"Deflating Intangible Investment: Some new ideas and estimates"

Leonard I. Nakamura

(Federal Reserve Bank of Philadelphia)

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PRELIMINARY AND INCOMPLETE

Deflating Intangible Investment: Some new ideas and estimates*

Leonard I. Nakamura

Federal Reserve Bank of Philadelphia

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Abstract

As economies shift from tangible to intangible investment, how to deflate intangibles becomes a more important issue in practice. In this paper, I discuss the ways in which intangible investments differ from tangible investments, particularly with regard to the explanation of output growth and thus in measures of factor productivity. I argue that

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*The views expressed in this paper are those of the author and do not necessarily reflect those of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Nakamura: Emeritus Economist, Federal Reserve Bank of Philadelphia, 10 Independence Mall, Philadelphia, PA 19106 (email: leonard.nakamura@phil.frb.org).

I. INTRODUCTION

As economies shift from tangible to intangible investment, how to deflate intangibles becomes a more important issue in practice. But how do we measure properly the real value of the intangible investment? What, indeed, do we mean by the real value of intangible investment? Can we draw a simple parallel between tangible and intangible investment?

In this paper, I attempt to explore the speed of change of intangible investment which leads to rapid depreciation. As I do so, I intend to raise questions about how to estimate the deflation of intangible investment and the contribution of intangible investment to the economy. Elsewhere I and other economists have raised questions about the scope of what to consider intangible investment, in particular, whether to include consumer and organization capital as part of intangible investment, but here we look to the core of intangible investment – research and development – to try to understand what we mean by depreciation and what we mean by deflation of intangible investment. In exploring this question, I raise more questions than I answer.

Intangible capital differs from tangible capital in that intangible capital is nonrival, and therefore needs to be protected by intellectual property rights. Depreciation of intangible capital appears to reflect a combination of the obsolescence of intangible capital and its loss of intellectual property protection. Patents – such as those that protect pharmaceuticals – are intended to provide rewards to innovators who develop the patent-protected novel products and processes in exchange for disclosure of the innovation; these rights may be contrasted with those that protect trade secrets, where disclosure is not part of the quid pro quo. This disclosure then becomes common knowledge that is permanently available to the economic system.

Our understanding of biology, biochemistry, biophysics, and biotechnology advanced rapidly over the course of the first two decades of the 21st century, spearheaded by a very rapid decline in the cost of sequencing DNA and RNA, a decline faster than the Moore's Law rate which made the latter half of the 20th century the digital age. This biochemical knowledge in turn has permitted us to understand, in real time, the evolution of the coronavirus and the waves of infection arising from its mutations. These advances do not appear in our measures of intangible investment.

However, they do appear in measures of profit. Although the proportion of GDP in the US devoted to tangible investment (gross domestic private investment less intellectual property (IP) products) has fallen from a ten-year moving average of 17 percent in 1976-85 to 12.6 percent in 2011-2020, intangible investment in IP has risen from 2.0 to 4.5 percent over the same periods. Despite the drop in tangible investment, corporate profits during this period have risen relatively dramatically. Using the same periods, corporate pre-tax economic profits were 7.9 % in 1976-85 and rose to 11.3 percent in 2011-2020, an increase of 3.4 percentage points. And after-tax economic profits rose from 5.7 percent to 9.5 percent, an increase of 3.8 percentage points. Thus intangible investments during this period appear to be showing up big time in measures of profit.

The extraordinarily rapid development and testing of the vaccines protective against COVID-19 showed both the importance of intangible investment and the difficulties of measuring its value. The intangible investments were not the end-product, rather they were intermediary to the production and distribution of the vaccines themselves. And this real value of the vaccines is not, under System of National Accounts (SNA) rules, measured as personal consumption expenditures but are government expenditures and therefore captured at input prices. For we all must appreciate the value to the global economy of having vaccines that – although they have proved unable to stop the virus from mutating and becoming endemic – greatly ameliorated the consequences of the pandemic. The development of the capability to rapidly vaccinate a large portion of the global population was certainly a triumph of the global economic system, but this value is not reflected in our GDP measures. Nevertheless, the real value of the vaccines, which have helped to moderate the pandemic and permitted the global economy to return toward normalcy is not captured. And the extraordinary speed with which vaccines were developed is a tribute to the rapid advance of intangible investment, but these too are unmeasured in our data.

The standard methodology of price measurement, which entails measuring a product of unchanged quality from one month to the next, is difficult to apply to innovation, where activities are inherently different from one period to the next. A solution is to use either a general price deflator, such as the PCE or GDP deflator, which captures the opportunity cost of the resources that go into intangible investment, or input price deflators (which posits zero productivity growth) and add back in a measure of productivity. This methodology has the effect of not affecting the aggregate productivity growth rate. In practice, this aim may not be achieved.

First, input price deflators may be poorly measured. We will present a number of instances in which input prices of products used in innovation fall dramatically but are not captured in existing deflators. These rapid price declines are generally not captured by wholesale price indexes. As I will show, it is possible to directly measure improvements in quantifiable dimensions of price and quality. For example, we can measure the rate of price decline of DNA sequencing, as tracked by the US National Human Genome Research Institute.[1]

Second, one could use the rate of obsolescence of intangibles as a method of deflation, arguing that the rate of obsolescence approximates the rate of technological progress. Unfortunately, calculating obsolescence for intangible investment is quite difficult, and alternative papers have delivered very disparate results. Alternative papers have used patent renewal, amortization, production function and market value (Li and Hall, 2016, Table 2 provides a literature review of recent studies.) Nevertheless, some measure of depreciation is necessary if we are to include intangible investment in our capital accounts, as SNA methods require. We will examine the spread of depreciation measures for some important categories of research and development.

Finally, one can look to the stream of outputs of the intangibles and the expected present value of the utility stream -- the consumer and producer surplus -- that the intangibles result in. This depends on the accurate measurement of this utility stream. Unfortunately, the gains in utility are often not captured in output measures, as the failure to capture the consumption benefits of the COVID-19 vaccines illustrates.

A further difficulty in measuring the real value of intangible investment arises because the social and private values of intangible assets diverge over time. A new method for accomplishing a goal permanently raises productivity, even if the patent that gives the inventor temporary monopoly rights over the product expires. In this case, the rate of obsolescence reveals the rate of technological progress, rather than a wearing out of the product or its loss of

[1] Wetterstrand KA. DNA Sequencing Costs: Data from the NHGRI Genome Sequencing Program (GSP) **www.genome.gov/sequencingcostsdata**

value. In contrast, information about the fashions that individuals prefer at one time may become less intrinsically valuable in a way similar to the wearing out of a machine.

Another illustration of the divergence between private and social value is open-source software, which is available freely but may embody considerable private value as well as distinct social values. Creators – programmers, scientists, artists, hobbyists, entertainers – often enjoy their acts of creation and may make their products freely available without compensation (e.g., Sichel and von Hippel, 2021). Moreover, a firm may use open-source software that supports its main business activity, if by using open-source the firm is able to gain cooperation from other firms without encountering concerns about hold-up problems. For example, Google provided its Android operating system on an open-source basis, which permitted cellphone producers such as Samsung to rapidly develop an alternative to the iPhone, enabling Google's search franchise to ensure continuing access to the mobile Internet.

Additional interesting issues arise because large data sets are increasingly recognized as intangible assets. Data may be of value for a prolonged period, or it may be perishable if its timeliness is important.

I take as a starting point for why we wish to measure real intangibles, the question of how we statistically explain economic growth, that is, the standpoint of growth accounting. As is well known, in Solow's (1957) early discussion of economic growth, he found that the growth of observable factors of capital and labor services did not account for all of US economic growth and that technological progress, quantified as a residual, accounted for an important fraction of the long run US growth rate. Beginning with Romer's (1990) work and followed by the steady inclusion of intangible investments in US national accounts, as suggested by Corrado et al (2005) and Nakamura (2003), endogenous growth theory has raised the possibility that the sources of technological growth might be quantified. However, there are fundamental differences between tangible investments and intangible investments that have made the nominal and real measurement of intangible investment more difficult; these difficulties have not been fully reckoned with in national accounts.

In this paper, I build upon the results in Nakamura (2020) to provide examples to illustrate these measurement methodsand issues and to provide some very crude estimates of the impact of implementing these on the growth rate of US investment output and inflation.

II. INVESTMENT DEFLATION IN THEORY AND MEASUREMENT

Before discussing intangible investment in particular, it is useful to discuss the difficulties of the measurement of tangible investment. These difficulties serve to remind us that the underlying measurement of GDP is not as cut and dried as we might hope, and that approximation and compromise are part of this tradition.

Investment is a thorny element in national income accounting because it is conceptually not a final product that is immediately consumed, but instead a long-lived intermediate input in production. As such, we can view current gross production at its opportunity cost, that we could have used these resources for current consumption, or in terms of its benefit, the future stream of output that arises from it. When we use rapid declines in the price of desktop computers and servers to deflate these tangible investments, we are using the latter.

Moreover, in GDP we measure gross investment, not net investment, because our measures of depreciation are considered somewhat shaky. Yet for many purposes, net product and income are of greater interest.

In addition, consumer durables other than owner-occupied housing are not considered investment but are included in consumption expenditures. This has the unfortunate side effect of creating inconsistencies in treatment that depend on the economic agent: if a car is leased by a consumer, for example, it is considered an investment on the part of the firm doing the leasing, and the stream of services is purchased by the consumer is considered transportation services. On the other hand, if the same consumer buys the car, there is no comparable stream of services, only the initial purchase is recorded.

In this section I lay out some theoretical considerations in addressing intangible investment and its real value. I try to do so using a simple example but this could easily be done within a quality-ladders framework in which the innovator loses monopoly rights after an exogenous period of time if no innovator has succeeded in improving on the existing innovation in the meantime. (For a textbook treatment of the quality-ladders model, see Aghion and Howitt, 1998).

II.1 Tangible investment and its deflation

Let us begin by considering what we mean by nominal and real tangible investment, using the example of a machine that produces a consumption good we will call a widget. Let us assume that one machine produces one widget with one hour of labor. Widget makers buy the widget-making machines from a machine producer. Naturally, two machines will produce two widgets with two hours of labor. So if the cost of the machine falls, but it still produces one widget with one hour of labor, then the real value of the new machine remains the same as the outmoded machine but its price has fallen; the outmoded machine loses some of its nominal value due to this obsolescence. If the new machine can produce two widgets with two hours of labor it has the value of two of the old machines. Assuming competition, in either case the price of the widget will fall to reflect the lower production cost. (As we see below, if the new machine is produced by a monopolist, then the price of the widget will fall less, but the difference will provide a producer surplus that pays for the cost of the intangible investment required to develop the new machine.)

How to measure the gross and net capital stocks is straightforward, assuming the depreciation rate (or the lifetime) of the machine is known. In line with Tobin's q theory, the value of the firm is not affected whether it borrows to purchase the machine or buys the machine using corporate savings. Real purchases of machines that increase the stock of machines, combined with the hiring of additional labor, results in an increase in the stream of output, increasing firm revenues. Note that in these cases, we can account completely for growth in output with labor and capital, as we have defined real capital. In practice, however, there may be a measurement issue: how do we know, for example, if an improved machine can produced two widgets with two hours of labor? Or suppose we just run the old machine faster to produce two widgets with one hour of labor? In either case, we face the familiar new goods problem that bedevils mismeasurement.

The depreciation rate of the tangible machine is clearly a compound of the rate of physical deterioration of the machine and the fall in price due to the arrival of superior machines.

II.2 Intangible investment embedded in a tangible machine

The improvement in output we can think, in a stylized way, as having two origins in a world in which patents grant a time-limited monopoly power. First, the innovator develops a new, improved machine, that it can then patent and sell at a monopoly price that outcompetes the old machine. In this period, there are two elements of productivity gain, producer surplus from the monopoly profit and consumer surplus from the decline in the widget price. In expectation, the producer surplus must be greater than or equal to the tangible investment.

The intangible investment, in a growth accounting sense, that results in a halving of the cost of the machine, is responsible for the cut in the cost of the capital needed to produce the widget.

Second, the producer's monopoly may end either because an improved model replaces it (obsolescence) or the producer's monopoly may reach the end of its patent protection, resulting in a fall of price as entry into the production of the machine becomes free. Both possibilities result in a further decline in the consumer price of the widget and additional consumer surplus, with the private value and producer surplus of the patent having disappeared. This end of the private value of the patent is like the end of the lifetime of the machine, in that the private capital in each case disappears, along with the revenue stream. However, the gain in output growth is permanent, and has not disappeared. Thus if we wish to explain output growth, we must consider the development of the widget as permanently raising the capital stock of intangibles. The loss of the patent (or its obsolescence if a further improvement has been made by a new producer) does not imply a loss of output, unlike the wearing out of a machine.

From the perspective of trying to measure the sources of growth, there is no depreciation in the value of the intangible investment. However, there is a loss of private value. This loss of private value will be reflected in the depreciation of the intellectual property, as measured in either profitability or in the stock market valuation of the innovative firm, as captured in Gourio and Rodanko (2014) and Peters and Taylor (2017).

The costs of developing the new machine must be repaid, at least in expectation, by the stream of profits above the cost of producing the machine earned during the period that the patent can be enforced. This parallels the stream of revenue that a firm purchasing the new machine would earn. However, empirically it is well-known that the cost of developing a new machine is often hard to estimate and the stream of profits arising may be highly uncertain, so that empirically verifying the link between costs and revenues is difficult. (A similar problem arises in "petroleum and natural gas drilling and exploration, including 'dry holes'" which is part of private investment in structures in the US NIA.) Thus streams of R&D, which within a firm tend to be relatively steady, may be hard to match up with variations in profit and stock market value.

Moreover, the nominal quantity of investment is not neatly viewed via market transactions, unlike the purchase of the machine from the machine maker. Instead, the development of the machine is typically done in-house by the machine producer. Separating out the costs of developing (and management and testing and marketing) the machine from the cost of producing the machine thus makes life harder for the national income accountant. In particular, capital and materials for research and development purposes may evolve at different rates, and the techniques and software available for researchers are also evolving.

In terms of software, an important difficulty is open-source software that is available without cost. As with scientific and mathematical advances, free products may also be sources of improved productivity in intangible investment. Low or zero cost advances may also emerge in tangible investment, to the extent that a given capital good may be improved with software updates.

A final difficulty with capturing the value of intangible capital both before and after it has been depreciated is that knowledge may be global and the location of the intangible capital itself may be ill-defined. A well-known example is that intellectual property may be sited in a low-tax country; Guvenen et al (2018) provide quantitative estimates of the importance of this problem. Another issue is that when a pharmaceutical patent expires in, say, the United States, production of the generic chemical may flow to a foreign country, such as India or China. In this case, the product ceases to to be produced in the country where the intangible investment was made and consumers in the US gain consumer surplus from the product, but from an import whose value is excluded from GDP. The intangible capital is supporting domestic consumption, but not domestic production.

III. EXAMPLES OF THE RISE OF INTANGIBLES AND RAPID GROWTH

What do we mean by real investment? Why does it matter? From the viewpoint of endogenous growth theory, real intangible investment, as we have discussed, is an investment that permanently raises productivity.

III.2 Deflating Intangible Investments

In the US national income accounts, from 2006 to 2018 the price of intellectual property investments in R&D rose at a 1.9 % annual rate, compared to a 1.7 % annual rate for all of GDP. Thus the real price of R&D rose at a 0.2 percent rate. This can be contrasted with the depreciation rates for R&D which are as low as 7 % and as high as 40 %. Are there reasonable grounds for thinking that the depreciation rates better reflect the rate of technological progress than the real prices currently in the national accounts?

Intangible investments are difficult to deflate. Since intangible investments are creative processes, what is being done in one period is necessarily different from what is done in the next. There is no "constant quality" product whose price can be traced from period to period and efforts to use hedonic measures to capture, say, the number of lines of code and their quality have not been very successful. Instead, standard practice is to use input prices to deflate outputs, which would omit any productivity gain, and a measure of aggregate productivity growth is added to avoid distortions. A further difficulty is often that input prices are difficult to measure accurately when rapid changes are occurring, which I document below.

III.2.1 Depreciation rates. One could use the rate of obsolescence of intangibles as a method of deflation, arguing that the rate of obsolescence must approximate the rate of technological progress. This may overstate the rate of progress to the extent that private obsolescence is due to patent expiration. Alternatively, we can attempt to quantify the rate of progress through some benchmark, much as Nordhaus () used the price of a lumen of light to measure lighting price declines, although he argued that the sort of tectonic advances made in lighting progress could not be included in measures of output. We shall follow both pathways.

We begin with Bureau of Economic Analysis measure of depreciation rates for intellectual property. And then I describe some areas where it is feasible to assess aspects of technological progress in inputs and outputs. One obvious example is Moore's Law, where the number of transistors on a chip was long used as a measure of the rate of technological progress.

Another example is the cost of sending a given quantity of data through broadband or wireless networks.

III.2.2. Grouping business research and development and obsolescence rates. Arguably the central investments from the perspective of endogenous growth are investments in research and development. In 2018, total domestic business research and development (R&D) was $441 billion. This number does not include government or nonprofit organization R&D. These data, taken from the US Business Research and Development Survey, is strictly limited to "planned, creative work aimed at discovering new knowledge or devising new applications of available knowledge." It specifically excludes indirect support to R&D, such as corporate personnel, routine product testing, technical services not directly part of R&D, or market research.[2]

I subdivide business R&D into five groups that constitute nearly ninety percent all business R&D, shown on Table 1: (1) medical and chemical businesses, the bulk being biotech and pharmaceutical R&D, 22 % of total, (2) machinery and electronics businesses, the bulk being computers and semiconductors, 23 % (3) transportation machinery, the bulk being aircraft and automotive, 11 %, (4) Information, the bulk being software publishers, cloud computing and Internet, 22 %, and (5) professional, scientific and technical services, the bulk being computer systems design and research and development businesses, 11 %.

Arguably one way to measure the rate of quality improvement in research and development can be surmised from its rate of depreciation, since research and development do not deteriorate as machinery does, but only becomes obsolete. If obsolescence is due to technological progress, then the rate of depreciation is the inverse of the rate of progress.

In table 2, the medical and chemical businesses include pharmaceutical and medical manufacturing, whose research and development BEA assigns a 10 annual percent rate of

[2] The instructions for the survey begin with this general introduction: Research and development (R&D) comprise creative and systematic work undertaken in order to increase the stock of knowledge and to devise new applications of available knowledge. This includes a) activities aimed at acquiring new knowledge or understanding without specific immediate commercial applications or uses (basic research); b) activities aimed at solving a specific problem or meeting a specific commercial objective (applied research); and c) systematic work, drawing on research and practical experience and resulting in additional knowledge, which is directed to producing new products or processes or to improving existing products or processes (development). R&D includes both direct costs such as salaries of researchers as well as administrative and overhead costs clearly associated with the company's R&D. https://www.census.gov/programs-surveys/brds/information/brdshelp.html#par_textimage_2092202926

depreciation. Other chemical manufacturing has more, about 16 percent. Sixteen percent appears to be the modal rate of depreciation for research and development. Government health research and development, representing the large research investments of the National Institutes of Health, depreciate 9 percent annually. Thus this group has a range of depreciation rates from 9 to 16 percent, a range of 7 percentage points.

For machinery and electronic manufacturing R&D, the depreciation rates are higher. Semiconductor manufacturing R&D depreciation is 25 percent annually, computer manufacturing is 40 percent, communications equipment is 27 percent, and instrument manufacturing is 29 percent. Thus machinery and electronic manufacturing has a range of 25 to 40 percent, a range of 15 percentage points.

For transportation R&D, the rates vary considerably. For motor vehicle manufacturing, the rate is 31 percent, and for aerospace it is 22 percent. On the other hand, government R&D is lower, 7 percent for NASA R&D, and 16 percent for government transportation R&D. Thus transportation R&D varies from 7 percent to 31 percent, a range of 24 percentage points.

For information R&D, software publishing R&D is assigned a depreciation rate of 16 percent, with computer system design also 16 percent. Own-account software, by contrast, has a much higher depreciation rate at 33 percent. Own-account software is for software developed by a business for its own business rather than sold.

Professional, scientific and technical businesses R&D is assigned a depreciation rate of 16 percent.

Looking back over all these depreciation rates, they are between 7 and 40 percent, as we see in Table 1. Of these, though, the two lowest, NASA and Government health, are government research estimates, where it is not how one could construct an economic measure of depreciation. The private industry estimates are between 10 and 40 percent, still a large range. A very conservative estimate of the rate of depreciation for research and development would appear to be about 10 percent. That would imply a ten percent rate of decline in price, if we believe R&D is, as the survey question suggests, for permanent increases in knowledge. Now we turn to specific examples of improvement of intangible productivity to see whether a ten percent rate of price decline could be reasonable.

III.3 Examples of acceleration in intangible inputs

Here I review important cases of improvement in intangible productivity where the improvements are tectonic: Cost changes are so fast they are hard to capture in any indexes. Note that we are trying to assess, as I have argued in the theory section, the rate at which the intangible investment is decreasing the cost of the input.

Let us begin by considering the measurement difficulties associated with the development of testing, tracing, and vaccination in the global pandemic. The vaccines themselves– regardless of their intrinsic value in reducing the pandemic to an endemic disease that is serious but generally not deadly – are, under SNA rules, made available for the public for free, paid for by governments, and thus are not deflated to reflect their value to households, but merely their opportunity cost. Yet it is the rapid development of our understanding of DNA and RNA in the wake of the Human Genome Project which has underlain our ability to understand, trace, and prepare defenses against the novel coronavirus.

III.3.1 DNA sequencing. Let us consider the US firm Illumina, which pioneered second-generation genome sequencing. By developing a technique that made sequencing more orderly and efficient relative to the first generation shotgun technique, Illumina was able to reduce the cost of sequencing a single human genome from around $1 million in 2007 to $1,000 in 2018,[3] and it has announced that its next generation will reduce the cost of such sequencing to $100 (Regalado, 2020). This rate of progress (1,000 times in 11 years) represents a 100 percent annual rate of growth in productivity, compared to a 41 percent rate of growth for Moore's Law. In the process, Illumina's stock market cap rose to $25 billion by 2017. From its startup through 2017, it spent less than $10 billion in intangible investment. Illumina dominates the market for genome sequencing, reports 2018 net profit of $800 million, and currently invests about $1 billion annually for R&D, marketing, and other intangibles. Illumina — which earns income from manufacturing machines and providing the consumables needed to use them — has made possible big data research on genomics, with over 1 million human genomes now sequenced. At the 2007 price of $1 million each, that amount of data would have cost $1 trillion. Now it

[3] Data taken from National Human Genome Research Institute. https://www.genome.gov/about-genomics/fact-sheets/DNA-Sequencing-Costs-Data.

appears that all the earth's nearly 8 billion human genomes could be sequenced for less than $1 trillion.

The steady decline in the price of represents not only the rapid depreciation and technological progress attributable to Illumina and its competitors, who both manufacture machines that perform the sequencing and the chemicals used by the machines, so that they are part of both machinery manufacture and chemical manufacture. At the same time, these are inputs into research projects by lab scientists and doctors. A major genomics project on the National Cancer Institute called The Cancer Genome Atlas has created a large, public database capturing 20000 cancerous and noncancerous cells among 33 major cancer types. This provides the basis for tailoring cancer treatments to the specific type of cancer cell that is attacking a given patient. There are now a handful of gene based cancer treatments approved by the FDA.

The speed with which the COVID19 virus was sequenced is testimony to this decline in costs. Broadly speaking, the speed with which biological and medical research can be done has been greatly accelerated.

The nominal economic magnitudes of these outcomes are difficult to fully evaluate. Illumina's revenue is about $3.5 billion in 2019. The industry thus far appears to be perhaps 0.02 percent of GDP. Nevertheless, at a 100 percent rate of growth, that would add 0.02 percent to real growth. And, as has been mentioned, the ability to cheaply sequence the pandemic coronavirus has allowed health workers to follow its mutations and understand the course of the pandemic, whose waves of infection would otherwise be deeply puzzling. Millions of virus samples have been sequenced inexpensively.

At the same time, 23andme lays claim to the world's largest genomic database available for research, with over 3 million samples available for testing; 80 percent of their clients have volunteered their DNA for research. A revolution has occurred in the data available for genetic research, with almost no impact on GDP. The value of the data may well be very large and is not accounted for in our measures of intangibles. Finally, these advances widely impact public and private medical, pharmaceutical, and biotech research and development, expenditures that exceed $100 billion. Moreover, rapid advances in productivity are occurring broadly in these areas: as noted below, there have occured in robotics, cloud computing and artificial intelligence.

III.3.2 DNA Manipulation with CRISPR. The proliferation of DNA data is complemented by inexpensive genetic manipulation via the CRISPR-Cas9 family of techniques, invented in 2012 by 2020 Nobel Laureates Jennifer Doudna and Emmanuelle Charpentier and their labs as a precise means to repair or modify individual DNA sequences (Doudna and Steinberg, 2017). Editing a genome has fallen in price from "tens of thousands of dollars" to $65 since 2012, about the same rate of decline as DNA sequencing. Setting up a basic laboratory with this technology for genetic manipulation can cost as little as $10,000, so we are embarked on a new and both exciting and perilous age of genetic therapy and manipulation. The Food and Drug Administration has approved at least four gene therapy treatments, with over a hundred treatments in trial.[4] Although manipulation of the heritable human genome has been declared off-limits for the time being by the scientific community, a Chinese scientist has illegally violated that sanction and two children were born with modified genomes.

The development of these technologies has generated a large number of biotech startups that are using CRISPR techniques to attempt to remedy genetic defects.

III.3.2 Robot chemistry. Burger et al (2020) describe a mobile robot chemist that can conduct 100 experiments a day compared to two experiments a day if performed manually by a scientist. The experimental set up they described is adaptable to many different types of chemical experiments. The robot was an automotive robot adapted to the purpose that cost $130 thousand and was equipped with a Bayesian updating program that allowed it to search the 10-dimensional experimental space autonomously and efficiently.

The robot was used to find a superior set of catalysts for improving removal of hydrogen from water, potentially of value in the design of solar panels and energy storage; the new process amplified hydrogen yield six-fold. In practice, the first 50 experiments showed minimal gain but progress thereafter was substantial with the optimal combination selected after about 400 experiments. Thus a two hundred day experiment was reduced to 4 days. This calculation does not take into account the programming and laboratory set up time for a specific experiment, but it makes possible rapid increases in number of experiments that can be performed and the

[4] See FDA news releases at https://www.fda.gov/news-events/press-annoucements/fda-continues-strong-support-innovation-development-gene-therapy-products and https://www.fda.gov/news-events/press-announcements/fda-approves-first-cell-based-gene-therapy-adult-patients-relapsed-or-refractory-mcl.

dimensionality of a set of tests. This is a specific output of a robotics lab but it could see wide usage in the development of chemical experiments and new chemicals.

III.3.3 Cloud computing. Another key innovation is cloud computing. Cloud computing, which has been made practical by the ability to move data quickly over the Internet, uses farms of computer servers to provide computer services. This permits much more efficient utilization of computer processing capacity, since a lot of the server capacity at any one firm is idle much of the time. The declines in price from cloud computing from 2010 to 2016 reduced the prices of cloud computing by one-half (Byrne et al., 2021). At the same time, it also conserves on IT resources by concentrating the best researchers to solve the problem of creating powerful virtual machines and running them in a highly efficient manner. In all, this has had the impact of greatly reducing the costs of Internet startups, as noted by Ewens et al. (2018). They quote venture capitalist Mark Andreesen, "In the '90s, if you wanted to build an Internet company, you needed to buy Sun servers, Cisco networking gear, Oracle databases, and EMC storage systems ... and those companies would charge you a ton of money even just to get up and running. The new startups today, they don't buy any of that stuff. ... They're paying somewhere between 100x and 1000x [less] per unit of compute, per unit of storage, per unit of networking." Ewens et al. show that these reductions in cost are so large that the business model of early-stage venture capital for Internet startups has changed dramatically: So many startups are being created that venture capitalists now tend to play a minor role in governance and mentorship, a role increasingly taken over by accelerators like YCombinator. Thus there has been a dramatic, one-time decrease in the cost of an internet startup.

As already mentioned, cloud computing has been pioneered by Amazon, whose cloud service has provided the bulk of its profits for the last several years. Amazon Web Services was relaunched in 2006 to take its current form, and it was with this announcement that cloud computing costs became a game changer.

Amazon's 2020 AWS revenues were $45 billion with operating revenues of $14 billion. Microsoft's Intelligent Cloud services have been, to date, AWS's most successful competitor, with 2020 revenues of $48 billion, having more than doubled since 2016, and operating income of $18 billion.

However, these revenues do not show up directly in GDP, since they are intermediate services. Also, both of these numbers refer to global supply of these services, not just domestic.

Software represented roughly 30 percent of R&D in 2018, when the BEA shifted software included in NSF's estimate of R&D out of software investment back into R&D. With some half of all business use of computation now located in the cloud.

Since this is a more efficient use of computational services, one main effect is a slowing in reported business investments in servers, reducing the growth rate of GDP. From 1985 to 1995, real growth in investment in computers and peripherals was 22 percent annually, from 1995 to 2005, 23 percent, and from 2005 to 2015, 7 percent. The net contributions to real GDP growth were 0.14 percent, 0.18 percent, and 0.04 percent.

IV.3.3 Artificial intelligence. Another example that has gotten many recent headlines is artificial intelligence (AI). A widely quoted blog post by Amodei and Hernandez (2018) shows that between early 2012 and late 2017, the rate at which AI training runs were increasing doubled every 3.4 months (10x annually), resulting in a 300 thousand-fold increase in the number of petaflops/sday[5] of training behind the latest AI advance, the latest being the 2,000 petaflops/sday used by AlphaGoZero, which trained itself to play the ancient game Go without reliance on knowledge of the human history of game play (Silver et al., 2018). After this training, AlphaGoZero was widely considered a superhuman Go player. Advances appear to be taking advantage of the falling cost of more and more training. An update to the blog post including data going back to 1959 showed that until 2012, training time increases approximated Moore's Law. Thus many of the astonishing advances in AI since 2012 appear to take advantage of a combination of cheaper computing and greater expenditures available from intangible investment in AI.

Advances in software often take the form of insightful simplification. An AI team at Carnegie Mellon recently completed two huge challenges in game play. Their programs aimed to achieve superhuman performance at what is widely considered to be the most challenging game of poker, Texas Hold 'Em. Poker is more difficult than Go in that players have imperfect information — they don't see the cards the other players have — and so there is scope for

[5] A petaflops/sday is 10^{15} neural net operations per second for one day, or about 10^{20} operations.

bluffing and other strategies that are not available in perfect information games such as chess or Go. But at least in one-to-one matches the game is zero-sum, which assures the existence of a solution. The team's first effort was called Libratus, published in 2017, and the program succeeded in beating four of the world's best poker players one on one. The team's second effort, Pluribus, was to see if they could build a program for multiplayer Texas Hold 'Em. In the end, Pluribus beat top players in two formats: playing multiple human players simultaneously, and with single human players playing against multiple versions of Pluribus (Brown and Sandholm, 2019). Most remarkably, the algorithms that the Carnegie Mellon team used in Pluribus required much less training time than Libratus: While Libratus required $1 million in compute time to train, Pluribus required only $150 in compute time (Simonite, 2019). This was done using a new counterfactual routine. Thus a more complicated problem was solved with a 6,000-fold reduction in computer requirements in less than two years. The much lower training time means that anyone can afford to build a superhuman poker player for use in online poker playing.

Advances in understanding protein folding. The "fundamental dogma" of biology is that DNA makes messenger RNA which creates the proteins that are the building blocks of life. Proteins, in turn, function (or misfunction) in folded three dimentional forms that until recently could only be visualized by painstaking use of X-ray crystallography or cryo-electromicroscopy, that could take months or years. It is estimated that only 170 thousand of the over 200 million proteins extant across life forms have had their 3-D structures solved.

The rapid fall in the cost of sequencing the protein creating parts of DNA has recently been crowned with an amazing success of artificial intelligence. The Google AI group Deep Mind has recently largely solved the mystery of protein folding for two-thirds of all simple protein structures; in brief, we have in principle gone from 170 thousand structures solved to over 100 million solved. This does not entirely solve the protein folding challenge as proteins in combination have yet to meet this level of success, and some protein sequences can fold in more than one way. In the summer 2021, DeepMind revealed the details of its program which it made freely available as an open source program to scientists (Jumper et al, 2021). In an accompanying paper (Tunyasunuvakool et al, 2021), the program was shown to have successfully solved the protein structures of over 60 percent of the human proteome, doubling the proportion of the structures understood; thus fifty years of progress had been accomplished in less than three years.

The potential for these large advances in software, both from decreasing costs of hardware runs and from inspired improvements, suggests that a 33 percent average rate of obsolescence and a 33 percent annual rate of price decline may not be absurd, although I have used an estimated rate of obsolescence that is far lower.

IV.3.4 Transportation, sensors, and batteries. Consider the self-driving car. Tesla has developed electric cars with some self-driving capability and sold some 378 thousand in 2019. Google's self-driving car group, Waymo, has been testing self-driving cars as taxis in relatively easy-to-navigate suburbs of Phoenix, Arizona; taxi rides include a human minder who doesn't touch pedals or steering wheel except in an emergency. Fully self-driving cars able to operate in difficult driving conditions are likely to be years away. Yet both these firms — and many others — are accumulating data and also driving down the cost of key components. When self-driving cars become available, they will save a tremendous amount of driving attention time: U.S. adults drive an hour a day, according to the American Time Use Survey 2018.

Lidar systems — systems that use light as radar uses radio waves — are capable of much more accurate sensing of the environment than radar and also can operate under a wider range of weather conditions. The device can see in 3D, not just 2D. In 2005–2007, lidar systems from Velodyne cost $75,000 each, much too expensive for mass production. By 2014, that had fallen to $8,000 for a system from Luminar. Waymo is selling its lidar system, but not to car competitors, for $7,500. Luminar has announced that by 2022 systems will cost from $500 to $1,000 (Ohnsman, 2019; Lambert, 2020). Those prices are low enough to become valuable options on practically every car and greatly reduce the cost of experimenting with self-driving cars using lidar. In 2021, Volvo announced that Luminar's lidar system would be standard in the next version of its flagship SUV, slated to be unveiled in 2022.

Electric cars, like Tesla's, can also be a big help in reducing carbon use. But electric cars require batteries. For example, the Tesla Mark 3 requires 75 kwh of battery storage capacity. According to the government-sponsored BNEF, the price of battery storage has fallen from $1,160 to $156 per kwh, from 2010 to 2019, a seven-fold improvement, for a 25 percent annual rate of productivity growth.[6] Recent announcements by Volkswagen suggest a further reduction to $100 per kwh (Ewing, 2019). To scale this 11-fold decline, the cost of 75 kwh falls from over $80,000 per car to $7,500.

This decline has evidently abruptly shifted the future economics of car manufacturing such that the automotive industry is expected to predominantly turn to electric motive power by 2030. Indeed, in the largest car market, China, one-fifth of vehicles are now electric.

IV.3.5 Electric generation. Two energy sources to reduce the amount of carbon use are solar and wind power. But the weather cannot be relied upon to deliver power at precisely the times it is demanded. That implies a role for electrical storage to time-shift electricity supply to meet demand. The reductions in battery costs just discussed has been such that studies show that in Germany, where time of day plays an important role in electricity pricing, itself relatively expensive, the most recent technology already has a high payoff for homeowner adoption (Comello and Reichelstein, 2019). In the U.S., the same is not so true at the homeowner end, but large electric storage facilities are being cost effective for the wholesale electrical grid.

IV.3.6 Space commercialization. Elon Musk's SpaceX developed the Falcon 9 rocket that is now being used to resupply the Space Station. The Falcon 9 and its precursor, the Falcon 1, cost respectively $300 million and $90 million to develop. NASA has estimated that using its normal procurement model, it would have paid $4 billion to develop the Falcon 9, and that might have been subject to cost overruns (NASA, 2011, Zapata, 2017). Thus development costs were 10 times lower. And the price per flight fell by roughly three times. The Atlas 5 rocket that is the Falcon 9's main U.S. competitor costs $110 million to $230 million per launch, whereas the Falcon 9 costs $61 million for a roughly comparable payload (Federal Aviation Agency, 2018).

SpaceX and other new rocket and space startups are also working to substantially further lower the cost of flights by ensuring that the hardware is reusable, so that the primary cost of an

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[6] https://about.bnef.com/blog/battery-pack-prices-fall-as-market-ramps-up-with-market-average-at-156-kwh-in-2019/

https://about.bnef.com/blog/battery-pack-prices-cited-below-100-kwh-for-the-first-time-in-2020-while-market-average-sits-at-137-kwh/

additional flight becomes the fuel cost. Musk has speculated that his newest rocket, the Starship, when fully reusable would be capable of putting 100 passengers in Mars orbit with out-of-pocket costs of as little as $2 million per launch, with fuel costs under $1 million.

U.S. rocket flights support an industry whose total value is very large — $50 billion to $100 billion annually (FAA, 2018). These expenditures are a combination of civilian and military uses, with some part of them related to science and technological development.

The remarkable declines in space exploration costs have triggered an era in which many for-profit companies are developing plans to commercially exploit space and countries including India, China, and Japan have joined a new race to the moon. The cost of the commercialization of space has fallen dramatically.

Indeed, NASA plans to replace the International Space Station (ISS) with public-private ventures capable of commercialization. It has helped fund Axiom, which plans to begin putting pieces of a private commercial space station in place in 2024, completing the station in 2027. Axiom estimates that it will be 100 times more cost effective than the ISS that was completed in 1998. That would be a 15 percent annual rate of depreciation over 29 years. And there are three or four other US efforts to establish commercial low earth orbit space stations.

Using Table 3 to look back over the rate of depreciation of some of the key technologies of the past ten or twenty years or more, we see numerous rates that exceed 20 percent rates of decline. Of course, this is only a very incomplete survey, but I have argued that they include some very important examples and are part of a very rapid transformation of the fundamental technologies that researchers and product developers are able to deploy in the pursuit of new products.

I have argued elsewhere (Nakamura, 2020) that inflation rates across products in US GDP have been substantially overestimated. This appears likely to be true for intangible assets. These estimates suggest substantial price declines.

IV.4 Summary

Very large declines in prices or increases in productivity arise from innovative expenditures. These declines in prices are often difficult to measure. In addition, when the price declines take the form of new products, the implicit price improvements and productivity gains are not captured in standard measurement procedures. Nordhaus (1996) has argued that large price changes — which he describes as tectonic — are inherently very difficult if not impossible for statistical agencies to capture. In the current period of rapid and broad scientific and technological advance, such tectonic changes have become ubiquitous.

We have shown that the tools available to innovators, and the innovations that they create, are advancing at a very rapid rate, perhaps as low as 6 or 7 percent annually and perhaps as high as 30 percent or more. We propose that the rates of depreciation of intellectual property be taken seriously as windows into the rate of progress of our innovation. A ten percent rate of price decline in R&D alone would increase the rate of GDP growth by over 0.2 percentage points. If we use the 16 percent rate which is most standard, we get close to 0.4 percentage points.

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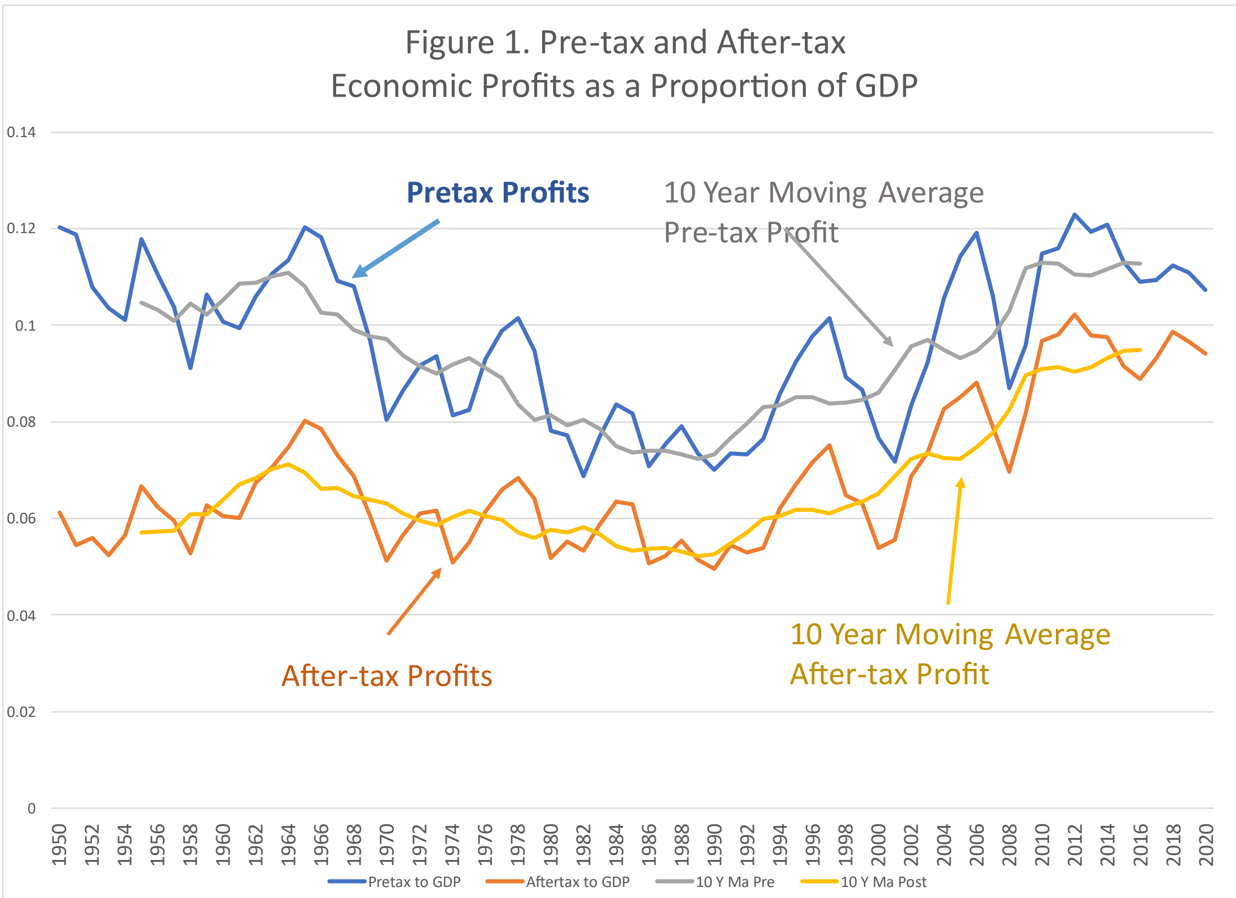

Sources: BEA data, Haver Analytics

Table 1. Domestic Research and Development, 2018, Total and Selected Groupings, National Center for Science and Engineering Statistics (NCSES)				
Business Activity	Industry codes	Billions of dollars	Percentage	Depreciation rate spread in percent
Total		441.0	100.0	
Medical and chemical	32500,33910,62150	98.7	22.4	9 to 16
Machinery and electronic	33300	103.4	23.4	25 to 40
Transportation machinery	33600	49.1	11.1	7 to 31
Information	51000	94.7	21.5	16 to 33
Professional, scientific and tech	54100	47.2	10.7	16
Subtotal of selected groupings		393.1	89.1	7 to 40

Source: National Science Foundation, NCSES, *Business Research and Development: 2018*, Table 74, pages 284-288. https://ncses.nsf.gov/pubs/nsf21312

Table 2. Depreciation Rate and Ranges		
Group		
	Industry	Depreciation Rate. Percent
Medical and Chemical		9 to 16
	Pharmaceutical and Medical Mfg	10
	Chemical Mfg, other	16
	Government health	9
Machinery and electronic		25 to 40
	Semiconductor Mfg	25
	Computer Mfg	40
	Communication Mfg	27
	Instrument Mfg	29
Transportation		7 to 31
	Motor Vehicle Mfg	31
	Aerospace Mfg	22
	Govt NASA	7
	Govt transportation	16
Information		16 to 33
	Software Pub	16
	Computer System Design	16
	Own Account Software	33
Professional, scientific and tech		16
	Research and Development	16

Source: US Bureau of Economic Analysis, Rates of Depreciation

Table 3. Rates of technological progress			
Type	Time Period	Improvement multiple	Rate of change, decline percent
Moore’s Law: number of transistors on a chip	1971 to 2020	25 x 10^6	29
DNA Sequencing	2007 to 2017	1000	47
CRISPR	2012 to 2018	150	57
Cloud computing	2006 to 2017	2	7
Internet start-up cost of experimentation	2006 to 2007	100 to 1000	
Rocket development	2007 to 2015	10	25
Rocket cost per flight	2007 to 2015	3	13
AI, Libratus to Pluribus	2017 to 2019	6000	
Sensor, Lidar	2007 to 2016	9	22
LEDs, cost per lumen	1975 to 2017	16000	21
Telecommunications			
Internet bytes	2008 to 2017	19	28
Cellular bytes	2008 to 2017	200	45

Source: see text

Appendix: BEA rates of depreciation Type of Asset	Rate of depreciation
Private intellectual property products	
Software /23/	
Prepackaged	0.5500
Custom	0.3300
Own-account	0.3300
Research and development /24/	
Pharmaceutical and medicine manufacturing	0.1000
Chemical manufacturing, excluding pharmaceutical and medicine	0.1600
Semiconductor and other electronic component manufacturing	0.2500
Other computer and electronic product manufacturing	
Other computer and electronic product manufacturing, nec	0.4000
Computers and peripheral equipment manufacturing	0.4000
Communications equipment manufacturing	0.2700
Navigational, measuring, electromedical, and control instrument manufacturing	0.2900
Motor vehicles, bodies and trailers, and parts manufacturing	0.3100
Aerospace products and parts manufacturing	0.2200
Other manufacturing	0.1600
Scientific research and development services	0.1600
All other nonmanufacturing	
Software publishers	0.2200
Financial and real estate services	0.1600
Computer systems design and related services	0.3600
All other nonmanufacturing, nec	0.1600
Universities and colleges	0.1600
Other nonprofit institutions	0.1600
Entertainment, literary, and artistic originals /25/	
Theatrical movies	0.0930
Long-lived television programs	0.1680
Books	0.1210
Music	0.2670
Other	0.1090

Source: Bureau of Economic Analysis, BEA Depreciation Rate

Table of Government Intellectual property depreciation.

Government intellectual property products /37/	Rate of Depreciation
Software:	
Prepackaged	0.5500
Custom	0.3300
Own-account	0.3300
Federal, National defense R&D:	
Extramural	0.1977
Intramural	0.1600
Federal, Nondefense R&D:	
NASA	0.0723
Health	0.0904
Energy	0.0935
Transportation	0.1600
Other	0.1600
State and local R&D	0.1600