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by

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Abstract

R&D is slow magic. It takes many years before research investments begin to affect productivity, but then they can affect productivity for a long time. Many economists get this wrong. Here we revisit the conceptual foundations for R&D lag models used to represent the temporal links between research investments and impact, review prevalent practice, and document and discuss a range of evidence on R&D lags in agriculture and other industries. Our theory and evidence consistently support the use of longer lags with a different overall lag profile than is typically imposed in studies of industrial R&D and government compilations of R&D knowledge stocks. Many studies systematically fail to recognize the many years of investment and effort typically required to create a new technology and bring it to market, and the subsequent years as the technology is diffused and adopted. Consequential distortions in the measures and economic understanding are implied.

Key Words: knowledge stocks and flows, industrial and agricultural sectors, R&D (research and development), adoption, technological change, innovation

JEL Codes: 031, Q16, L10

> We also need studies that pay much more attention to the estimation of the various lag structures between R&D expenditures and productivity growth… .
>
> Griliches (*Bell Journal of Economics*, 1979, p. 115)

1. INTRODUCTION

Over the 70 years since Ted Schultz and Zvi Griliches launched the enterprise, initially focused on agriculture, two distinct strands of literature have emerged in economic studies linking measures of productivity to research investments. Agricultural economists have continued to adhere to and build directly on the foundations laid by Schultz and Griliches (see, e.g., Schultz 1950, 1953 and 1956; Griliches 1957, 1958, 1964 and 1979), while a separate body of work has developed on returns to industrial R&D—also led in the early years by Griliches along with others such as Jora Minasian (e.g., Miniasin 1962) and Edwin Mansfield (e.g., Mansfield 1965, 1968a, 1968b, 1972). Over time, the initially strong cross-connections between the two strands of literature have progressively weakened.

Compared with economists studying returns to R&D in other industries, agricultural economists have had the advantage of richer data sets in longer time series, and they have amassed a larger body of evidence. They have also employed different conceptual models, with potentially important empirical, practical and policy implications. Many researchers assessing R&D-productivity links use models that misconstrue and understate the length of the time lags between an initial research investment and its ultimate economic impacts, and their findings are consequently distorted. This is especially so in studies of industrial R&D where the typical models impose effectively very short, simplistic, and questionable lag structures.

Research can take a long time to begin to affect production, and then it can affect production for a long time. The dynamic structure linking research spending and productivity involves a confluence of processes—including the creation and destruction of knowledge stocks and the adoption and disadoption of innovations over space and time—each of which has its own complex dynamics. That science is a cumulative process, in which today's new ideas are derived from the accumulated stock of past ideas, influences the nature of the research-productivity relationship as well. It makes the creation of knowledge unlike other production processes (see, e.g., Rosenberg 1975).

Reflecting the complexities of cumulative knowledge creation and depreciation, and the progressive adoption and eventual disadoption of the resulting technologies, the lag relationship between research investments and their consequences can be envisioned as entailing three phases: (1) an initial "gestation" or "invention" lag before research has any effects on production or productivity (or other measures of economic performance such as sales or profit), (2) an "adoption" lag during which the lag weights rise to a maximum, and eventually (3) a phase of declining weights as the impact of past research investments on current productivity fades into unimportance, for one reason or another. However, the overall length and particular shape of the R&D lag distribution in any specific context is an empirical issue: the detail of the distribution of lag weights varies from case to case. In practice, researchers typically define a simple ad hoc model, linking, say, production or productivity to a finite distributed lag of past research investments, without reference to any formal theory. And, in empirical work, they usually impose untested assumptions about the length and shape of the R&D lag, which can have profound implications for the results.

In studies of agricultural R&D, the predominant models explicitly acknowledge the various elements of the R&D lag relationship, enumerated above, with rising and falling phases representing the processes of knowledge creation, adoption, and depreciation. Evenson (1967) included all these elements. In studies of industrial R&D, in contrast, the conventional practice is to assume a perpetual inventory model of the R&D knowledge capital stock (Hall et al. 2010, Serfas et al. 2022). These models treat current research investment as providing an immediate (or almost immediate) increment to the knowledge stock, which begins to depreciate immediately, such that the entire lag structure can be represented by a single parameter, the depreciation rate. Hence, paraphrasing Griliches (1998), Hall (2007, p. 2) observed that "... the measurement of the depreciation of R&D assets is the central unsolved problem in the measurement of the returns to [industrial] research." Li and Hall (2018) echo this perspective.

However, the relevant issue goes beyond the depreciation process to the specification of the processes of knowledge creation and adoption—the "invention lag" and the "adoption lag," which have been omitted altogether from almost all models of industrial R&D. The same measures of industrial R&D capital stocks have been used not only in econometric models of productivity growth and the like, but also as part of the national accounts used for other purposes by government agencies such as the U.S. Bureau of Economic Analysis (BEA) or the U.S. Bureau of Labor Statistics (BLS) and by international organizations such as the OECD (see, e.g., Moylan and Okubo 2020 and OECD 2013a, 2013b). So the relevance extends beyond the narrow issue of modeling returns to R&D, which is our primary motivation and focus.

In what follows, we first discuss conceptual models of innovation lags and the creation and depreciation of knowledge stocks, and on that basis we question some common practice. We argue from principle and using stylized facts that these processes are time-consuming, implying very different lag structures than are often imposed in empirical models. Against this background, we consider evidence on the length and form of the R&D lag in different contexts, including details on technology timelines, and the adoption and disadoption processes for specific examples of various kinds of innovations. Throughout, we find comprehensive support for a much longer lag with a different shape than is typically imposed in studies of industrial R&D.[1] Against that background, we present a summary meta-assessment in which we document and discuss the development of the main ideas and predominant practice in studies of returns to agricultural versus industrial R&D. We highlight the substantial divergence in modeling approaches and consider the implications of the comparisons, drawing on an illustrative application using data for U.S. agriculture.

2. MODELS OF INNOVATION LAGS AND STOCKS OF KNOWLEDGE

Over the past 50 years economists have conducted hundreds of studies of the contributions of public and private R&D to productivity growth and other measures of economic performance. Much of this effort and accomplishment can be attributed to T.W. Schultz and his students and other colleagues at the University of Chicago, and those who studied under them.[2] As Griliches (1998) noted, agricultural economics was central to early progress on the broader subject.[3] In many of those hundreds of studies, productivity was modeled as a function of a distributed lag of past research investments, conceived of as representing an R&D knowledge stock, a form of

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[1] Even social science research takes much more time than we might reasonably assume or wish, and even longer to take effect! The first incarnation of the present paper was as an invited paper presented to the Economic History Association annual conference in 2008 (see Alston and Pardey 2008). Parts of this work draw on the companion piece by Pardey et al. (2010) as well as more recent work by Pardey and Alston (2021) and Alston and Pardey (2021). How long might it take before the presentation of the findings herein lead to a meaningful change in prevalent practice?

[2] Significant contributors associated directly with the University of Chicago include D. Gale Johnson, Vernon Ruttan, Zvi Griliches, Robert Evenson, G. Edward Schuh, Theodore W. Schultz, Willis Peterson, Bruce Gardner, and Wallace Huffman. The "Tree of Zvi" illustrates the pervasive influence of one of these founders on the scholars working on this subject (http://people.bu.edu/cockburn/tree_of_zvi.html).

[3] Griliches (1998, p. 269) observed that "Current work on the role of public and private research in productivity growth has deep roots in the early work of agricultural economics. The first micro-production function estimates (Tintner 1944), the first detailed total-factor productivity (TFP) calculations (Barton and Cooper 1948), the first estimates of returns to public research and development (R&D) expenditures (Griliches 1958; Schultz 1953), and the first production function estimates with an added R&D variable (Griliches 1964) all originated in agricultural economics."

intangible capital (Corrado et al. 2009 and Crouzet et al. 2022).[4] In most cases, strong restrictions were imposed a priori on the lag structure linking R&D spending to the knowledge stock and thus to production and productivity. Only a few studies have presented much in the way of formal theoretical justification for the particular lag models they employed in modeling returns to research.

Alston et al. (1995) sketched out a conceptual framework, subsequently elaborated by Alston et al. (1998), in which (agricultural) production uses service flows from a stock of knowledge that is augmented by research. In this framework, a finite lag distribution relates past investments in research to current increments to the stock of knowledge. But even if knowledge depreciates in some fashion over time, under reasonable views of the nature, rate, and form of depreciation of knowledge, some effects of research may persist forever. Thus, the R&D lag is infinite. As a practical matter, these effects can be modeled using a finite distributed lag that approximates the underlying infinite distributed lag, and represents the confounded effects of the lags in the knowledge creation process and the dynamics of the knowledge stock in use, reflecting the time paths of technology development and diffusion, adoption and disadoption, and other forms of economic depreciation.[5] Allowing for these multiple dynamic elements implies a longer overall lag and different lag distribution shape compared with the R&D lag specifications used in many studies, especially those related to business R&D.

[4] Terleckyi (1980a, p. 56) wrote: "Research and development act as capital. When expenditures are treated as investments and an R&D capital stock is derived, more stable estimates of research and development effects are obtained than when R&D expenditures are used in such estimations and assumed to be instantaneously depreciated." See also Terleckyi (1980b).

[5] Noting Boulding's (1966) point that knowledge does not physically deteriorate, Griliches (1979) and Pakes and Shankerman (1984) argue that its *value* to the firm who owns a patent does depreciate, owing to displacement by new innovations and rising appropriability problems; see, also Caballero and Jaffe (1993).

2.1. A Conceptual Model Linking Research and Productivity

The dynamics of the stock of useful knowledge is at the heart of empirical models used to explore the rate of return to research, if only implicitly. Studies of returns to agricultural or other industrial R&D typically begin with a model of production in which a measure of multifactor productivity, MFP_t, is a function of (flows of services from) a stock of useful knowledge K_t, a vector of nonmarket inputs, $\boldsymbol{Z}_t$, such as weather, and purely random elements, u_t:[6]

$$(1) \qquad MFP_t = \frac{Q_t}{X_t} = \mathrm{f}(K_t, \mathbf{Z}_t, u_t).$$

R&D is incorporated in these models through its contribution to the stock of knowledge capital. In many cases, MFP_t is defined as a multifactor productivity index, equal to the ratio of an output quantity index, Q_t, to an input quantity index, X_t, as in (1).

In our conceptual framework, we want to distinguish between the creation and depreciation of knowledge. The stock of knowledge increases as new ideas or innovations are added to the old stock through the research process.[7] In addition, the stock of useful knowledge may depreciate over time. Hence, the net increment, N_t, to the stock of useful knowledge is equal to the difference between current innovations (gross increments, I_t) and current depreciation (gross decrements, D_t) to the stock of useful knowledge or knowledge in use. That is

$$(2) \qquad K_t = K_{t-1} + N_t = K_{t-1} + I_t - D_t.$$

[6] The same conceptual model could be implemented either (1) by estimating the production function directly or in a dual, cost function, representation of the same technology (as done by Hall et al. 2010 who do both applied to industrial R&D) or (2) by estimating a model of productivity (see, e.g., Acquaye 2000 who compared all three approaches applied to U.S. agriculture).

[7] OECD (2015, 2018) defines measures of research and development, invention, and innovations and related concepts, along with the measurement challenges associated with these concepts.

The creation of knowledge and technology itself takes time, and we take gross increments to knowledge, I_t in the current year, t to be a function of research investments, R, in the current year and up to L_I past years:

(3) $$I_t = \mathrm{i}\left(R_t, R_{t-1}, R_{t-2}, \ldots, R_{t-L_I}\right).$$

If all knowledge were fungible and non-depreciable such that the net increment would be equal to the gross increment ($N_t = I_t$), the aggregate stock of knowledge would evolve according to

(4) $$K_t = K_{t-1} + I_t = \sum_{s=0}^{\infty} I_{t-s}.$$

Implicit in (4) is the idea that increments to knowledge in the past, that were caused by research in the very distant past, are just as effective today as the most recent innovations; knowledge grows unidirectionally and utilization does not vary according to the vintage of the innovations. However, it seems reasonable to presume that, in general, current production is affected more by recent innovations than by innovations in the very distant past; as if knowledge-in-use depreciates.

Suppose we take gross decrements to the current stock of useful knowledge, like gross increments, to be a function of research investments in the current year and up to L_D past years:

(5) $$D_t = \mathrm{d}\left(R_t, R_{t-1}, R_{t-2}, \ldots, R_{t-L_D}\right).$$

Then, combining (3) and (5), the net increment to the stock of knowledge, N_t is a function of research investments in the current year and up to L_N past years (L_N is the greater of L_I and L_D):

(6) $$N_t = I_t - D_t = \mathrm{n}\left(R_t, R_{t-1}, R_{t-2}, \ldots, R_{t-L_N}\right).$$

Now the aggregate stock of useful knowledge is a function of *all* past *net* increments to knowledge, and thus *all* past research investments, a challenge for empirical analysis as discussed by Alston et al. (1998, 2010):

$$(7) \qquad K_t = K_{t-1} + N_t = \sum_{s=0}^{\infty} N_{t-s} = \sum_{s=0}^{\infty} \mathrm{n}\big(R_{t-s}, R_{t-s-1}, R_{t-s-2}, \dots, R_{t-s-L_N}\big).$$

A practical approach is to assume a fixed set of lag weights, with the shape of the lag distribution reflecting the roles of research and knowledge creation, followed by technology development, adoption, disadoption, and depreciation:

$$(8) \qquad K_t = \sum_{s=0}^{\infty} w_s R_{t-s}.$$

The model in equation (8) does not impose any specific structure on the R&D lag profile, but most empirical studies do impose some structure a priori, not least because available data are usually insufficient for estimating free-form lag weights.[8]

2.2. Archetype R&D Lag Distribution Models in Use

Two R&D lag distribution models, reflecting these ideas, have come to the fore in recent applications to agriculture: the 35-year trapezoidal model from Huffman and Evenson (1989) and the 50-year gamma distribution model from Alston et al. (2010), illustrated in Figure 1. These models have in common a finite overall R&D lag process comprising first, an initial gestation period of waiting before R&D has any impact on productivity; next, a period of rising impact; and finally, a period of falling impact, eventually to zero. Huffman and Evenson (1989, 1992, 1993), Alston et al. (2008, 2010, 2011), Pardey et al. (2010), Huffman (2018), and Alston and

[8] To our knowledge, Robert Evenson (1967) was the first to lay out a formal model like this linking agricultural production to depreciable knowledge stocks created by research.

Pardey (2021) provide detailed documentation justifying the use of models of this nature to represent the links between agricultural R&D and productivity.

[Figure 1. *Predominant R&D lag distribution models in use*]

In applications to other industries, as described by Hall et al. (2010, p. 1047) "…the workhorse of R&D stock estimation remains the perpetual inventory model, leaving us with the problem of choosing a depreciation rate." In this model, as suggested by Griliches (1980, 1986), a proportional declining balance or geometric depreciation rule is used to represent changes in an aggregate stock of knowledge. Using δ to denote the depreciation rate and *g* to represent the gestation lag before research spending begins to affect productivity, the aggregate stock of knowledge evolves over time according to:

$$(9) \qquad K_t = (1-\delta)K_{t-1} + R_{t-g} = \sum_{k=0}^{\infty}(1-\delta)^k R_{t-k-g} = \sum_{s=g}^{\infty}(1-\delta)^{s-g} R_{t-s}.$$

Equation (9) can be seen as a special case of equation (8) in which the entire (infinitely long) distribution of lag weights is represented by one parameter, δ (or two parameters if a nonzero gestation lag is included): $w_s = (1-\delta)^{s-g}\ \forall\ s \geq g$.[9]

While it is analytically and empirically convenient, this model imposes strong restrictions on both the length and shape of the R&D-productivity lag relationship. As typically used, this model allows little or no time for the sequential processes of research, knowledge creation, and the development, diffusion and adoption of technology. The assumed gestation lag is usually very short (if not absent) as is the effective overall lag: in the benchmark case, as described by Li and Hall (2018), δ = 0.15 and $g \leq 2$. Research has its maximum impact on productivity

[9] The knowledge stock in the base period, *T*, is approximated as $K_T = R_T / (\delta - \gamma)$ where γ is the applicable growth rate of spending on research.

immediately or almost immediately, and thereafter the lag weights decline monotonically, geometrically and typically rapidly given high assumed rates of knowledge depreciation.

This perpetual inventory, geometric depreciation model seems implausible—and more so with no gestation lag—even when applied to research of the most applied and immediate nature, but especially when applied to the more basic research that typically takes considerable time. It can take many years to create knowledge capital and incorporate it into production processes, after which it may depreciate very slowly if at all. Likewise, knowledge capital embodied in new products takes time to gain a market presence, which in many cases subsequently recedes, but only with time. The implied relationship between research investments and the knowledge stock in use, and thus the effect of research on productivity or profits, must have a very different shape than that implied by the analytically convenient but otherwise undesirable geometric depreciation model—even if a short gestation lag is added.

In addition, and possibly more important, the relevant lag between research investments and productivity impacts is likely to be much longer than those implied by the typically assumed rates of geometric depreciation. For instance, in a model with a geometric depreciation rate of 15% per year, the marginal impact of research would have declined to less than one-half of its initial value after five years, and less than one-fifth after ten years. Thus, and as the numerous examples detailed in the next section illustrate, a model with a 15% per year geometric depreciation rate imposes a much shorter overall research lag structure, in effect, than can be justified in view of the typical research lags likely to be found in reality; also, much different timing of the research impact.

3. STYLIZED FACTS ABOUT INDUSTRIAL AND AGRICULTURAL R&D LAGS

It takes only a moment's reflection to raise doubts about the appropriateness of models that allow no time for R&D or the diffusion of innovations. In this section we present illustrative examples of technology timelines and adoption timelines showing that for important innovations, whether in agriculture or other industries, the relevant R&D process takes many years or decades followed by a diffusion and adoption process that can also take many years or decades.

3.1. Agricultural Innovations

Consider an investment in crop improvement research which leads to the successful development of a new crop variety that is adopted and used by some growers for a time. We can think about the process as involving streams of costs and eventually benefits over time, distributed across successive phases of the overall R&D lag profile: research, development, diffusion, adoption, and disadoption. Costs are incurred in the early years, in the processes of research, development, and facilitating early adoption, and in some cases, "maintenance" research might be required over the life of a technology, to sustain its usefulness and use (see, e.g., Olmstead and Rhode 2002, 2008 and the "Curse of the Red Queen"). As the new variety is adopted benefits begin to increasingly flow and, for profitable investments, eventually they become large enough to outweigh the costs of the investment in present value terms.

Depending on the type of crop and the specific varietal innovation, the first phase, the "research lag," can take 8–15 years using conventional breeding methods and 3–7 years using so-called speed-breeding methods involving molecular markers, in vitro culture methods, or other techniques (Samantara et al. 2022).[10] This phase includes experimental work in crossing parental lines, propagating the resulting seed, evaluating the results in experimental trials, and making selections for further development. The next phase, the "development lag" takes several more years, as selected varieties are field tested under varying growing conditions and undergo further rounds of screening and selection before founder seed is then bulked into commercial quantities for sale. For some types of technologies, such as biotech crop varieties, the development lag phase can be extended by the several years spent developing and providing information required for regulatory approval, before the technology can be released for adoption (e.g., see Kalaitzandonakes et al. 2006). Development lags for traits of widespread use are extended by the time taken to incorporate them into locally adapted varieties.

Consider the crop varietal technology timelines summarized in Figure 2. The relevant R&D story that gave rise to hybrid corn technology began at least 20 years before commercial planting of hybrid corn became significant—and 40 years before the adoption process had been completed in the sense that the percentage of corn planted to hybrids had reached a stable maximum or ceiling rate of adoption (Griliches 1957; Dixon 1980). Notwithstanding innovations in the science of science, modern crop varietal technologies still take many decades to develop and diffuse, especially when we give appropriate consideration to prior art. The first commercial use of Bt corn (a genetically engineered form of corn that produces proteins that control pests, especially European corn borer) began in the United States in 1997. However, the scientific lineage of this technology dates back to at least the early 1900s with the discovery of the soil-dwelling bacterium *Bacillus thuringiensis* (Bt) whose spores and insecticidal proteins

[10] In perennial crops, the lags are appreciably longer: for example, using all the modern breeding methods and fast-tracking the process, it currently takes at least 15 years to develop and release a new cultivar of table grapes (personal communication, David Marguleas, President and CEO, Sun World).

have been used to control crop pests since the 1920s. Getting corn plants to express these proteins took a good deal of science—most actively during the 1980s and 1990s—before the technology passed regulatory scrutiny and was deemed suitable for commercial use. Likewise, the development of herbicide-tolerant (e.g., Roundup Ready®) varieties of soybeans took decades of research prior to their first commercial release in 1996.

[Figure 2: *Technology Development Timelines*]

First commercial release marks the beginning of the next phase: the process of diffusion and adoption of a given innovation, which often can take years or even decades, depending on the nature of the technology and information systems.[11] For example, during the "adoption lag" a new variety is progressively adopted and planted in larger quantities, and the aggregate net benefits progressively increase until eventually a maximum is reached (Figure 3, Panel a). The diffusion of many agricultural innovations has a uniquely spatial dimension, since the applicability of the innovation varies systematically with space, and this aspect adds to the time spent creating, evaluating and adapting varietal technologies for local adoption. Hence, the adoption lag reflects the time it takes for individual farmers to learn about the new variety and evaluate its usefulness in their specific environments, and in many instances it reflects further time spent adapting the variety to better suit different agroecological conditions.[12] This is so for annual crops, planted every year. For perennial crops, such as fruits and nuts grown on trees or

[11] Evenson and Kislev (1975) made seminal contributions to the study of the economics of innovation and adoption of agricultural technology. Subsequently, the lag to adoption was the focus of a suite of decision-theoretic models developed by economists including Pakes (1978), Lindner et al. (1979) and Feder and O'Mara (1982). Pannell and Zilberman (2020) and other authors in a recent guest issue of *Applied Economic Perspectives and Policy* provide a contemporary assessment of the literature on adoption of agricultural innovations.

[12] For example, Griliches (1957) noted that hybrid corn varieties suitable for adoption in growing conditions found in Iowa were first made available in 1936, whereas in the smaller corn market of Georgia, farmers began accessing locally adapted hybrid corn varieties in 1948, a difference which he dubbed the lag in "availability."

vines that last for decades, it takes even longer to incorporate new varieties into production systems (Alston et al. 2014, Alston and Sambucci 2019).

[Figure 3: *Technology Uptake in the United States*]

The adoption lag may also reflect lags as the market beyond the farm adapts to make use of the products of the new technology. For instance, it takes time for the food processing industry and consumers to adapt to the introduction of a new farm product innovation such as canola (derived from rape seed that was not edible for humans given its high concentration of erucic acid) (Phillips and Khachatourians 2001). Consumer or other market resistance has dramatically slowed the adoption of many significant process innovations used in agriculture and the food industry—e.g., pasteurization of milk, irradiation of food, chemical pesticides and herbicides, and transgenic crop varieties—with implications for the shape of the R&D lag profile for those innovations (see, also, Saitone et al. 2015, and Alston 2022). In some cases, government regulation reinforces market resistance (see, e.g., Just et al. 2006).

Benefits might flow indefinitely, but for stereotypical technologies, the rate of benefits will decline over time. Eventually, a particular crop variety will be disadopted by some farmers as it becomes less effective against (co-)evolving pests and diseases, or is made obsolete by the development of superior varieties. Chai et al. (2022a, 2022b), for example, reported that the average age of commercially grown wheat varieties throughout the United States was 36.4 years in 1919. Improvements in crop breeding and seed bulking techniques increased the annual rate of varietal development over time, such that planted varieties turned over at a faster rate, yet by 2019 the average age of all the wheat varieties found in U.S. farmers' fields was still 9.3 years. However, in many cases a variety may serve as breeding stock, contributing to the varieties that replace it, with vintage carryover effects. Hence, the benefit stream will continue to flow so long as the variety *or its offspring* continue to be grown by some farmers (see, e.g., Pardey et al. 2010 and Chai et al. 2022a).[13] These cumulative adoption profiles (often, but not always, S-shaped) are typical for all sorts of agricultural technologies, including the chemical, digital, mechanical and genetic innovations plotted in Figure 3, Panel a.

Combining these various elements of lags, it is easy to imagine a typical varietal technology with a research and development lag of 5–10 years, in which no benefits are earned; this followed by an extended adoption phase, with peak benefits in the range of 15–25 years after the initial investment; then sustained use after the peak, with benefits extending for a further 10 years and longer. Some other types of research (for instance, genomics and proteomics) may have significantly longer lags, especially the more fundamental types of research that lead to the most important and valuable types of innovations, some of which ultimately may be built into the new varieties. When innovations are embodied in livestock breeds or perennial crops that last for many years or decades, the biological dynamics add to both the research and adoption lags; similarly, when innovations are embodied in durable physical capital such as tractors or combine harvesters.[14] Some other types of public investments, including applied research and extension, might have significantly shorter R&D lags and less-enduring impacts. When we model the effects of *aggregate* R&D spending on multifactor productivity the R&D lag profile represents a value-share-weighted average of the complete range of different types of agricultural R&D and

[13] A new model of smart phone or other specific product innovation might be analogous to a new wheat variety in this context. The particular model (or variety) might be adopted relatively quickly after its release, which follows some years of focused R&D and product development, and then it might dominate active use in its category for only half a dozen years (or less) before it begins to be supplanted by newer models (see, e.g., Mixpanel 2022). But much (perhaps most) of the technology embodied in that model (or variety) will be carried through to the next generation. In this way, increments to the knowledge capital stock can remain effectively in use for many years beyond the typical lifespan of particular technologies that use the knowledge stock.

[14] Some innovations involve packages of technologies. Eastwood et al. (2017) describe critical elements of a 14-year timeline (1999–2013) for the development of a precision dairy information system in Australia and a 20-year timeline (1992–2012) from initiation to widespread adoption of automatic milking systems in Europe.

their impacts across the entire range of agriculture, encompassing all the different lag distributions for the different types of R&D.

3.2. Industrial Innovations

In his book *How Innovation Works And Why It Flourishes in Freedom* Matt Ridley (2020) explores the evolutionary processes of innovation through the stories of many innovations on a broad scale—chapter headings like "Energy," "Public health," Transport," "Low technology innovation," "Communication and computing," and "Prehistoric innovation." Each of these chapters tells stories of technologies coming and going in processes lasting decades or centuries—such as in transportation with the transition since the 1820s first from horses to steam-powered locomotives and ships until steam was supplanted by the internal combustion engine; then gasoline- and diesel-powered cars and trucks and heavier-than-air flying machines driven first by propellors and now jet engines.

As Ridley summarizes "innovation is nearly always a gradual, not a sudden thing" (2020, p. 240). A great many smaller innovations in many of the details of those evolving forms of transportation, and the engines that powered them, were part and parcel of the process. He stresses the evolutionary nature of the process: "In the case of the motor car, the closer you look the more the early versions look like older versions of preceding technologies, like carriages, steam engines and bicycles, reminding us that with very few exceptions, man-made technologies evolve from previous man-made technologies and are not invented from scratch" (2020, p. 241). Thinking about these ideas leads us to think about innovation as a slow and cumulative process, with innovation timelines and technology timelines stretching over many decades.

Indeed, in industrial R&D like agricultural R&D, the real-world lags from ideation or initial research through to widespread use of the resulting technologies or knowhow are often long. In this respect, as some selected examples illustrate next, industrial and agricultural technologies and their R&D processes are much more similar than different. Figure 2 gives an illustrative summary of the technology timelines for mRNA vaccines and semiconductors & microcontrollers. From the discovery of mRNA in 1961, it took a constellation of complementary innovations over the course of half a decade before the first mRNA vaccine for an infectious disease (rabies) was clinically trialed, and another seven years before mRNA COVID vaccines were given expedited authorization for widespread human use. The timelines for semiconductors & microcontrollers, that are embodied in an ever-expanding array of consumer and industrial products, are even longer. Faraday's 1833 discovery of the semiconductor effect—where the electrical conductivity of silver sulfide crystals increased with increasing temperature, opposite to the conductivity-temperature relationship found in metals like copper—instigated 138 years of cumulative innovation endeavor before a commercial result was realized with Intel's first widely produced microprocessor in 1971 (see also Nelson 1962).

Gross et al. (2018) report that the R&D lags for 13 major consumer and energy-related technologies (including cathode ray tubes for TVs, video cassette recorders, ATM/cash cards, mobile phones, LED lights, wind electricity, lithium ion rechargeable batteries, solar photovoltaics and more) ranged from 20–69 years (median 32 years) from invention (the year in which the product was conceived and tested at laboratory scale) to widespread use (the year when the number of products installed or in use reached 20 percent of peak use). Even setting aside the time taken for the relevant basic and applied research, the median lag from invention to commercial release was 18 years, ranging from five years (for Thin Film Transistor Liquid Crystal Display for TVs) to 37 years (for combined cycle gas turbines).

In earlier work, Enos (1962) reverse-engineered the lags between nine major "inventions" used by the U.S. petroleum refining industry and the one or two underlying innovations that "first revealed the general ideas" (Enos 1962, p. 300). For these oil-cracking processes he reports the interval between invention and innovation averaged 12.1 years, ranging from 5 to 24 years (Enos, 1962, Table 1). Broadening his analysis to encompass 35 diverse products and processes—such as the safety razor, fluorescent lamps, DDT, triode vacuum tubes, turbo jet engines, the ball point pen, xerography, plexiglas, radar, and so on—the invention-to-innovation lag averaged 13.5 years, ranging from three years for DDT, the long playing record, and plexiglass, to 27 years for the zipper, 56 years for the gyro-compass and 79 years for the fluorescent lamp (Enos 1962, Table 2). Summarizing his overall finding, Enos (1962, p. 309) wrote: "Mechanical innovations appear to require the shortest time interval, with chemical and pharmaceutical innovations next. Electronic innovations took the most time. The interval appears shorter when the inventor himself attempts to innovate than when he is content merely to reveal the general concept."

Much of this commentary refers to the years entailed in the research and development process leading up to the first commercial release of a technology or early-stage adoption. The full adoption and diffusion process for industrial innovations, which also can be time consuming, adds significantly to the overall length and shape of the lag structure linking industrial R&D to productivity (or profits) by way of the knowledge stock identified in equation (1). From commercial release to 20 percent of peak use, Gross et. al. (2018) reports a median "market deployment and commercialization" lag of 18 years, with a low of eight and a high of 46 years.

The adoption profiles for the U.S. uptake of consumer products arising from industrial R&D we present in Figure 3, Panel b, look similar in structure (variable but loosely S-shaped) and lag length (measured in decades) to those for agricultural technologies in Panel a.

In sum, there is no basis in the evidence we have assembled here to suggest the lag structures for industrial R&D are intrinsically different from those widely used in applications to agriculture. Indeed, contrary to the lag structures typically used by economists studying industrial innovations—allowing for minimal or no gestation lag—this evidence indicates that, as for agricultural R&D, it takes years or decades of investment before industrial R&D begins to bear fruit. Then, as for agricultural R&D, it takes additional years or decades before the full consequences of industrial R&D are reflected in market outcomes, as the adoption and diffusion processes play out.

Of course, in any specific application the overall length and shape of the lag profile is an empirical question. Griliches (1980, p. 424) commented "In the U.S. about three-fourths of all expenditures on R and D in industry have been spent on development and most of the rest on 'applied research.' Only about 5% of the total R and D expenditure has gone to 'basic' research. Thus, one should not expect long lags on the average."[15] But this does not excuse adopting a model that does not allow any time at all for the applied research and development work to be done, and that ignores the adoption process altogether. On this score, the R&D lag assumptions typically used in models of the productivity consequences of much industrial R&D fail to square

[15] Griliches was silent on the overall length of the R&D lag he had in mind. However, when reporting on preliminary evidence regarding the patent-R&D lag relationship—which, as an empirical analogue to equation 3, accounts for only part of the overall R&D lag length—Pakes and Griliches (1984, p. 64) concluded that their five-year lag length and structure was probably subject to truncation bias (see, also, Hall et al. 1986).

with how this segment of the economy actually works. A more focused assessment of practice in the field bears out this striking contrast with their counterparts for agricultural R&D.

4. META-EVIDENCE ON R&D LAG MODELS IN USE

The models used in recent prominent applications to agricultural R&D involve a 35- or 50-year lag profile with initially rising and eventually declining lag weights, consistent with the stylized facts, general conceptions, and illustrative examples of technology timelines and adoption lag processes presented above. The models applied to industrial R&D are not.

4.1. R&D Lags in Models of Industrial R&D

As noted by Hall et al. (2010) in studies of industrial R&D, views about the research lag structure are often reflected in assumptions about the rate of geometric depreciation of the knowledge stock (the "converse" of the overall lag length that has more often been the key parameter of the research lag in agricultural R&D studies). In studies of industrial R&D, while various geometric depreciation rates have been used in the creation of R&D capital stocks, the rates are generally large, implying much shorter effective research lag lengths than found by studies of agricultural R&D that explicitly tested for lag lengths. A remarkable consensus of practice has developed, for reasons that are not entirely clear.

In a couple of influential earlier studies, Adams (1990) estimated an annual depreciation rate for basic research of 9 to 13%, while Nadiri and Prucha (1993) estimated a rate of 12% for industrial R&D.[16] Based on this and other evidence, the Bureau of Economic Analysis or BEA (Carson et al. 1994) used a straight-line life span that corresponds to a geometric depreciation

[16] In one earlier study, Griliches (1980) considered annual depreciation rates of 0, 10 and 20%; in another (Griliches 1986), 15%.

rate of 11% in constructing estimates of R&D net capital stocks. This rate implies that only one-tenth of today's knowledge stock will remain in use in 20 years' time. The Bureau of Labor Statistics or BLS (1989) used a slightly smaller rate of 10% as its central estimate, which also implies a rapid rundown of the stock of useful knowledge. BLS (1989) also considered annual depreciation rates of 0 and 20%, and they noted that the choice of a specific rate of depreciation had important implications for the implied effect of R&D on productivity growth.

The same general thinking prevails in more recent work, with some narrowing of the range of depreciation rates being considered, converging on 15% per year. Sliker (2007) summarized the methodology used to create the knowledge capital stocks reported in the 2007 version of the BLS satellite accounts for R&D.[17] In a companion paper Mead (2007) concluded from a review of five studies of industry-specific R&D that "… the 15 percent depreciation rate for R&D capital that is commonly assumed in studies of the net return to [business] R&D capital is consistent with the empirical evidence, which seems to indicate that the range of 15–20 percent is correct for the depreciation rate of business R&D" (Mead 2007, p. 5).[18] In constructing their measures of stocks, the BLS set aside the estimates from Hall (2005), averaged the industry-specific depreciation rates reported in the remaining four studies, and then scaled down these mid-points "... so the recommended rates are more closely centered on a value of 15 and that the overall ranking of industry-level rates suggested by the literature is preserved" (Mead 2007, p. 6).

[17] See, also, Robbins and Moylan (2007) and Moylan and Obuko (2020). The 2007 version of these R&D satellite accounts can be obtained online at http://www.bea.gov/industry/index.htm#satellite.

[18] The five studies included Lev and Sougiannis (1996), Ballester et al. (2003), Bernstein and Mamuneas (2006), Hall (2005) and Huang and Diewert (2007), that reported (annual) R&D depreciation rates ranging from -11 to 52 percent.

Similar approaches also have been adopted by other countries. For example, Shanks and Zheng (2006) reported an extensive review of literature and new econometric results on the relationship between business R&D and economy-wide productivity for the Australian economy (see, also, Productivity Commission 2007). Their main model entailed an R&D capital stock with an annual depreciation rate of 15% applied to business enterprise research and development (BERD). The OECD (2013a) discussed many of the relevant conceptual and measurement issues in a comprehensive report titled *Supporting Investment in Knowledge Capital, Growth and Innovation*. In the "Synthesis Report" (OECD 2013b, p. 69) they reported: "Obtaining consistent industry-level depreciation rates for R&D investments has proved challenging, and there is no commonly agreed methodology. In the past, estimated R&D depreciation rates ranged between 12% and 29% for the business sector overall, and between 11% and 52% for specific industries."

In the past decade or so, several other studies (e.g., Hall et al. 2010, Ugur et al. 2016, and Li and Hall 2018) have conducted partial reviews of the extant literature on modeling and measuring business R&D capital. In their more comprehensive meta-review, Serfas et al. (2022) include all the studies encompassed in these prior reviews and some others, beginning with the 58 studies covered by Ugur et al (2016), which included and augmented the 37 covered by Hall et al. (2010). The 128 studies of industrial R&D compiled by Serfas et al. (2022) yielded 1,464 rate-of-return estimates. Of these, almost all (97.3%) were based on a perpetual inventory model. Most of them (88.2%) did not allow for any gestation lag and a majority (68.9%) used a knowledge depreciation rate of $\delta \geq 15\%$ per year: 64.4% used $\delta = 15\%$ per year, and another 4.5% used $\delta > 15\%$ per year.[19]

[19] R&D gestation lags are also absent from economic growth models (e.g., Bloom et al. 2020, Jones 2022) but Jones and Summers (2020, p. 14) recently questioned this practice and suggested "Aggregating across the different types of research, a middle-of-the-road delay estimate may be 6.5 years… ."

4.2. R&D Lags in Models of Agricultural R&D

In applications to agriculture, the geometric lag distribution model has been used sparingly, and as noted above, the crucial aspect of the models is the overall lag length. As documented in various reviews (Alston et al. 2000, 2008, 2010, 2011; Evenson 2001, Rao et al. 2019, 2020), most studies of returns to agricultural R&D have used short lags. Until relatively recently, it was common to restrict the lag length to less than 20 years and to use just a few parameters to represent the lag distribution. Pardey and Craig (1989) found "… strong evidence that the impact of research expenditures on agricultural output may persist for as long as thirty years" (1989, p. 9) and that "… long lags—at least thirty years—may be necessary to capture all of the impact of research on agricultural output" (1989, p. 18). Around the same time, Huffman and Evenson (1989) introduced a trapezoidal lag model, as depicted in Figure 1, applied to U.S. agriculture. This model, which has an overall lag length of 35 years represented by four linear segments, remains popular.

More recently, in their application using long-run, state-specific data on U.S. agriculture, Alston et al. (2010, 2011) tested for longer lags, and found in favor of a gamma lag distribution model with a much longer research lag than most previous studies used—a research lag of at least 35 years and up to 50 years for U.S. agricultural research, with a peak lag around year 24. A similar gamma lag distribution model has been adopted by several studies since (examples include Andersen and Song 2013; Andersen 2015; Fuglie et al. 2017; Khan et al. 2017; Fuglie 2018; Baldos et al. 2019; Yang and Shumway 2020; and Wang et al. 2022), though some others continue to use the trapezoidal lag model (Plastina and Fulginiti 2011; Wang et al. 2012, 2017; Jin and Huffman 2016; Yang and Shumway 2016, 2020; and Huffman 2018). All these models imply longer overall lags, and considerably longer mean lags, compared with the agricultural

R&D models used prior to the 1990s, and compared with the industrial R&D models up to the present.

4.3. Implications For Estimated Rates of Return

No doubt, the imposition of questionable restrictions on the length and shape of the R&D lag distribution can distort our view of the time path of the R&D knowledge stock, the temporal linkages between investments and their economic consequences. While both the direction and magnitude of the likely bias in estimated rates of return to R&D from restricting the length and shape of the lag profile are empirical issues, we suspect the bias has been more often upward (see, e.g., Alston and Pardey 2001).

This suspicion is supported to some extent by the evidence in the literature. For example, Myers and Jayne (1997) and Thirtle et al. (2008) tried various lag structures and concluded that more positively skewed lag distributions (i.e., with heavier weight on the shorter lags) give rise to higher estimated rates of return. Likewise, in their statistical meta-analysis of studies of returns to agricultural R&D Alston et al. (2000) found that:

> "Several key assumptions about the lag structure were found to have significant implications for the reported rate of return. First, a longer gestation lag meant a lower rate of return (lower by 4.6 per cent per annum for each additional year of gestation). Second, overall lag length matters. Studies that assumed short lags (<15 years) for research benefits found rates of return similar to those that used longer lags, although the point estimate suggests that truncation of the lag reduces the rate of return. This effect would be expected in a non-econometric study where truncation of the lags means the omission of some benefits. However, … econometric studies that used short lags found rates of return that were 38 per cent per annum higher than those that used longer lags. This statistically significant coefficient reflects the result that, because of the omitted variables problem discussed earlier, truncation of lags in the stream of net benefits from research biases the rate of return up" (Alston et al. 2000, pp. 211–212)

This is indirect evidence based on variation across studies rather than a more direct comparison of different methods using a single dataset. In previous work we investigated the R&D lag structure and its returns-to-research implications using state-level U.S. data on agricultural research investments over 1890–2007 and multifactor productivity (MFP) over 1949–2007 (Alston et al. 2010, 2011). We found support for a gamma lag distribution model with an overall lag length of 50 years and a peak impact at 24 years but with most of the impact exhausted within 35 years (see Figure 1). We tried different lag distributions, allowing for different lag shapes and different maximum lag lengths, along with other variations in model specification. The consequences for rates of return were mixed. In some cases, as anticipated, shorter lags resulted in larger estimated BCRs but, for reasons that are not yet fully understood, other modeling details were an important co-determinant of the sensitivity of results to truncating the lag length.

More recently, with the current review article specifically in mind we used the same data to undertake a more focused analysis of the implications of alternative lag distribution models including (1) four alternative parameterizations of the gamma lag distribution model used by Alston et al. (2011); (2) the trapezoidal lag model used by Huffman and Evenson (1989); and (3) two variants of the geometric lag distribution model (i.e., the perpetual inventory model) with annual knowledge stock depreciation rates of 10% and 15%, respectively (Wang et al. 2022). In all seven of these models the lag distribution is truncated at 50 years, and a gestation lag of two years is imposed.

The quantitative results are surprising in some ways. First, the models all yielded rather similar estimates of elasticities of productivity with respect to the R&D knowledge stock and, in turn, quite comparable estimates of BCRs—all well within the range of widely accepted status quo estimates (see, e.g., the review by Fuglie 2018). If someone had naïvely estimated just one (any one) of these models by OLS, viewing the estimates uncritically they might have been well pleased by the seemingly strong and apparently credible results. But even if they appear to work well, two of these models (the geometric lag distribution models) are not at all plausible in the application to U.S. agriculture, if anywhere.

Interestingly, the gamma lag distribution model preferred by Wang et al. (2022) is quite different in its general shape from the gamma model preferred by Alston et al. (2010, 2011). Even though it allows for a longer, 50-year, lag it has a very similar overall shape to the shorter (35-year) Huffman and Evenson (1989) trapezoidal lag model. It also appears to be very similar in shape to the preferred gamma lag model identified by Baldos et al. (2019), which also implies a similar value for the BCR. Moreover, the estimate of the elasticity of productivity with respect to the knowledge stock (0.31) from that model is remarkably close to what Baldos et al. (2019) estimated (0.29) using a Bayesian hierarchical approach.[20] Across all the models estimated by Wang et al. (2022) the range of BCRs is fairly narrow: 18.5 to 27.3.

We cannot say as much about the effect of the lag distribution model on findings in studies of industrial R&D that report rates of return. For a start, most of the studies reviewed by Serfas et al. (2022) use essentially the same model—97.3% of the estimates were based on a perpetual inventory model, 88.2% did not allow for any gestation lag and 64.4% used a knowledge depreciation rate of 15% per year—so we cannot look across studies to gauge the effect of modeling choices, as done by Alston et al. (2000).

[20] Fuglie (2018, p. 437) reports an elasticity of MFP with respect to national public agricultural R&D equal to 0.30 for North America, computed as the average of estimates across seven studies.

Whether in applications to agriculture or other industries most researchers are not in a position to estimate a flexible lag distribution model and test among alternative specifications. Instead, almost all studies linking R&D to productivity simply impose untested assumptions about the length and shape of the R&D lag, which can potentially have profound implications. Some such assumptions are inevitable and indeed desirable, as illustrated by Wang et al. (2022): even when testing among models is possible the results might not be informative. Forty years ago, Zvi Griliches suggested

> "… it is probably best *to assume* a functional form for the lag distribution on the basis of prior knowledge and general considerations and not to expect the data to answer such fine questions. That is, a 'solution' to the multicollinearity problem is a moderation of our demands on the data—our desires have to be kept within the bounds of our means." (Griliches 1979, p. 106, emphasis in original).

Griliches does not tell us what to assume about the form for the R&D lag distribution, and at issue is whether specific assumptions cause significant distortions in findings. The implication is that researchers must rely heavily on priors for specifying lag distribution models. Having informed priors takes work. Economists studying returns to agricultural R&D have often been close to the processes of research, knowledge creation, and the development, adoption, and disadoption of the innovations they are modeling, and well informed about them. Such empirical groundedness is less apparent in the preponderance of studies of industrial R&D.

5. SYNTHESIS AND CONCLUSION

The theme of this article is a schism and a contradiction. Starting from a common foundation, researchers studying industrial R&D or "endogenous growth" have gravitated to models with implausible shapes and little or no allowance for research and adoption lags. Meanwhile, researchers studying agricultural R&D have progressively adopted models with ever-longer lags and shapes that conform better to the evidence of rising and eventually falling productivity consequences as R&D plays out its hand through often lengthy technology commercialization and adoption and disadoption processes. Why is it so? We can only speculate.

Availability of data is clearly a big part of the story. Studies of industrial R&D are more often based on cross-sections or short panels : 90 of the 128 studies reviewed by Serfas et al. (2022) used 20 years of R&D data or fewer, and among those, 36 used 10 years or fewer; only 14 studies used 30 years or more; studies of agricultural R&D typically have R&D spending data in much longer time-series, leaving scope for models entailing longer lags with more realistic shapes, especially in more recent decades. One-third of the rates of return reported by Rao et al. (2020) were from models with lags of 35 years or more (requiring many more than 35 years of data), while one-quarter were from models with lags of 20 years or fewer. When data are available only for a decade or two, it is simply not possible to use models like the trapezoidal or gamma lag models with lags of 35 or 50 years or longer. In these circumstances, the geometric lag model apparently offers a convenient solution: using this model a measure of the R&D knowledge stock can be inferred no matter how short the time-series. But as we have shown, this model is rarely if ever appropriate, even with a substantial gestation lag, which is typically not included.

Some other sources of the differences could be connected to the nature of the industries and the R&D investments being studied, and the focus of the studies. Notably, a majority (52%) of the economic studies linking industrial R&D to its economic consequences are predominantly based on firm-level data, while agricultural R&D studies are much more often based on national or regional commodity- or sector-specific aggregate data.[21] The emphasis in industrial R&D studies is on private benefits from proprietary research investments, where studies typically take as "given" the (prior) R&D conducted by other firms or public agencies that enable innovations arising from the firms' research.[22] In many instances they may also refer to very applied research or development work, the results from which might be adopted entirely in-house, implying shorter adoption processes compared with the public R&D that is more often the focus of agricultural R&D studies; though the same cannot be said for adoption of innovations related to marketed producer and consumer products. And in contrast to econometric studies of agricultural R&D that typically use a measure of sectoral multifactor productivity as the dependent variable, a majority (71%) of studies of industrial R&D use other measures like labor productivity, gross or net sales, or profit; different concepts and measures of the rate of return are implied, leaving it unclear as to whether they are directly comparable (Serfas et al. 2022).

These differences might justify to some extent and in some applications models with shorter lags and different shapes compared with those that are relevant for agricultural R&D. But even large differences of these types cannot justify models that allow no time whatsoever for the processes of research, development and diffusion of innovations. In some cases the use of such models might reflect conceptual errors. While the idea of a depreciable R&D knowledge stock is fundamental, it is not clear that all of those engaged in this kind of work have been thinking explicitly in those terms and paying specific attention to the idea that R&D itself is a

[21] Rao et al. (2020) compiled 516 studies yielding 2,963 estimates of rates of return to agricultural R&D. Of these, 80% of the studies and 75% of the estimates refer to a government-type agricultural R&D performer; only 28% of the studies and 15% of the observations refer to individual projects.

[22] The development of many industrial technologies involves tangible and lengthy R&D processes some of the costs of which are either directly incurred by the firm, or implicitly incurred by way of licensing technologies or acquiring firms (and their IP portfolios) to ensure freedom to operate, leverage complementary assets, or gain other market advantages (see Figure 2 and, for example, Teece 1986 and Symeonidou and Bruneel 2017).

production process that takes time. We suspect that the authors of a higher proportion of the studies of agricultural R&D, especially those that employ models that seem more plausible to us, may have had these ideas explicitly in mind—but this is hard to gauge formally. In any event, agricultural economists can and do fall into the same trap. Indeed, economists modeling agricultural R&D have also tended to use models with shorter lags than our arguments would support unless they had access to measures of R&D investments in uncommonly long time series; the majority of the studies that used models with explicit lags of 35 years or more used U.S. national or state-level R&D data that are available in exceptionally long time-series. We hope this review might serve some purpose in reducing the prevalence of conceptual error as a reason for the use of unjustifiable models to quantify R&D and its economic consequences over time.

What should we do? A workable, defensible solution for cases where R&D data are available in short time-series remains elusive. While the do-nothing option is unattractive, it is hard to justify the continued widespread use of models that are grossly at odds with the real-world phenomena they purport to represent. As Griliches (1994. p. 17) asked in a related context "Why does it feel as if the glass is half empty? … We are caught up in a mixture of unmeasurement, mismeasurement, and unrealistic expectations." In our specific context, as always and everywhere, more and better data would surely help since data constraints are a primary contributor to the problems we have identified. But equally or more important is for modelers (1) to have more realistic expectations about what *really* can be accomplished with the available data, and (2) to give more serious empirical attention to understanding the relevant aspects of the data-generating process; having better-informed priors to equip them to learn as much as possible from the data—but not more than that!

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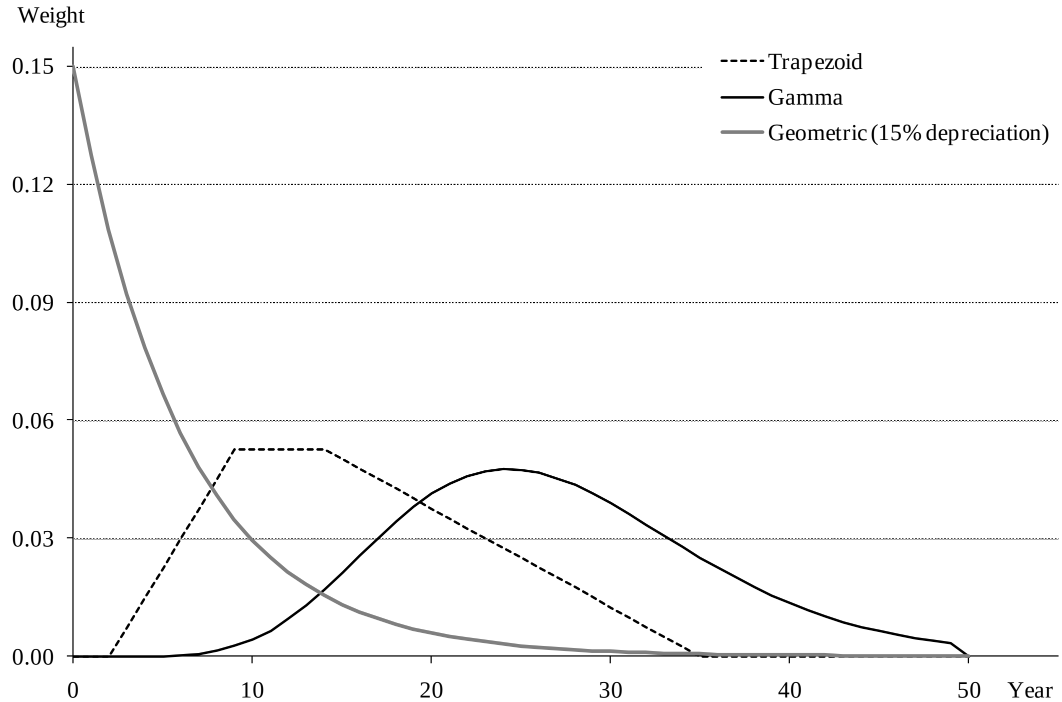
Figure 1. *Predominant R&D lag distribution models in use*



Source: Developed by the authors.

Figure 2: *Technology development timelines*

Agricultural Innovations

Hybrid Corn

1877	Beal conducts first controlled crosses/hybrid vigor
1905-1912	Shull developed correct understanding of inbreeding and cross breeding
1918	Jones developed double-cross hybrid
1922	Iowa State station began corn in-breeding program
1933	First commercial planting of Hybrid Iowa 939 developed by Merle Jenkins
1936	First release of a widely popular double-cross hybrid developed at Purdue University
1960	Vastly improved in-breds led to shift to single-cross hybrids
1960	95 percent of U.S. corn acreage in hybrids

Bt Corn

1901	Bacillus thuringiensis (Bt) discovered in Japan (and in Germany, 1911)
1950s	Bt used as a control agent and registered
1986	Cry1Ab gene sequence published
1986	Cry1Ab cloned into root colonyzing Pseudomonas bacteria
1992	YieldGard insect-protected corn event Mon810 produced by "gene gun"
1996	FDA, USDA & EPA approvals for Yield Guard
1997	Bt corn (corn borer protection) commercialized in U.S.
1998	Stacked with other traits (e.g., herbicide tolerance)
2004	U.S. patent issued to Monsanto for Mon810
2008	Regulatory approval in 20 countries

Roundup Ready® Soybean

1970	Glyphosate shown to have herbicidal activity
1976	Roundup® herbicide commercialized in U.S.
1980	Identification of three mechanisms to infer glyphosate tolerance
Late 1980s	Several genes encoding glyphosate insensitivity isolated
1987	First soybean transformation achieved
1990 & 91	Glyphosate tolerant seeds evaluated
1996	Roundup Ready® Soybeans commercialized

Industrial Innovations

mRNA Vaccines

1961	mRNA discovered
1965	First liposomes produced
1969	First proteins produced from isolated mRNA in lab
1974	Liposomes used for vaccine delivery
1984	mRNA synthesized in lab
2005	Discovery that modified RNA evades immune detection
2013	First clinical trial of mRNA vaccine for infectious disease (rabies)
2020	mRNA-based COVID vaccines win emergency authorization

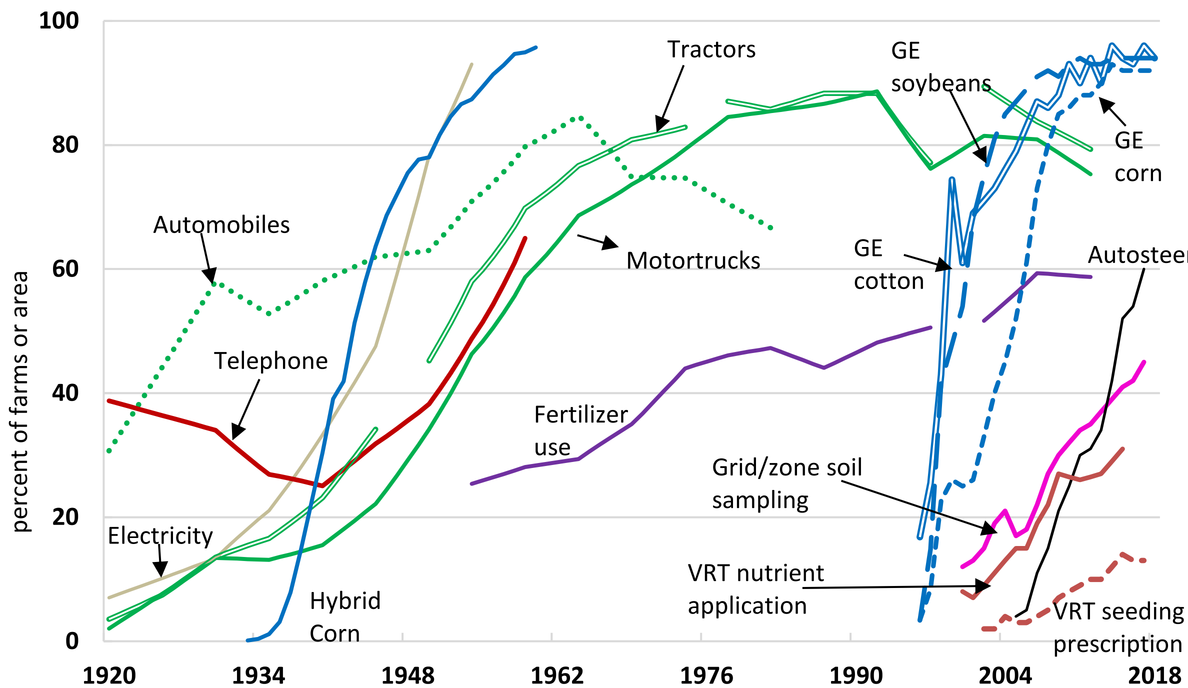
Semidconductor-Transistors-Microcontrollers

1833	Semiconductor effect discovered by Michael Faraday [Theory]
1947	Invention of point contact transistor by Shockley, Bardeen, Brattain [Proof of Concept]
1953	First widely available BJT transistor (CK722) by Raytheon [Practical]
1954	First consumer product using transistors (Regency TR-1 radio) [Consumer]
1954	First transistor based computer (TRADIC), developed by Jean Felker and L.C. Brown for US Air Force [Proof of Concept]
1958	First integrated circuit demonstrated by Jack Kilby and Robert Noyce [Proof of Concept]
1967	First hand-held calculator (powered by integrated circuits) produced by Texas Instruments, developed by Jack Kilby [Consumer]
1971	First widely produced microprocessor (Intel 4004) produced by Intel and Busicom [Consumer]

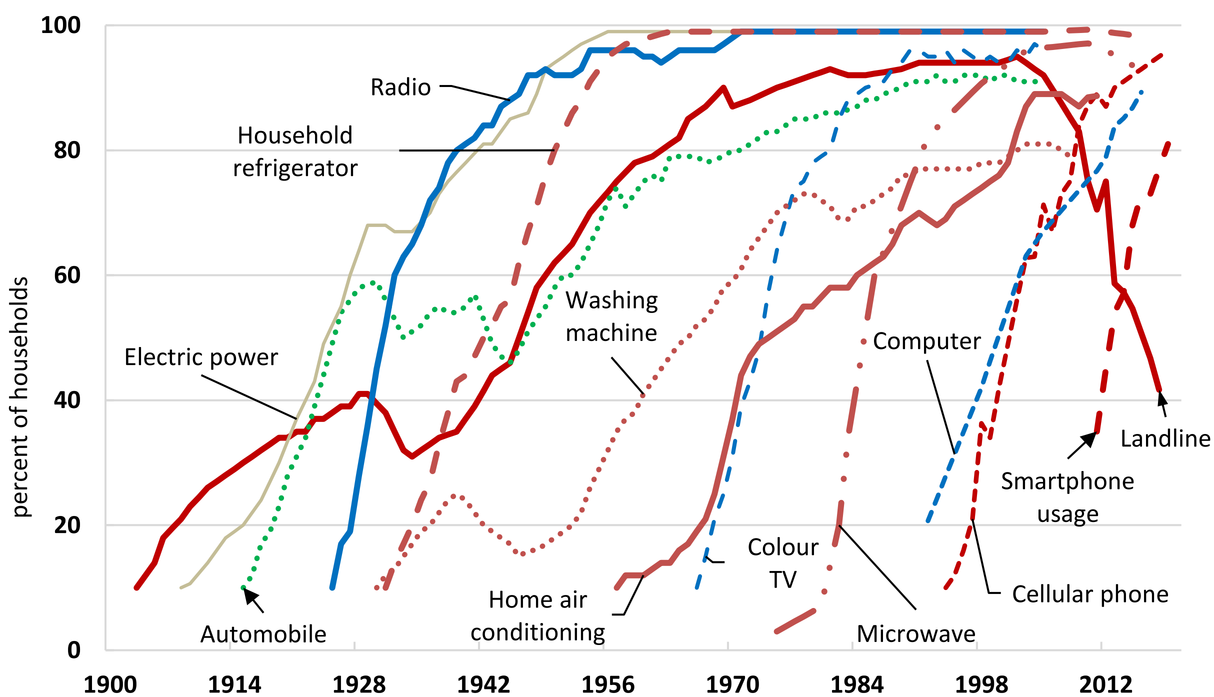
Sources: Agricultural R&D technologies are from Pardey and Beddow (2013); mRNA technology from Dolgin (2021); and semiconductor-transitor-microcontroller technologies from CHM (2022).

Figure 3: *Technology uptake in the United States*

Panel a: Farm adoption of agricultural innovations



Panel b: Household adoption of industrial innovations



Sources: Agricultural innovations are from Pardey and Alston (2020). Industrial innovations are from Ritchie and Roser (2022).