \left(\frac{K_t}{Y_t} \right)^{\frac{\theta}{1-\theta}} A_t L. \quad (9)$$

Then, letting $s_t := R_t/Y_t$ denote the share of the final good spent on research, the idea production function in (6) can be expressed as

$$\dot{A}_t = \alpha R_t = \alpha s_t Y_t = \alpha s_t \left(\frac{K_t}{Y_t} \right)^{\frac{\theta}{1-\theta}} A_t L. \quad (10)$$

And rearranging gives

$$\frac{\dot{A}_t}{A_t} = \underbrace{\alpha \left(\frac{K_t}{Y_t} \right)^{\frac{\theta}{1-\theta}}}_{\text{idea TFP}} \times \underbrace{s_t L}_{\text{"scientists"}} \quad (11)$$

It is now easy to see how this setup generates endogenous growth. Along a bal-

anced growth path, the capital-output ratio K/Y will be constant, as will the research investment share s_t . If we assume there is no population growth, then equation (11) delivers a constant growth rate of total factor productivity in the long-run. Moreover, a permanent increase in the R&D share s will permanently raise the growth rate of the economy.

Looking back at the idea production function in (6), the question is then how to define idea TFP there. The answer is both intuitive and simple: we deflate the R&D expenditures R_t by the wage to get a measure of “effective scientists.” Letting $w_t = \bar{\theta}Y_t/L_t$ be the wage for labor in this economy, (6) can be written as

$$\frac{\dot{A}_t}{A_t} = \frac{\alpha w_t}{A_t} \times \frac{R_t}{w_t}. \quad (12)$$

Importantly, the two terms on the right-hand side of this equation will be constant along a balanced growth path in a standard endogenous growth model. It is easy to see that $\tilde{S}_t := \frac{R_t}{w_t} = \frac{R_t}{Y_t} \cdot \frac{Y_t}{w_t} = s_t L / \bar{\theta}$. And of course w_t/A_t is also constant along a BGP.

In other words, if we deflate R&D spending by the economy’s wage rate, we get \tilde{S}_t , a measure of the number of researchers the R&D spending could purchase. Of course, research labs spend on other things as well, like lab equipment and materials, but the theory makes clear how \tilde{S}_t is a useful measure for constructing idea TFP. Hence we will refer to \tilde{S}_t as “effective scientists” or “research effort.”

The idea production function in (12) can then be written as

$$\frac{\dot{A}_t}{A_t} = \tilde{\alpha}_t \tilde{S}_t \quad (13)$$

where both $\tilde{\alpha}_t$ and \tilde{S}_t will be constant in the long run under the null hypothesis of endogenous growth. We can therefore define idea TFP in the lab equipment setup in a way that parallels our earlier treatment:

$$\text{Idea TFP: } iTFP_t := \frac{\dot{A}_t/A_t}{\tilde{S}_t}. \quad (14)$$

The only difference is that we deflate R&D expenditures by a measure of the nominal wage to get \tilde{S} . Under the null hypothesis of endogenous growth, this measure of idea TFP should be constant in the long run (and would only vary outside the long-run

because of changes in the capital-output ratio).

An easy intuition for (14) is this: endogenous growth requires that a constant population — or a constant number of researchers — be able to generate constant exponential growth. Deflating R&D spending by the wage puts the R&D input in units of “people” so that constant idea TFP is equivalent to the null hypothesis of endogenous growth.

Equation (12) above also makes clear why deflating R&D spending by the wage is important. If we did not and instead naively computed idea TFP by dividing \dot{A}_t/A_t by R_t , we would find that idea TFP would be falling because of the rise in A_t , even in the endogenous growth case. In other words, this naive approach to idea TFP would not really correspond to anything economically useful. Economic theory suggests deflating by the research wage in order to get a meaningful concept of idea TFP, in this case, one that corresponds to an important hypothesis in the growth literature.

As a measure of the nominal wage in our empirical applications, we use mean personal income from the Current Population Survey for males with a Bachelor’s degree or more of education.⁵ This approach means that researchers of heterogeneous quality are combined according to their relative wages. For example, if the best researchers are hired first and subsequent researchers are less talented, the additional researchers will be given a lower weight in our research measure. The potential depletion of research talent is then appropriately incorporated in our empirical approach.

3.3. Heterogeneous Goods and the Lab Equipment Specification

In the previous two subsections, we discussed (i) what happens if idea TFP is only constant within each product while the number of products grows and (ii) how to define idea TFP when the input to research is measured in goods rather than bodies. Here, we explain how to put these two together.

Among the very first models that used both horizontal and vertical research to neutralize scale effects, only Howitt (1999) used the lab-equipment approach. In that pa-

⁵These data are from Census Tables P18 and P19, available at <http://www.census.gov/topics/income-poverty/income/data/tables.html>. Prior to 1991, we use the series for “4 or more years of college.” For years between 1939 and 1967, we use the series Bc845 from the Historical Statistics for the U.S. Economy, Millennial Edition. Finally, for the aggregate idea TFP calculation in Figure 1, we require a deflator from the 1930s. We extrapolate the college earnings series backward into the 1930s using nominal GDP per person for this purpose.

per, it turns out that the method we have just discussed — deflating R&D expenditures by the economy’s average wage — works precisely as explained above. That is, idea TFP for each product should be constant if one divides the growth rate by the effective number of researchers working to improve that product.⁶ This is true more generally in these horizontal/vertical models of growth whenever product variety grows at the same rate as the economy’s population. Peretto (2016a) cites a large literature suggesting that this is the case: product variety and population scale together over time and across countries.⁷ The two previous subsections then merge together very naturally.

3.4. Stepping on Toes

One other potential modification to the idea production function that has been considered in the literature is a duplication externality. For example, perhaps the idea production function depends on S_t^λ , where λ is less than one. Doubling the number of researchers may less than double the production of new ideas because of duplication or because of some other source of diminishing returns.

We could incorporate this effect into our analysis explicitly but choose instead to focus on the benchmark case of $\lambda = 1$ for three reasons. First and foremost, our measurement of research effort already incorporates a market-based adjustment for the depletion of talent: R&D spending weights workers according to their wage, and less talented researchers will naturally earn a lower salary. If more of these workers are hired over time, R&D spending will not rise by as much. Second, adjusting for λ only affects the magnitude of the trend in idea TFP, but not the overall qualitative fact of whether or not there is a downward trend. It is easy to deflate the growth rate of research effort by whatever value of λ you’d like to get a sense for how this matters;

⁶The main surprise in confirming this observation is that w_t/A_{it} is constant. In particular, w_t is proportional to output per worker, and one might have expected that output per worker would grow with A_t (an average across varieties) but also with N_t , the number of varieties. However, this turns out not to be the case: Howitt includes a fixed factor of production (like land), and this fixed factor effectively eats up the gains from expanding variety. More precisely, the number of varieties grows with population while the amount of land per person declines with population, and these two effects exactly offset.

⁷Building on the preceding footnote, it is worth also considering Peretto (2016b) in this context. Like Howitt, that paper has a fixed factor and for some parameter values, his setup also leads to constant idea TFP. For other parameter values (e.g. if the fixed factor is turned off), the wage w_t grows both because of quality improvements and because of increases in variety. Nevertheless, deflating by the wage is still a good way to test the null hypothesis of endogenous growth: in that case, idea TFP *rises* along an endogenous growth path. So the finding below that idea TFP is declining is also relevant in this broader framework.

cutting our growth rates in half — an extreme adjustment — would still leave the nature of our results unchanged. Third, one might expect a “short-run” value of λ to differ from its “long-run” value. For example, the duplication and talent depletion effects could certainly apply if we tried to double the amount of research in a given year. However, to the extent that the increase occurs gradually over time, one might expect these effects to be mitigated. Finally, there is no consensus on what value of λ one should use — Kremer (1993) even considers the possibility that it might be larger than one because of network effects. Appendix A shows the robustness of the main results in the paper to this assumption by considering the case of $\lambda = 3/4$, for example.

The remainder of the paper applies this framework in a wide range of different contexts: Moore’s Law for semiconductors, agricultural crop yields, pharmaceutical innovation and mortality, and then finally at the firm level using Compustat data. Our consistent finding everywhere we’ve looked is that idea TFP is declining at a substantial rate over long periods of time.

4. Moore’s Law

One of the key drivers of economic growth during the last half century is Moore’s Law: the empirical regularity that the number of transistors packed onto an integrated circuit serving as the central processing unit for a computer doubles approximately every two years. Figure 3 shows this regularity back to 1971. The log scale of this figure indicates the overall stability of the relationship, dating back nearly fifty years, as well as the tremendous rate of growth that is implied. Related formulations of Moore’s Law involving computing performance per watt of electricity or the cost of information technology could also be considered, but the transistor count on an integrated circuit is the original and most famous version of the law, so we use that one here.⁸

A doubling time of two years is equivalent to a constant exponential growth rate of 35 percent per year. While there is some discussion of Moore’s Law slowing down in recent years (there always seems to be such discussion!), we will take the constant exponential growth rate as corresponding to a constant flow of new ideas back to 1971. That is, we assume the output of the idea production for Moore’s Law is a stable 35

⁸See the Wikipedia entry at https://en.wikipedia.org/wiki/Moores_law.

percent per year. Other alternatives are possible. For example, we could use decadal growth rates or other averages, and some of these approaches will be employed later in the paper. However, from the standpoint of understanding steady, rapid exponential growth for nearly half a century, the stability implied by the straight line in Figure 3 is a good place to start. And any slowing of Moore's Law would only reinforce the finding we are about to document.⁹

If the output side of Moore's Law is constant exponential growth, what is happening on the input side? Many commentators note that Moore's Law is not a law of nature but is instead a result of intense research effort: doubling the transistor density is often viewed as a goal or target for research programs. We measure research effort by deflating nominal R&D expenditures of key semiconductor firms by the nominal wage of high-skilled workers, as discussed above. Our semiconductor R&D series, from Compustat data, sums research spending by Intel, Fairchild, National Semiconductor, Motorola, Texas Instruments, and a number of other semiconductor firms and equipment manufacturers.¹⁰

The striking fact, shown in Figure 4, is that research effort has risen by a factor of 78 since 1971. This massive increase occurs while the growth rate of chip density is more or less stable: the constant exponential growth implied by Moore's Law has been achieved only by a staggering increase in the amount of resources devoted to pushing the frontier forward.

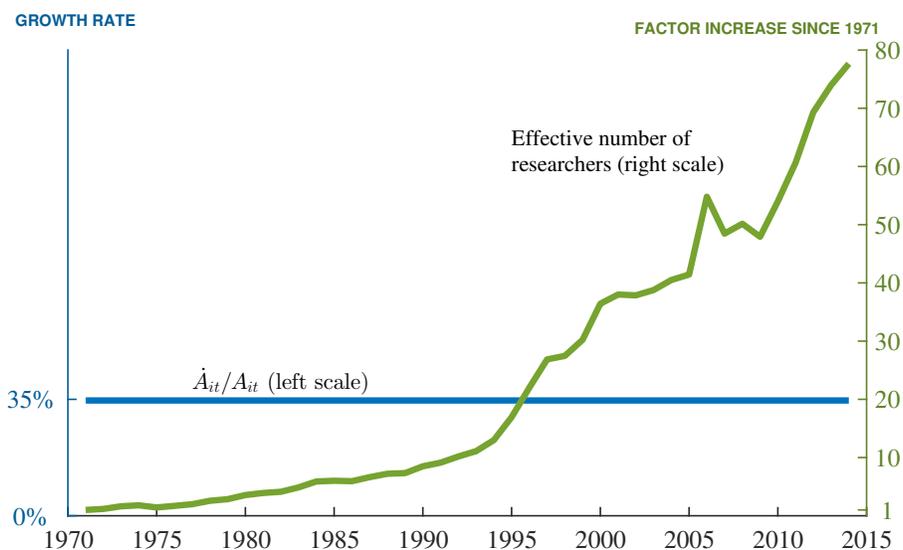
Assuming a constant growth rate for Moore's Law, the implication is that idea TFP has fallen by this same factor of 78, an average rate of 10.1 percent per year. If the null hypothesis of constant idea TFP were correct, the growth rate underlying Moore's Law should have increased by a factor of 78 as well. Instead, it was remarkably stable. Put differently, because of declining idea TFP, it is *around 78 times* harder today to generate the exponential growth behind Moore's Law than it was in 1971.

Table 1 reports the robustness of this result to various assumptions about which R&D expenditures should be counted. No matter how we measure R&D spending, we see a large increase in effective research and a corresponding large decline in idea TFP. Even by the most conservative measure in the table, idea TFP falls by a factor of 25

⁹For example, there is a recent shift away from speed and toward energy-saving features; see Flamm (forthcoming). However, our analysis still applies historically.

¹⁰We are grateful to Unni Pillai for his collaboration in constructing the semiconductor research series; see Pillai (2016). More details are provided in Table 1 below.

Figure 4: Data on Moore's Law



Note: The effective number of researchers is measured by deflating nominal R&D expenditures by key semiconductor firms by the average wage of high-skilled workers. The R&D spending used is the sum of research by Intel, Fairchild, National Semiconductor, Texas Instruments, Motorola, and a number of other semiconductor firms and equipment manufacturers; see Table 1 for more details.

between 1971 and 2014.

The null hypothesis at the heart of many endogenous growth models — the constancy of idea TFP — is resoundingly rejected in the case of Moore's Law. The rise of information technology is an integral part of economic growth in recent decades. One might have expected this rapidly-growing sector to be one of the more natural places to find support for this aspect of endogenous growth theory. Instead, it provides one of the sharpest critiques.

4.1. Caveats

Now is a good time to consider what could go wrong in our idea TFP calculation at the micro level. Mismeasurement on both the output and input sides are clearly a cause for concern in general. However, there are two specific measurement problems that are worth considering in more detail. First, suppose there are “spillovers” from other sectors into the production of new ideas related to semiconductors. For example,

Table 1: Idea TFP Results for Moore’s Law, 1971–2014

R&D measure	Factor increase	Average growth	Implied half-life of idea TFP
Baseline	78	10.1%	6.8
(a) Narrow (no equipment)	25	7.5%	9.2
(b) Broad (no equipment)	44	8.8%	7.9
(c) Broad + equipment	89	10.4%	6.6
(d) Intel only	1265	16.6%	4.2
(e) Intel+AMD	1382	16.8%	4.1

Note: The R&D measures are based on Compustat data assembled in collaboration with Unni Pillai; see <https://sunypoly.edu/research/econ-technology/data/>. The baseline measure, called “Moore-Narrow” by Pillai, sums research spending by Intel, Fairchild, National Semiconductor, Qualcomm, and a number of other semiconductor firms and equipment manufacturers (both in the U.S. and abroad); it also includes 21% of Motorola’s research spending and 50% of Texas Instruments’ spending, reflecting the fact that these firms were heavily involved in other products (TVs and calculators, for example). Other measures are (a) which excludes research by semiconductor equipment manufacturers; (b) which includes more firms such as Broadcom, Applied Materials, and Nvidia; (c) the broader set of firms plus research by semiconductor equipment manufacturers, called “Moore-Broad” by Pillai; (d) Intel only; (e) Intel plus AMD, the two companies that appear most often in the basic Moore’s Law graph shown in Figure 3. In private communication to us, Pillai recommended measure (c) to us, while noting that it might overstate research growth slightly (for example because it omits research by large firms like AT&T and IBM). To be conservative, we report the slightly narrower measure as our baseline. We are currently working on using patent data to decompose the R&D spending of many large firms to recover their semiconductor-related efforts. These firms include AT&T, IBM, Toshiba, NEC, Fuji, Hitachi, Sanyo, General Electric, Raytheon, RCA, Philips, Siemens, Mitsubishi, Matsushita, and Samsung.

progress in a completely different branch of materials science may lead to a new idea that improves computer chips. Such positive spillovers are not a problem for our analysis since they would show up as an *increase* in idea TFP rather than as the declines that we document in this paper.¹¹

A type of measurement error that could cause our findings to be misleading is if we systematically understate R&D in early years and this bias gets corrected over time. In the case of Moore's Law, we are careful to include research spending by firms that are no longer household names, like Fairchild Camera and Instrument (later Fairchild Semiconductor) and National Semiconductor so as to minimize this bias: for example, in 1971, Intel's R&D was just 2.7 percent of our estimate for semiconductor R&D in that year. Throughout the paper, we try to be as careful as we can with measurement issues, but this type of problem must be acknowledged.

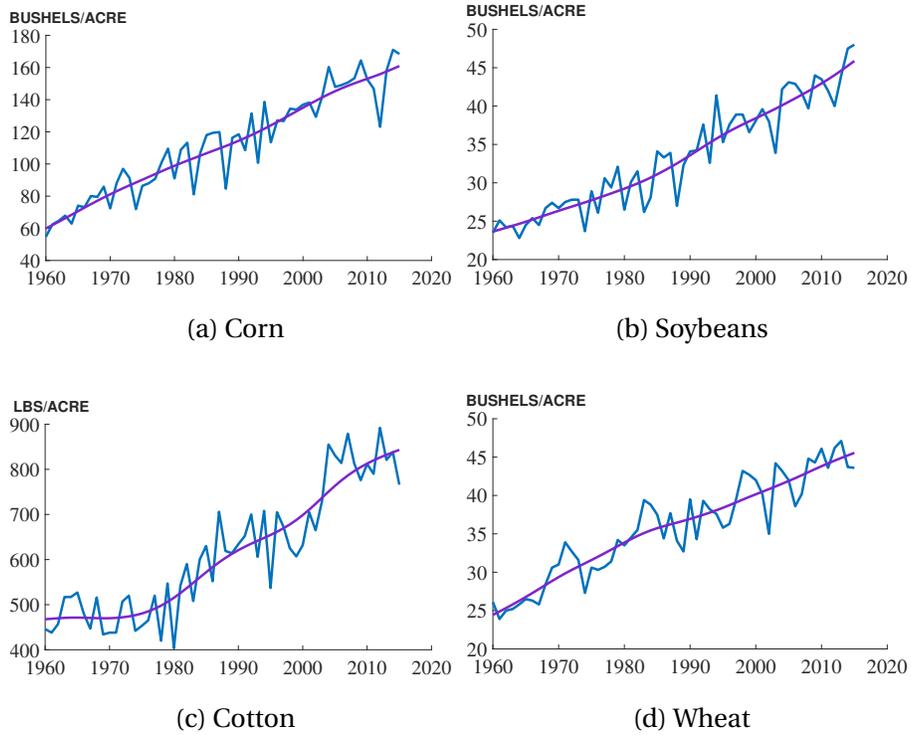
5. Agricultural Crop Yields

Our next application for measuring idea TFP examines the evolution of crop yields for various crops over time. Due partly to the historical importance of agriculture in the economy, crop yields and agricultural R&D spending are relatively well-measured for various crops. For each of corn, soybeans, cotton, and wheat, we measure ideas as crop yields, and research inputs as R&D expenditure directed at improving those yields. Crop R&D is generally broken down into research on biological efficiency (cross-breeding and bioengineering), mechanization, management, protection and maintenance, and post-harvest (see, for example, Huffman and Evenson (2006)). We count research on biological efficiency and protection and maintenance as the portion devoted to improving crop yields. Figure 5 shows these measures for our four crops back to the 1960s.¹²

¹¹If such spillovers were larger at the start of our time period than at the end, we could be underestimating the impact of semi-conductor R&D on productivity growth. We do not know of evidence suggesting this.

¹²For our measure of ideas, we use the national realized yields series for each crop available from the U.S. Department of Agriculture National Agricultural Statistics Service (2016). Our measure of R&D inputs consists of the sum of R&D spending by the public and private sectors in the U.S. Data on private sector biological efficiency and crop protection R&D expenditures are from an updated USDA series based on Fuglie et al. (2011), with the distribution of expenditure by crop taken from Perrin et al. (1983), Fernandez-Cornejo et al. (2004), Traxler et al. (2005), Huffman and Evenson (2006), and University of York (2016). Data on U.S. public sector R&D expenditure by crop are from the U.S. Department of Agriculture National Institute of Food and Agriculture Current Research Information System (2016) and Huffman and Evenson

Figure 5: U.S. Crop Yields



Note: Smoothed yields are computed using an HP filter with a smoothing parameter of 400.

The figure show yields for each crop, measured in bushels or pounds harvested per acre planted. These correspond to average yields realized on U.S. farms. They are therefore subject to many influences, including choice of inputs and random shocks. These shocks, especially adverse weather and pest events, tend to have asymmetric effects: adverse events cause much larger reductions in yields than favorable events increase them, as indicated by the many large one-year reductions followed by recoveries in the figure (see Huffman, Jin and Xu (2016)). Nevertheless, yields across these four crops roughly doubled between 1960 and 2015.

Figure 6 shows the annualized average 5-year growth rate of yields (after smoothing to remove shocks mostly due to weather). Yield growth has averaged around 1.5 percent per year since 1960 for these four crops, but with ample heterogeneity. These 5-year growth rates serve as our measure of idea output in studying the idea production function for seed yields.

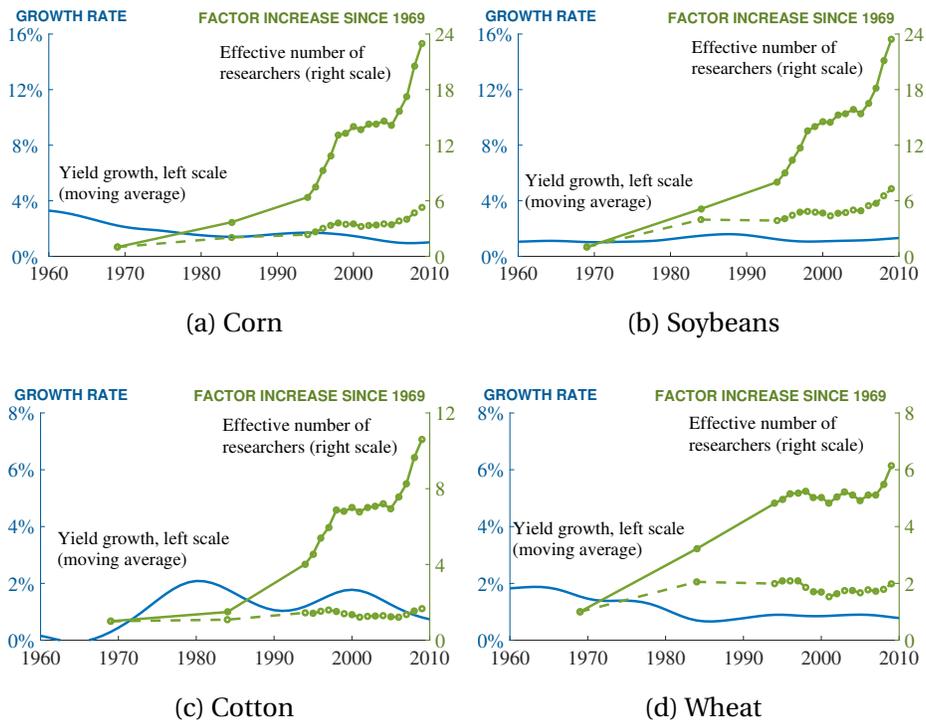
The green lines in Figure 6 show measures of the “effective” number of researchers working on each crop, measured as the sum of public and private R&D spending deflated by the wage of high-skilled workers. Two measures are presented. The faster-rising number corresponds to research targeted only at so-called biological efficiency. This includes cross-breeding (hybridization) and genetic modification directed at increasing yields, both directly and indirectly via improving insect resistance, herbicide tolerance, and efficiency of nutrient uptake, for example. The slower-growing number additionally includes research on crop protection and maintenance, which includes the development of herbicides and pesticides. The effective number of researchers has grown sharply since 1969, rising by a factor that ranges from 3 to more than 25, depending on the crop and the research measure.

It is immediately evident from comparing Figures 6 that idea TFP has fallen sharply for agricultural yields: yield growth is relatively stable or even declining, while the effective research that has driven this yield growth has risen tremendously. Idea TFP is simply the ratio of average yield growth divided by the number of researchers.

Table 2 summarizes the idea TFP calculation for seed yields. As already noted, the effective number of researchers working to improve seed yields rose enormously between 1969 and 2009. For example, the increase was more than a factor of 23 for

(2006), with the distribution of expenditure by research focus taken from Huffman and Evenson (2006).

Figure 6: Yield Growth and Research Effort by Crop



Note: The blue line is the annual growth rate of the smoothed yields over the following 5 years, from Figure 5. The two green lines report “Effective Research”: the solid line is based on R&D targeting seed efficiency only; the dashed line additionally includes research on crop protection. Both are normalized to one in 1969. See footnote 12 for data sources.

Table 2: Idea TFP Results by Crop, 1969–2009

Crop	— Effective research —		— Idea TFP —	
	Factor increase	Average growth	Factor decrease	Average growth
<i>Research on seed efficiency only</i>				
Corn	23.0	7.8%	52.2	-9.9%
Soybeans	23.4	7.9%	18.7	-7.3%
Cotton	10.6	5.9%	3.8	-3.4%
Wheat	6.1	4.5%	11.7	-6.1%
<i>Research includes crop protection</i>				
Corn	5.3	4.2%	12.0	-6.2%
Soybeans	7.3	5.0%	5.8	-4.4%
Cotton	1.7	1.3%	0.6	+1.3%
Wheat	2.0	1.7%	3.8	-3.3%

Note: In the first panel of results, the research input is based on R&D expenditures for seed efficiency only. The second panel additionally includes research on crop protection. R&D expenditures are deflated by a measure of the nominal wage for high-skilled workers.

both corn and soybeans if we restrict attention to seed-yield research narrowly-defined. If yield growth were constant (which is not a bad approximation across the four crops as shown in Figure 6), then idea TFP would on average decline by this same factor. The last 2 columns of Table 2 show this to be the case. On average, idea TFP declines for crop yields by about 6 percent per year using the narrow definition of research and by about 4 percent per year using the broader definition.

6. Mortality and Life Expectancy

Health expenditures account for around 18 percent of U.S. GDP, and a healthy life is one of the most important goods we purchase. Our third collection of industry case studies examines the productivity of medical research.

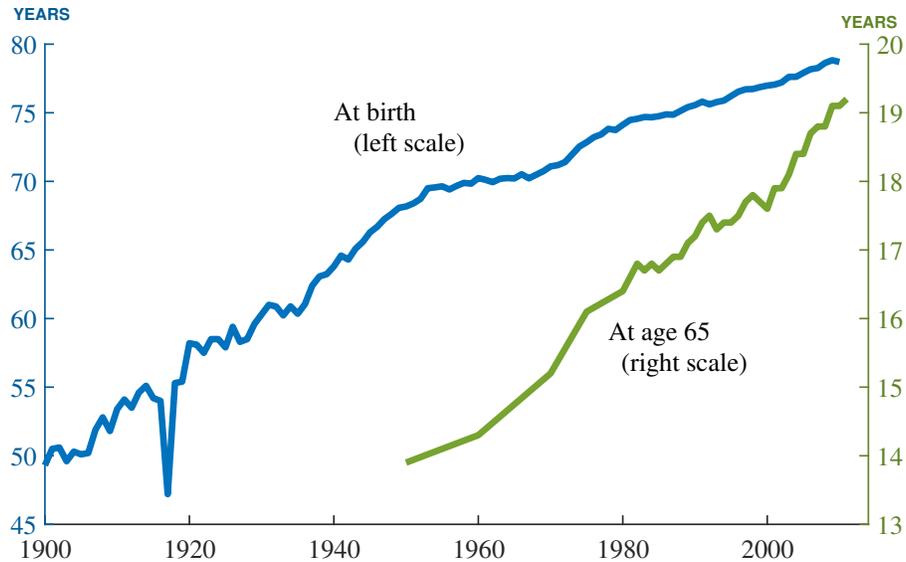
Figure 7 shows U.S. life expectancy at birth and at age 65. This graph makes the important point that life expectancy is one of the few economic goods that does not exhibit exponential growth. Instead, arithmetic growth provides a better description of the time path of life expectancy. Since 1950, U.S. life expectancy at birth has increased at a relatively stable rate of 1.8 years each decade, and life expectancy at age 65 has risen at 0.9 years per decade (see Deaton, 2013).

Also shown in the graph is the well-known fact that overall life expectancy grew even more rapidly during the first half of the 20th century, at around 3.8 years per decade. This raises the question of whether even arithmetic growth is an appropriate characterization. We believe that it is for two reasons. First, there is no sign of a slowdown in the years gained per decade since 1950, either in life expectancy at birth or in life expectancy at age 65. The second reason is a fascinating empirical regularity documented by Oeppen and Vaupel (2002). That paper shows that “record female life expectancy” — the life expectancy of women in the country for which they live the longest — has risen at a remarkably steady rate of 2.4 years per decade ever since 1840. Steady linear increases in life expectancy, not exponential ones, seem to be the norm.

6.1. New Molecular Entities

Our first example from the medical sector is a fact that is well-known in the literature, recast in terms of idea TFP. Figure 8 shows the number of new molecular entities

Figure 7: U.S. Life Expectancy



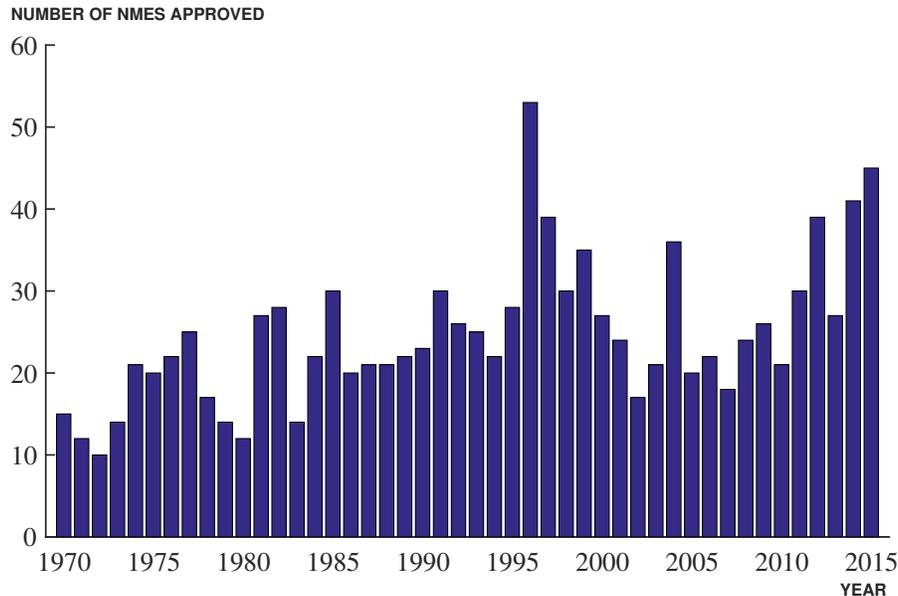
Source: *Health, United States 2013* and <https://www.clio-infra.eu>.

(“NMEs”) approved by the Food and Drug Administration. NMEs are new drugs, including both chemical and biological products, that have been approved by the FDA. Virtually all pharmaceutical advances in the last 50 years show up in these counts (Zambrowicz and Sands, 2003). Famous examples that became commercial blockbuster drugs are Zocor (for cholesterol), Prilosec (for gastroesophageal reflux), Claritin (for allergies), Celebrex (for arthritis), and Taxol (for treating various types of cancer). Only two or three of the NMEs in any given year become commercial successes. Among famous drugs, only morphine and aspirin do not show up in these counts, because their discovery pre-dates the FDA. The flow of NMEs is well-known to show very little trend, although 2014 and 2015 are two of the years with the most approvals.

We obtain data on pharmaceutical R&D spending from the Pharmaceutical Research and Manufacturers of America (Phrma), which has conducted an annual survey of its members back to 1970 and includes R&D performed both domestically and abroad by these companies.¹³ Using the procedures described earlier, we get the idea TFP and effective research numbers shown in Figure 9. Research effort rises by a factor of 9,

¹³A limitation is that it does not include R&D done by foreign companies that is performed abroad. However, Figure 1 of Congressional Budget Office (2006) suggests that this is still a very useful measure.

Figure 8: New Molecular Entities Approved by the FDA



Note: Historical data on NME approvals are from Food and Administration (2013). Data for recent years are taken from Pharmaceutical Research and Manufacturers of America (2016).

while idea TFP falls by a factor of 11 by 2007 before rising in recent years so that the overall decline by 2014 is a factor of 5. Over the entire period, research effort rises at an annual rate of 6.0 percent, while idea TFP falls at an annual rate of 3.5 percent.

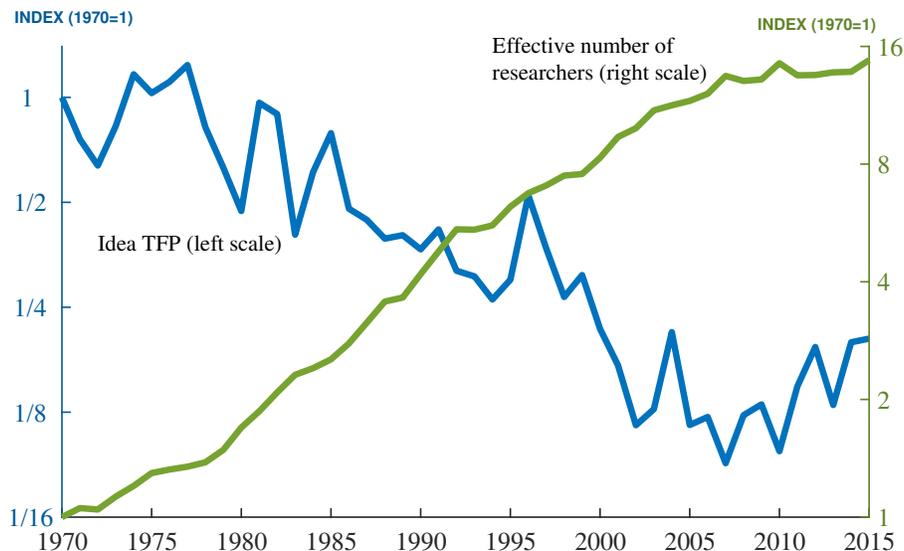
Of course, it is far from obvious that simple counts of NMEs appropriately measure the output of ideas; we'd really like to know how important each innovation is. In addition, the NMEs still suffer from an important aggregation issue, adding up across a wide range of health conditions. These limitations motivate the approach described next.¹⁴

6.2. Mortality

Consider a person who faces two age-invariant Poisson processes for dying, with arrival rates δ_1 and δ_2 . We think of δ_1 as reflecting a particular disease we are studying, such as cancer or heart disease, and δ_2 as capturing all other sources of mortality. The

¹⁴Lichtenberg (2016) provides a complementary approach in using NMEs to measure the output of ideas and their value. He studies NME approvals by cancer site and shows that each new approval is associated with a reduction in years of life lost before age 75 of 2.3%.

Figure 9: Idea TFP for New Molecular Entities



Note: Historical data on NME approvals are from Food and Administration (2013). Data on research spending by the pharmaceutical industry are from the 2010, 2013, and 2016 editions of Pharmaceutical Research and Manufacturers of America (2016).

probability a person lives for at least x years before succumbing to type i mortality is the survival rate $S_i(x) = e^{-\delta_i x}$, and the probability the person lives for at least x years before dying from any cause is $S(x) = S_1(x)S_2(x) = e^{-(\delta_1 + \delta_2)x}$. Life expectancy at age a , $LE(a)$ is then well known to equal

$$LE(a) = \int_0^{\infty} S(x) dx = \int_0^{\infty} e^{-(\delta_1 + \delta_2)x} dx = \frac{1}{\delta_1 + \delta_2}. \quad (15)$$

Now consider how life expectancy changes if the type i mortality rate changes slightly. It is easy to show that the expected years of life saved by the mortality change is

$$dLE(a) = \frac{\delta_i}{\delta_1 + \delta_2} \cdot LE(a) \cdot \left(-\frac{d\delta_i}{\delta_i} \right). \quad (16)$$

That is, the expected years of life saved from a decline in, say, cancer mortality is the product of three terms. First is the fraction of deaths that result from cancer. Second is the average years of life lost if someone dies from cancer at age a , and finally is the percentage decline in cancer mortality.

Vaupel and Canudas-Romo (2003) show that this expression generalizes to a much richer setting. In particular, the expected years of life saved is the product of three terms with the same interpretation. For example, they allow for an arbitrary number of causes of death each of which has a mortality rate that varies arbitrarily with age.¹⁵

As discussed at the start of this section, life expectancy tends to rise linearly. Therefore, constant exponential growth in income per person is associated with constant arithmetic increases in life expectancy, which in the aggregate average 1.8 years per decade in the U.S. We therefore take the quantity described in equation (16) as our measure of the output of ideas associated with declines in mortality for a given disease.¹⁶

The research input aimed at reducing mortality from a given disease is at first bluish harder to measure. For example, it is difficult to get research spending broken down into spending on various diseases. Nevertheless, we think we have a useful solution to this problem: we measure the number of scientific publications in PUBMED that have “Neoplasms,” for example, as a MESH (Medical Subject Heading) term. MESH is the National Library of Medicine’s controlled vocabulary thesaurus.¹⁷ We do this in two ways. Our broader approach (“publications”) uses all publications with the appropriate MESH keyword as our input measure. Our narrower approach (“trials”) further restricts our measure to those publications that according to MESH correspond to a clinical trial. Rather than using scientific publications as an *output* measure, as other studies have done, we use publications and clinical trials as *input* measures to capture research effort aimed at reducing mortality for a particular disease.

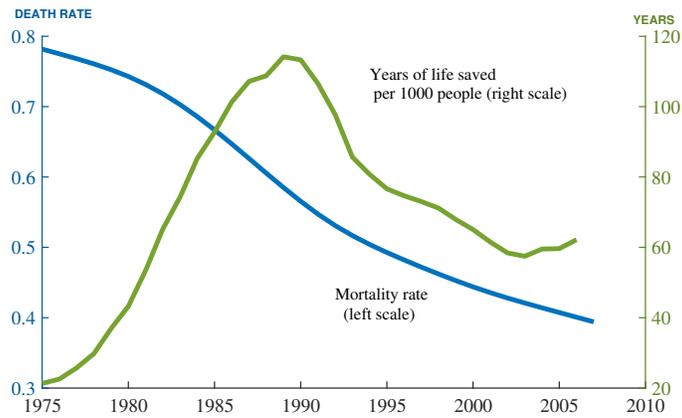
Figure 10 shows our basic “idea output” measures for mortality from all cancers, from breast cancer, and from heart disease. Heart disease and cancer are the top two

¹⁵Their formula involves an extra covariance term as well. In particular, the covariance between the age-specific percentage decline in mortality associated with cancer and the years of life saved at age a when cancer is averted. When the percentage decline in mortality rates is the same across ages, this covariance is zero. More generally, it can differ from zero, but in many of the calculations in their paper, the covariance is small.

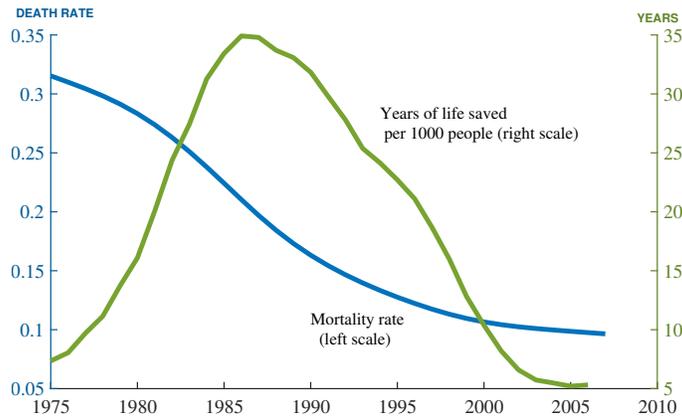
¹⁶Our measures of life expectancy and mortality from all sources by age come from the Human Mortality Database at <http://mortality.org>. To measure the percentage declines in mortality rates from cancer, we use the age-adjusted mortality rates for U.S. women ages 50 and over computed from 5-year survival rates, taken from the National Cancer Institute’s Surveillance, Epidemiology, and End Results program at <http://seer.cancer.gov/>.

¹⁷For more information on MESH, see <https://www.nlm.nih.gov/mesh/>. Our queries of the PUBMED data use the webtool created by the Institute for Biostatistics and Medical Informatics (IBMI) Medical Faculty, University of Ljubljana, Slovenia available at <http://webtools.mf.uni-lj.si/>.

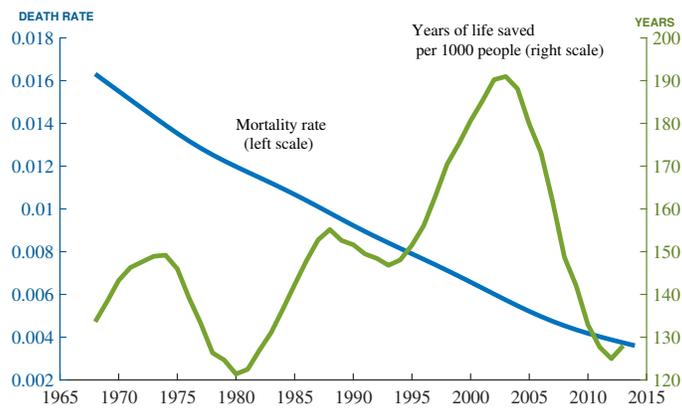
Figure 10: Mortality and Years of Life Saved



(a) All cancers



(b) Breast cancer



(c) Heart Disease

Note: For the two cancer figures, the mortality rate is computed as negative the log of the (smoothed) five-year survival rate for cancer for people ages 50 and higher, from the National Cancer Institute’s Surveillance, Epidemiology, and End Results program at <http://seer.cancer.gov/>. For heart disease, we report the crude death rate in each year for people aged 55–64. The “Years of life saved per 1000 people” is computed using equation (16), as described in the text.

leading causes of death in the United States, and in the spirit of looking as narrowly as possible, we also chose to look at breast cancer mortality. For the two cancer types, we use the 5-year mortality rate conditional on being diagnosed with either type of cancer and see an S-shaped decline since 1975. This translates into a hump-shaped “Years of life saved per 1000 people” — the empirical analog of equation (16) — as the mortality rate first rises and then slows. For example, for all cancers, the years of life saved series peaks around 1990 at more than 100 years of life saved per 1000 people before declining to around 60 years in the 2000s. For heart disease, a substantial part of the decline in deaths comes from people not contracting the disease in the first place, so we focus on the (smoothed) crude death rate for people aged 55 to 64. The death rate declines at different rates in different periods, leading to a series of humps in years of life saved, but overall there is no large trend in this measure of idea output.

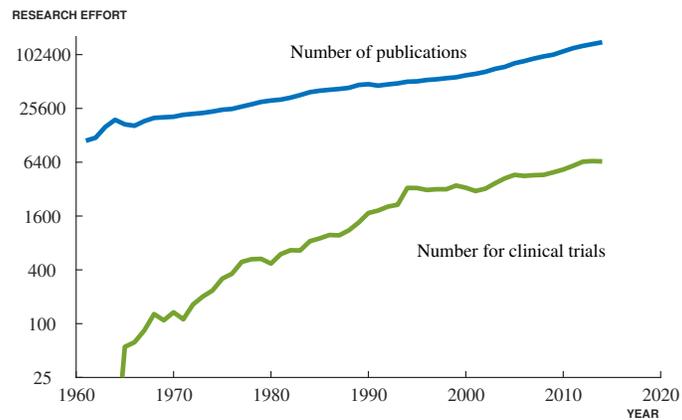
Figure 11 shows our research input measure based on PUBMED publication statistics. Total publications for all cancers increased by a factor of 3.5 between 1975 and 2006 (the years for which we’ll be able to compute idea TFP), while publications restricted to clinical trials increased by a factor of 17.1 during this same period. A similar pattern is seen for research on breast cancer and heart disease.

Idea TFP for our medical research applications is computed as the ratio of years of life saved to the number of publications. Figure 12 shows our idea TFP measures. The hump-shape present in the years-of-life-saved measure carries over here. Idea TFP rises until the mid 1980s and then falls. Overall, between 1975 and 2006, idea TFP for all cancers declines by a factor of 1.2 using all publications and a factor of 4.8 using clinical trials. The declines for breast cancer and heart disease are even larger, as shown in Table 3.

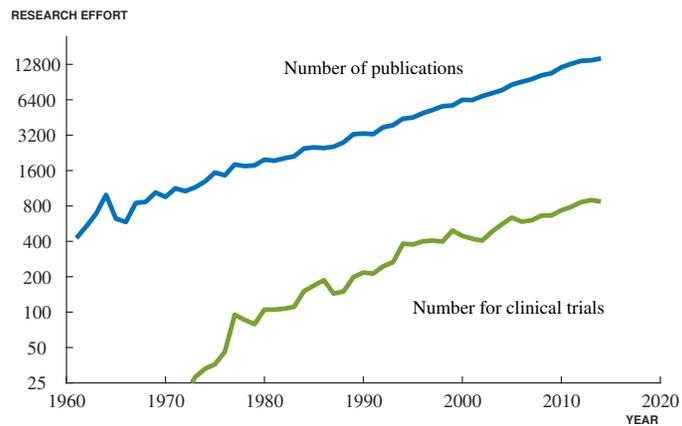
Several general comments about idea TFP for medical research deserve mention. First, for this application, the units of idea TFP are different than what we’ve seen so far. For example, between 1985 and 2006, declining idea TFP means that the number of years of life saved per 100,000 people in the population by each publication of a clinical trial related to cancer declined from more than 8 years to just over one year. For breast cancer, the changes are even starker: from around 16 years per clinical trial in the mid 1980s to less than one year by 2006.

Next, however, notice that the changes were not monotonic if we go back to 1975.

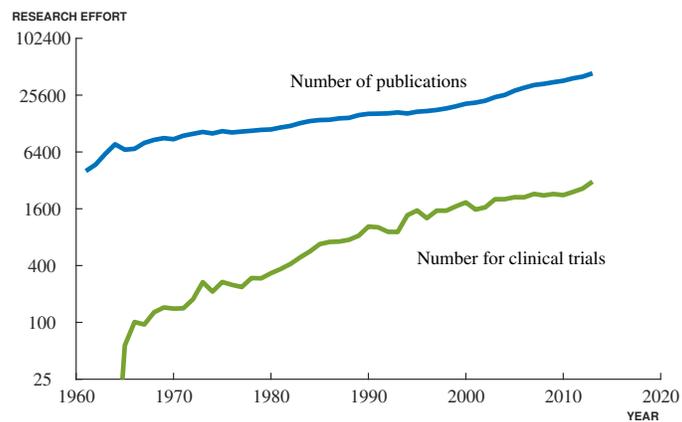
Figure 11: Medical Research Effort



(a) All cancers



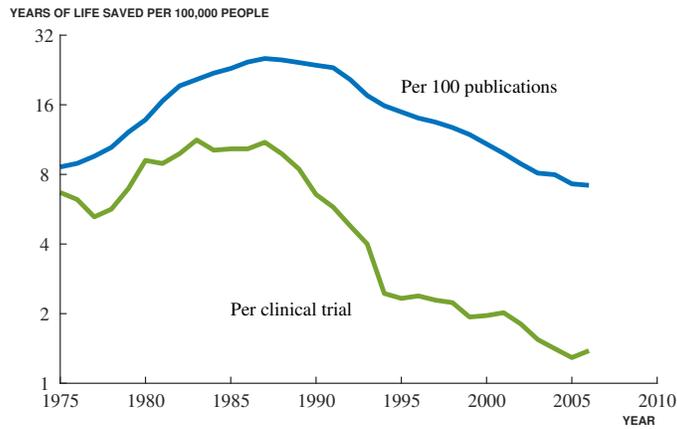
(b) Breast cancer



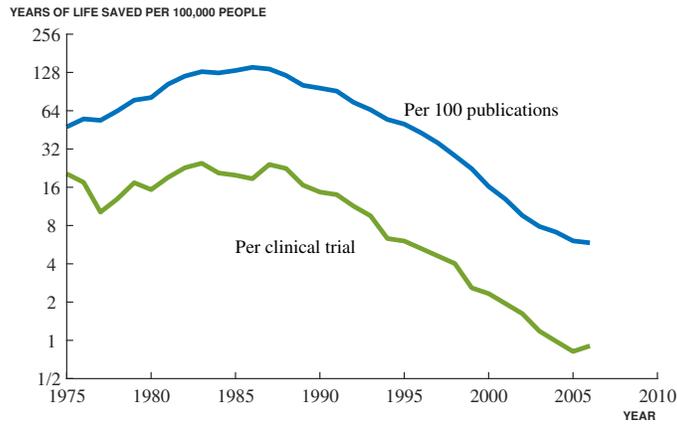
(c) Heart Disease

Note: The number of publications and clinical trials are taken from the PUBMED publications database. For “publications,” the research input is based on all publications in PUBMED with “Neoplasms” or “Breast Neoplasms” or “Heart Diseases” as a MESH keyword. The lines for “clinical trials” restrict further to publications involving clinical trials.

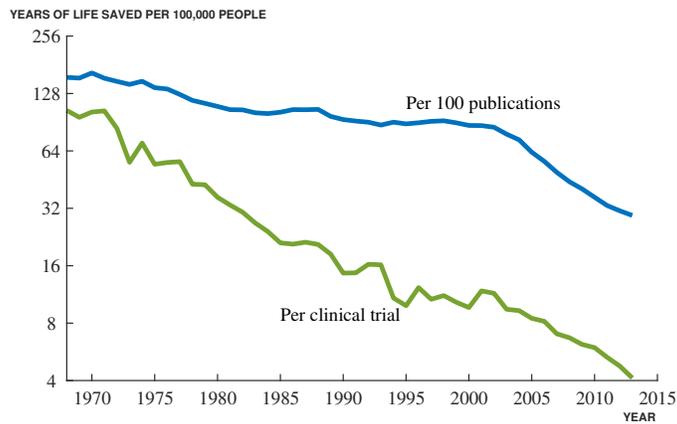
Figure 12: Idea TFP for Medical Research



(a) All cancers



(b) Breast cancer



(c) Heart Disease

Note: Idea TFP is computed as the ratio of years of life saved to the number of publications.

Table 3: Idea TFP Results for Medical Research

Disease	— Effective research —		— Idea TFP —	
	Factor increase	Average growth	Factor decrease	Average growth
<i>All publications</i>				
Cancer, all types	3.5	4.0%	1.2	-0.6%
Breast cancer	5.9	5.7%	8.2	-6.8%
Heart disease	5.1	3.6%	5.3	-3.7%
<i>Clinical trials only</i>				
Cancer, all types	14.1	8.5%	4.8	-5.1%
Breast cancer	16.3	9.0%	22.6	-10.1%
Heart disease	24.2	7.1%	25.3	-7.2%

Note: In the first panel, the research input is based on all publications in PUBMED with “Neoplasms” or “Breast Neoplasms” or “Heart Diseases” as a MESH keyword. The second panel restricts to only publications involving clinical trials. Results for cancer and breast cancer cover the years 1975–2006, while those for heart disease apply to 1968–2011.

Between 1975 and the mid-1980s, idea TFP for these two cancer research categories increased quite substantially. The production function for new ideas is obviously complicated and heterogeneous. These cases suggest that it may get easier to find new ideas at first before getting harder, at least in some areas.

7. Idea TFP in Firm-Level Data

The case studies considered so far are useful for many reasons already explained. However, at the end of the day, they are just case studies, and one naturally wonders how representative they are of the broader economy. In addition, some growth models associate each firm with a different variety: perhaps the number of firms making corn or semiconductor chips is rising sharply, so that research effort per firm is actually constant, as is idea TFP at the firm level. Declining idea TFP for corn or semiconductors could in this view simply reflect a further composition bias.¹⁸

To help address these concerns, we turn to Compustat data on US publicly-traded firms. The strength of these data is that they are more representative than the case studies, but of course they too have limitations. Publicly-traded firms are still a select sample, and our measures of “ideas” and research inputs are likely less precise. However, as a complement to the case studies, we find this evidence helpful.

As a measure of the output of the idea production function, we use decadal averages of annual growth in sales revenue, market capitalization, employment, and revenue labor productivity within each firm. We take the decade as our period of observation to smooth out fluctuations.

Why would growth in sales revenue, market cap, or employment be informative about a firm’s production of ideas? This approach follows a recent literature emphasizing precisely these links. Many papers have shown that news of patent grants for a firm has a large immediate effect on the firm’s stock market capitalization (e.g. Blundell, Griffith and Van Reenen, 1999; Kogan, Papanikolaou, Seru and Stoffman (2015)). Patents are also positively correlated with the firm’s subsequent growth in employment and sales.

¹⁸For example, Peretto (1998) and Peretto (2016b) emphasize this perspective on varieties, while Aghion and Howitt (1992) take the alternative view that different firms may be involved in producing the same variety. Klette and Kortum (2004) allow the number of varieties produced by each firm to be heterogeneous and to evolve over time.

More generally, in models in the tradition of Lucas (1978), Hopenhayn (1992), and Melitz (2003), increases in the fundamental productivity of a firm show up in the long run as increases in sales and firm size, but *not* as increases in sales revenue per worker.¹⁹ This motivates our use of sales revenue or employment to measure fundamental productivity. Hsieh and Klenow (2009) and Garcia-Macia, Hsieh and Klenow (2016) are recent examples of papers that follow a related approach. Of course, in more general models with fixed overhead labor costs, revenue labor productivity (i.e. sales revenue per worker) and TFPR can be related to fundamental productivity (e.g. Bartelsman, Haltiwanger and Scarpetta, 2013). And sales revenue and employment can change for reasons other than the discovery of new ideas. We try to address these issues by also looking at revenue productivity and through various sample selection procedures, discussed below. These problems also motivate the earlier approach of looking at case studies.

To measure the research input, we use a firm's spending on research and development from Compustat. This means we are restricted to firms that report formal R&D, and such firms are well-known to be a select sample (e.g. disproportionately in manufacturing and large). We look at firms since 1980 that report non-zero R&D, and this restricts us to an initial sample of 15,128 firms. Our additional requirements for sample selection in our baseline sample are

1. We observe at least 3 annual growth observations for the firm in a given decade. These growth rates are averaged to form the idea output growth measure for that firm in that decade.
2. We only consider decades in which our idea output growth measure for the firm is positive (negative growth is clearly not the result of the firm innovating, and our framework cannot make sense of negative idea TFP).
3. We require the firm to be observed (for both the output growth measure and the

¹⁹This is obvious when one thinks about the equilibrium condition for the allocation of labor across firms in simple settings: in equilibrium, a worker must be indifferent between working in two different firms, which equalizes wages. But wages are typically proportional to output per worker. Moreover, with Cobb-Douglas production and a common exponent on labor, sales revenue per worker would be precisely equated across firms even if they had different underlying productivities. In a Lucas (1978) span of control setting, more productive firms just hire more workers, which drives down the marginal product until it is equated across firms. In alternative settings with monopolistic competition, it is the price of a particular variety that declines as the firm expands. Regardless, higher fundamental productivity shows up as higher employment or sales revenue, but not in higher sales per employee.

research input measure) for two consecutive decades. Our decades are the 1980s, the 1990s, the 2000s (which refers to the 2000-2007 period), and the 2010s (which refers to the 2010-2015 period); we drop the years 2008 and 2009 because of the financial crisis.

We relax many of these conditions in our robustness checks.

Table 4 shows our idea TFP calculation for various cuts of the Compustat data: using sales revenue, market cap, employment, and revenue labor productivity as our idea output measure and following firms that we observe for two, three, and four decades. In all samples, there is substantial growth in the average number of effective number of researchers within each firm, with growth rates averaging between 2.4% and 8.8% per year. Under our null hypothesis, this rapid growth in research should translate into higher growth rates of firm-level sales and employment with a constant level of idea TFP. Instead, what we see in Table 4 are steady, rapid declines in firm-level idea TFP across all samples, at growth rates that range from -4.2% to -14.5% per year for multiple decades.

Put differently, and reporting the results using sales revenue as a baseline, idea TFP declines by an average factor of 3.9 for firms that we can compare across only two decades, by a factor of 9.2 across firms we can compare across three decades, and by a factor of 40.3 across firms that we can compare across our entire 4 decade sample, between 1980 and 2015.²⁰

Averaging across all our samples, idea TFP falls at a rate of about 9% per year, cumulating to a 2.5-fold decline every decade. At this rate, idea TFP declines by a factor of about 15 over three decades of changes; put differently, it requires 15 times more researchers today than it did 30 years ago to produce the same rate of economic growth.

The next three figures characterize the heterogeneity across firms in our Compustat sample by showing the distribution of the factor changes in effective research and idea TFP across all the firms; to keep things manageable, we focus on the results for sales revenue, but the results with other output measures are similar. Figure 13 shows this distribution for the firms we observe for only two decades, while Figures 14 and 15 shows the distributions for the firms observed for three and four decades.

The heterogeneity across firms is impressive and somewhat reminiscent of the het-

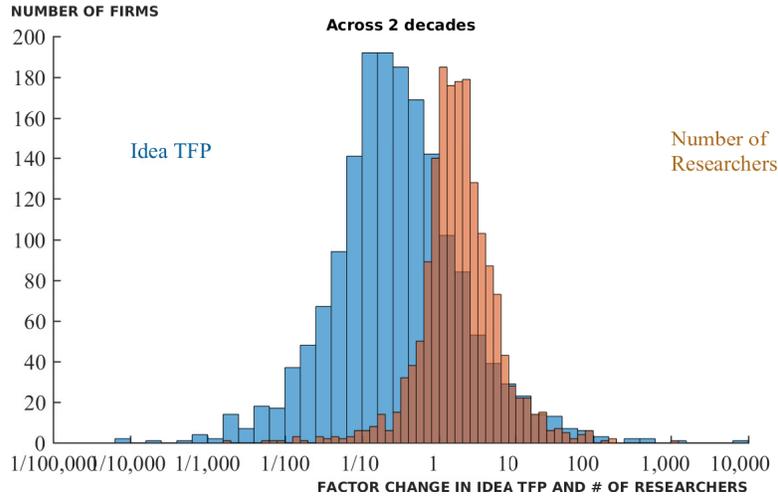
²⁰The averages we report throughout are weighted averages, using the effective number of researchers in each firm as weights.

Table 4: Idea TFP Results using Compustat Firm-Level Data

Sample	— Effective research —		— Idea TFP —	
	Factor increase	Average growth	Factor decrease	Average growth
<i>Sales Revenue</i>				
2 decades (1712 firms)	2.0	6.8%	3.9	-13.6%
3 decades (469 firms)	3.8	6.7%	9.2	-11.1%
4 decades (149 firms)	13.7	8.7%	40.3	-12.3%
<i>Market Cap</i>				
2 decades (1124 firms)	2.2	8.0%	3.4	-12.2%
3 decades (335 firms)	3.1	5.6%	6.3	-9.2%
4 decades (125 firms)	7.9	6.9%	14.0	-8.8%
<i>Employment</i>				
2 decades (1395 firms)	2.2	8.0%	2.8	-10.3%
3 decades (319 firms)	4.0	6.9%	18.2	-14.5%
4 decades (101 firms)	13.9	8.8%	31.5	-11.5%
<i>Revenue Labor Productivity</i>				
2 decades (1444 firms)	1.9	6.4%	2.2	-7.9%
3 decades (337 firms)	1.6	2.4%	2.5	-4.5%
4 decades (109 firms)	2.5	3.1%	3.5	-4.2%

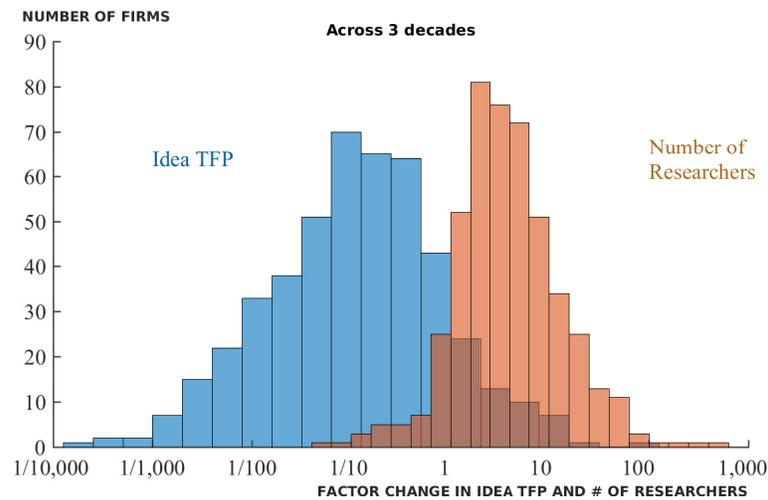
Note: The table shows averages of firm-level outcomes for effective research and idea TFP. Sales Revenue and Market Cap are deflated by the GDP implicit price deflator. Revenue Labor Productivity is deflated Sales Revenue divided by Employment. R&D expenditures are deflated by a measure of the nominal wage for high-skilled workers. The average growth rate across 2 decades is computed by dividing by 10 years (e.g. between 1985 and 1995); others follow this same approach. Averages are computed by weighting firms by the median number of effective researchers in each firm across the decades.

Figure 13: Compustat Distributions, Sales Revenue (2 Decades)



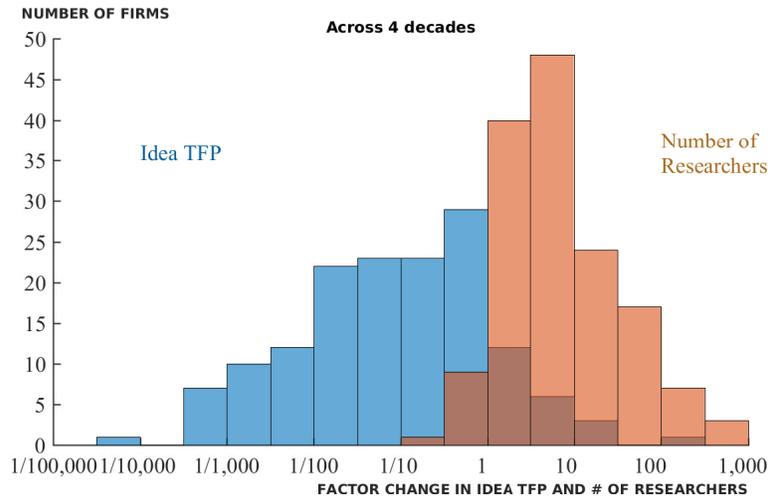
Note: Based on 1712 firms. 22.1% of firms have increasing idea TFP. Only 3.0% have idea TFP that is roughly constant, defined as a growth rate whose absolute value is less than 1% per year.

Figure 14: Compustat Distributions, Sales Revenue (3 Decades)



Note: Based on 469 firms. 11.9% of firms have increasing idea TFP. Only 4.3% have idea TFP that is roughly constant, defined as a growth rate whose absolute value is less than 1% per year.

Figure 15: Compustat Distributions, Sales Revenue (4 Decades)



Note: Based on 149 firms. 14.8% of firms have increasing idea TFP. 4.7% firms in this sample have idea TFP that is roughly constant, defined as a growth rate whose absolute value is less than 1% per year.

erogeneity we see in our case studies. Nevertheless, it is clear from these histograms that there is essentially no evidence that constant idea TFP is a good characterization of the firm-level data. The average, median, and modal firms experience large declines in idea TFP. There is a long tail of firms experiencing even larger declines but also a small minority of firms that see increases in idea TFP. The fraction of firms that exhibit something like constant idea TFP is tiny. For example, less than 5% of firms in any of the histograms have idea TFP changing (either rising or falling) by less than 1% per year on average.

Table 5 provides additional evidence of the robustness of these results. In the interests of brevity, we report these results for the sales revenue output measure for firms that we observe across three decades, but the results for our other output measures and time frames are similar. The first row of the table repeats the benchmark results described earlier. The second and third rows relax the requirement that sales growth is positive. In the second row, we replace all growth rates less than 1% with 1%, while in the third row we additionally windorize an equal number of firms at the top of the growth rate distribution. This increases the sample size considerably and brings the R&D growth numbers down substantially. In both cases, idea TFP falls sharply,

Table 5: Compustat Sales Data across 3 Decades: Robustness

Case	— Effective research —		— Idea TFP —	
	Factor increase	Average growth	Factor decrease	Average growth
Benchmark (469 firms)	3.8	6.7%	9.2	-11.1%
Windsorize $g < .01$ (986 firms)	2.3	4.1%	7.9	10.3%
Windsorize top/bottom (986 firms)	2.3	4.1%	6.0	-8.9%
Research must increase (356 firms)	5.1	8.1%	11.6	-12.3%
Drop if <i>any</i> negative growth (367 firms)	5.6	8.6%	17.9	-14.4%
Median sales growth (586 firms)	3.8	6.6%	6.3	-9.2%
Unweighted averages (469 firms)	3.8	6.7%	9.2	-11.1%

Note: Robustness results reported for the sample of changes across 3 decades. “Windsorize $g < .01$ ” means we replace any idea output measure that is less than 1% annually with a value of 1%. “Windsorize top/bottom” does this same thing but windsorizes an equal number of firms at the top of the idea output distribution. “Research must increase” means we require that the research measure be rising across the decades. “Drop if any negative growth” means we drop firms that have any decade (across our 1980–2015 period) in which average market cap growth is negative. “Median sales growth” uses the median of sales revenue growth in each decade rather than the mean. “Unweighted averages” gives each firm equal weight in computing summary statistics, rather than weighting each firm by its effective number of researchers.

reassuring us that this sample selection criteria is not driving the results. The fourth row imposes the restriction that research is increasing across the observed decades. The fifth row tightens our restrictions and drops firm in which sales revenue declines on average in any decade. The sixth row uses median sales growth in each decade rather than mean sales growth as our output measure. And the last row reports unweighted averages rather than weighting the firms by the effective number of researchers. The general finding of substantial declines in idea TFP is robust.

8. Discussion

The evidence presented in this paper concerns the extent to which a constant level of research effort can generate constant exponential growth, either in the economy as a whole or within relatively narrow categories, such as a firm or a seed type or a health condition. We provide consistent evidence that the historical answer to this

question is no: as summarized in Table 6, idea TFP is declining at a substantial rate in virtually every place we look. The table also provides a way to quantify the magnitude of the declines in idea TFP by reporting the half-life in each case. Taking the aggregate economy number as a representative example, idea TFP declines at an average rate of 5.3 percent per year, meaning that it takes around 13 years for idea TFP to fall by half. Or put another way, the economy has to double its research efforts every 13 years just to maintain the same overall rate of economic growth.

A natural question is whether or not these empirical patterns can be reproduced in a general equilibrium model of growth. One class of models that is broadly consistent with this evidence is the semi-endogenous growth approach of Jones (1995), Kortum (1997), and Segerstrom (1998).²¹ These models propose that the idea production function takes the form

$$\frac{\dot{A}_t}{A_t} = \alpha \frac{S_t}{A_t^\beta} \implies iTFP_t = \frac{\alpha}{A_t^\beta}. \quad (17)$$

Idea TFP declines as A_t rises, so that it gets harder and harder to generate constant exponential growth. The elasticity β governs this process. That is, it measures the extent of dynamic diminishing returns in idea production, with a higher β meaning that idea TFP declines more rapidly as A_t increases.

Comparing both sides of the first equation in (17), one can see that constant exponential growth requires a growing number of researchers S_t . In fact, if \dot{A}_t/A_t is constant over time, it must be that the numerator and denominator of the right-hand side of that equation grow at the same rate. This means that constant exponential growth requires

$$g_A = \frac{g_S}{\beta} \quad (18)$$

where g_x denotes the constant growth rate of any variable x . The growth rate of the economy equals the growth rate of research effort deflated by the extent of diminishing returns in idea production. Rising research effort and declining idea TFP offset — endogenously in this framework — to deliver constant exponential growth.

Finally, this analysis can be applied across different firms, goods, or industries, following the insights of Ngai and Samaniego (2011), who develop a semi-endogenous growth model with heterogeneity in the dynamic spillover parameters of the idea pro-

²¹Jones (2005) provides a broad overview of this class of models.

Table 6: Summary of the Evidence on Idea TFP

Scope	Time Period	Average annual growth rate of idea TFP	Half-life of idea TFP (years)	Extent of Diminishing Returns, β
Aggregate economy	1930–2015	-5.3%	13	3.4
Moore's law (narrow)	1971–2014	-7.5%	9	0.22
Moore's law (baseline)	1971–2014	-10.1%	7	0.29
Corn, version 1	1969–2009	-9.9%	7	7.2
Corn, version 2	1969–2009	-6.2%	11	4.5
Soybeans, version 1	1969–2009	-7.3%	9	6.3
Soybeans, version 2	1969–2009	-4.4%	16	3.8
Cotton, version 1	1969–2009	-3.4%	21	2.5
Cotton, version 2	1969–2009	+1.3%	-55	-0.9
Wheat, version 1	1969–2009	-6.1%	11	6.8
Wheat, version 2	1969–2009	-3.3%	21	3.7
New molecular entities	1970–2015	-3.5%	20	...
Cancer (all), publications	1975–2006	-0.6%	116	...
Cancer (all), trials	1975–2006	-5.7%	12	...
Breast cancer, publications	1975–2006	-6.1%	11	...
Breast cancer, trials	1975–2006	-10.1%	7	...
Heart disease, publications	1968–2011	-3.7%	19	...
Heart disease, trials	1968–2011	-7.2%	10	...
Compustat, sales	3 decades	-11.1%	6	1.1
Compustat, market cap	3 decades	-9.2%	8	0.9
Compustat, employment	3 decades	-14.5%	5	1.8
Compustat, RLP	3 decades	-4.5%	15	1.1

Note: The growth rates of idea TFP are taken from other tables in this paper. The half life is the number of years it takes for idea TFP to fall in half at this growth rate. The last column reports the extent of diminishing returns in producing exponential growth, according to equation (17). This measure is only reported for cases in which the idea output measure is an exponential growth rate (i.e. not for the health technologies, where units would matter).

duction functions. Some goods, like semiconductors, can have rapid productivity growth because their β is small, while other goods like the speed of airplanes or perhaps the education industry itself could have slow rates of innovation because their β is large. Nevertheless, all of these products could exhibit constant exponential growth if the amount of research effort put toward innovation is itself growing exponentially.

This framework helps us to address a phenomenon that might at first have appeared puzzling: idea TFP is declining most rapidly in the fastest growing sector in the economy, semiconductors. Why? In particular, why are we throwing so many resources at a sector that has the sharpest declines in idea TFP?

The last column of Table 6 reports estimates of β for each of our case studies, according to equation (17), and the results speak to the semiconductor puzzle we just highlighted. In particular, semiconductors is the application with the smallest value of β , coming in at 0.29, suggesting that it is the sector with the *least* degree of diminishing returns in idea production: A is growing at 35% per year, while idea TFP is falling at 10% per year. From (17), this implies a value of β of $10/35 \approx 0.3$. In contrast, economy-wide TFP growth averages about 1.5% per year, while idea TFP is declining at a rate of about 5% per year, yielding a β of more than 3! So in fact, semiconductors shows much *less* diminishing returns than the economy as a whole.

Idea TFP for semiconductors falls so rapidly, not because that sector has the sharpest diminishing returns — the opposite is true. It is instead because research in that sector is growing more rapidly than in any other part of the economy, pushing idea TFP down. A plausible explanation for the rapid research growth in this sector is the “general purpose” nature of information technology. Demand for better computer chips is growing so fast that it is worth suffering the declines in idea TFP there in order to achieve the gains associated with Moore’s Law.

One way in which the overall interpretation of the evidence in this paper could be wrong is if there is indeed declining idea TFP in every sector, but the entire increase in aggregate R&D occurs in making quality/productivity improvements for individual varieties. The separate idea production function for producing new varieties could then exhibit constant idea TFP if in fact the research going to create new varieties is not increasing over time. While this is conceptually possible, it seems unlikely. We do not have any growth models in the literature that suggest this could occur in an equilibrium

in which there is population growth. Why, despite a growing population and constant idea TFP, would the equilibrium allocation feature a constant number of researchers creating new varieties? Nevertheless, this loophole is one that future research may wish to consider.

9. Conclusion

A key assumption of many endogenous growth models is that a constant number of researchers can generate constant exponential growth. We show that this assumption corresponds to the hypothesis that the total factor productivity of the idea production function is constant, and we proceed to measure idea TFP in many different contexts.

Our robust finding is that idea TFP is falling sharply everywhere we look. Taking the U.S. aggregate number as representative, idea TFP falls in half every 13 years — ideas are getting harder and harder to find. Put differently, just to sustain constant growth in GDP per person, the U.S. must double the amount of research effort searching for new ideas every 13 years to offset the increased difficulty of finding new ideas.

This analysis also has implications for the growth models that economists use in our own research, like those cited in the introduction. The standard approach in recent years is to use models that assume constant idea TFP, in part because it is convenient and in part because the earlier literature has been interpreted as being inconclusive on the extent to which this is problematic. We believe the empirical work we've presented speaks clearly against this assumption. A first order fact of growth empirics is that idea TFP is falling sharply.

That this particular aspect of endogenous growth theory should be reconsidered does not diminish the contribution of that literature. Quite the contrary. The only reason models with declining idea TFP can sustain exponential growth in living standards is because of the key insight from that literature: ideas are nonrival. And if idea TFP were constant, sustained growth would actually not require that ideas be nonrival; Akcigit, Celik and Greenwood (2016) show that fully rivalrous ideas in a model with perfect competition can generate sustained exponential growth in this case. Our paper therefore clarifies that the fundamental contribution of endogenous growth theory is not that idea TFP is constant or that subsidies to research can permanently raise

growth. Rather it is that ideas are different from all other goods in that they do not get depleted when used by more and more people. Exponential growth in research leads to exponential growth in A_t . And because of nonrivalry, this leads to exponential growth in per capita income.

A Robustness Results: Allowing $\lambda < 1$

Table A1 shows the robustness of our results to the baseline assumption that there is no diminishing returns to research in the idea production function. See the discussion in Section 3.4. for more details. For this set of results, we assume the input into the idea production function is S^λ where $\lambda = 3/4$. As expected, the growth rates of idea TFP are about three-fourths as large as in the baseline case, reported in the main text in Table 6, but they are substantially negative nearly everywhere we look.

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Table A1: Robustness Results for Idea TFP: $\lambda = 0.75$

Scope	Time Period	Average annual growth rate of idea TFP	Half-life of idea TFP (years)
Aggregate economy	1930–2015	-4.1%	17
Moore's law (narrow)	1971–2014	-5.6%	12
Moore's law (baseline)	1971–2014	-7.6%	9
Corn, version 1	1969–2009	-7.9%	9
Corn, version 2	1969–2009	-5.2%	13
Soybeans, version 1	1969–2009	-5.4%	13
Soybeans, version 2	1969–2009	-3.2%	22
Cotton, version 1	1969–2009	-1.9%	37
Cotton, version 2	1969–2009	+1.6%	-44
Wheat, version 1	1969–2009	-5.0%	14
Wheat, version 2	1969–2009	-2.9%	24
New molecular entities	1970–2015	-2.0%	34
Cancer (all), publications	1975–2006	+0.4%	-166
Cancer (all), trials	1975–2006	-3.4%	20
Breast cancer, publications	1975–2006	-4.7%	15
Breast cancer, trials	1975–2006	-7.7%	9
Heart disease, publications	1968–2011	-2.8%	25
Heart disease, trials	1968–2011	-5.4%	13
Compustat, sales	3 decades	-9.4%	7
Compustat, market cap	3 decades	-7.8%	9
Compustat, employment	3 decades	-12.8%	5
Compustat, RLP	3 decades	-3.9%	18

Note: This table shows results paralleling those in Table 6 when we allow for diminishing returns to research. In particular, we assume the input into the idea production function is S^λ where $\lambda = 3/4$, as opposed to our baseline case of $\lambda = 1$.

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