ECONOMIST IMPACT

Innovation matters

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Methodological note

In a four-part series supported by Pictet Wealth Management, Economist Impact measured and analysed sixty years of innovation activity in four key technological sectors—artificial intelligence, biotechnology, energy and healthcare—to better understand how the pace of innovation in these fields has changed over time.

Working in partnership with data science studio Flamingo, Economist Impact developed a unique approach to measuring innovation activity based on a big data analysis of the language used in academic papers and patents.

Our model detects the emergence of novel language in the literature. Building on the work of Kelly et al. (2021) and Arts, Hou and Gomez (2021), we measure the similarity of papers and patents' textual content to those filed before and after. Important papers and patents are identified as those whose content is different from previous ones but similar to subsequent ones. These are thought to be both novel, since they are distinct from previous papers and patents, and influential, since they are similar to subsequent papers and patents. This textual analysis aims to capture innovation in a way that overcomes some of the limitations of directly measuring numbers of patents or measuring forward citations (see literature review for further discussion).

Our findings have been supplemented by secondary research and in-depth expert interviews and have been published in a series of four articles at impact.economist.com/innovationmatters.

Scoring

Our model identifies when new concepts first appear (such as *gene therapy*, *CRISPR*, or *deep learning*) and measures how significant concepts are in the long term by their subsequent usage. Keywords that go on to appear more frequently can be regarded as more significant and influential, and are scored more highly. Scores are assigned to the year in which they are first mentioned.

The titles and abstracts for each paper and patent document were tokenised and translated into bigrams and trigrams (two and three word phrases). For each n-gram in the dataset, we calculate the first time it appears and how many times it is re-used. In an attempt to remove long-term bias (older bigrams have more time to be reused), we devised an additional score to be used alongside the re-use score of a bigram. For the bigram's lifetime we calculate per year the number of times it is used divided by the total number of papers in that year for that sector. We then take the lifetime average of this yearly "penetration" score to arrive at the average publication density. These weighted scores were the primary subject of our analysis.

Sources

The academic papers studied were drawn from a subsampled Microsoft Academic Graph dataset made available by relianceonscience.org. For each sector we used the following fields of study, according to MAG's 'fields of study' categorisation:

- **Healthcare:** Medicine; Public Health; Healthcare; Bioinformatics
- **Biotechnology:** Biotechnology, Gene and Biochemistry
- **Artificial Intelligence:** Artificial Intelligence and Machine Learning
- **Energy:** Renewable Energy; Solar Energy; Thermal Energy; Alternative Energy; Fossil Fuel; Wind Power.

Patents were sourced from Google BigQuery, a repository of all patents uploaded to Google Patents up to and including January 2021. Patents were sorted according to the same fields of study, using related CPC codes.

Advisory board

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Literature review

Is innovation slowing down?

1. Introduction

Technological innovation has been the driving force behind our transition from a world of economic stagnation to our current world of economic growth and relative prosperity. As Mokyr (1990) notes, technological innovation disproves the old economics adage that there is no such thing as a free lunch. In fact, by increasing the productivity of the economy, innovation is a constant source of free lunches, allowing us to produce more of the goods and services we want using fewer resources. Despite its foundational role in our lives and our livelihoods, innovation remains a difficult concept to measure. This presents a problem, as reliable measures are needed in order to ensure that our policies and institutions continue to promote innovation and bring us greater prosperity.

In this document we review the literature on measuring innovation and explore whether these measures suggest that innovation is slowing down. We begin with economy-wide measures of innovation, in particular GDP growth and TFP growth, in Section 2. We then discuss more direct measures of technological progress in Section 3, and measures of scientific progress in Section 4. In Section 5, we examine the mechanisms that may lead to an innovation slowdown. Section 6 concludes with a brief discussion.

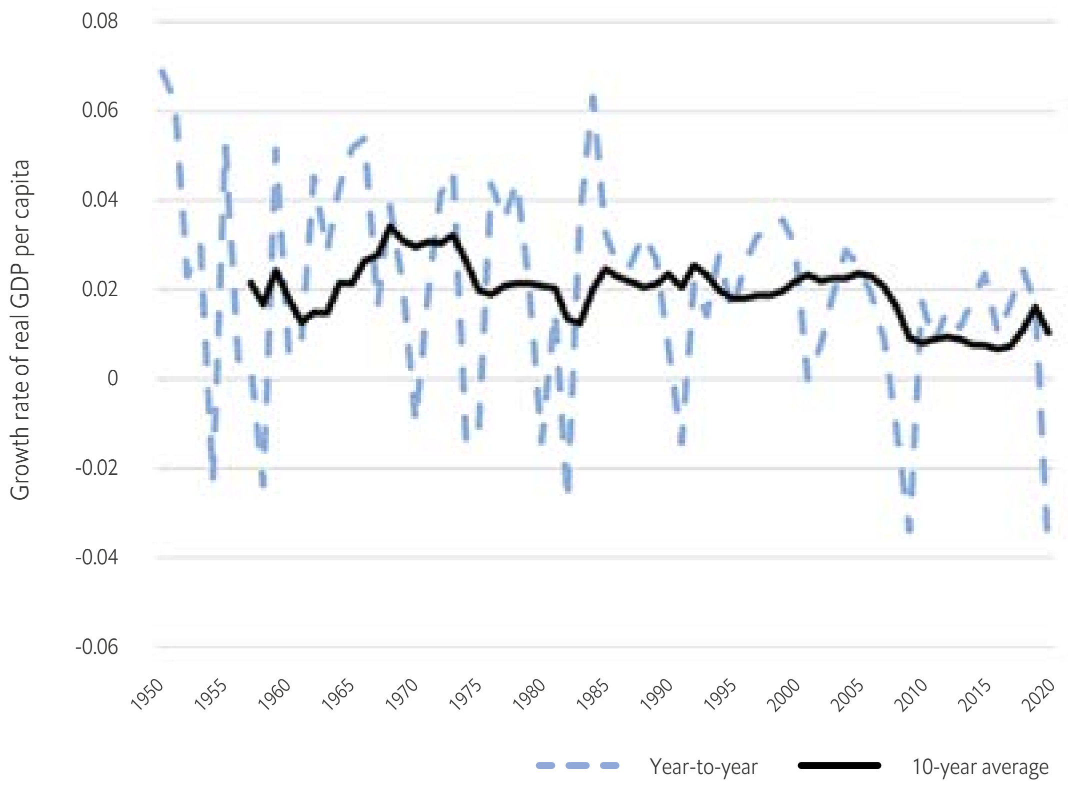
2. Economy-wide measures of innovation

2.1 GDP growth

At the end of the day, we care about innovation because it allows us to produce more of the goods and services we want. A good place to start in measuring innovation, then, is to simply measure the goods and services produced in the economy. This is usually captured with real Gross Domestic Product, or GDP, which measures the total value of final goods and services produced in an economy in a given year. Importantly, GDP is not designed to be a full measure of well-being or of quality of life. For example, it does not capture the value of home production, and it likely fails to fully capture subjective improvements to well-being, especially from innovations in areas like healthcare and public health (see e.g., Feldstein 2017 and Gordon 2016). Still, GDP is useful as a barometer of how “efficaciously human beings can take the material resources at their disposal and convert those resources into useful outputs” (Cowen and Southwood 2019).

The specific GDP measurement that is most relevant for discussions of innovation is the growth rate of GDP per capita, which we’ll refer to as “economic growth” for simplicity. Because of short- term year-to-year randomness and medium-term business cycle fluctuations, it is

Figure 1
Growth rate of real GDP per capita: year-to-year growth rate and 10-year average growth rate.



Source: Author's calculations based on data from U.S. Bureau of Economic Analysis, Real gross domestic product per capita [A939RX0Q048SBEA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/A939RX0Q048SBEA, March 16, 2021.

somewhat difficult to pin down exact trends in economic growth over time. But, as Figure 1 shows, it is clear that economic growth has been slower over the past two decades than it was throughout the 20th century (Gordon 2016, 2018; Vollrath 2020).

Measuring the magnitude of the slowdown depends on choosing somewhat arbitrary cutoff dates between different periods of growth. Broadly speaking, growth was strongest during the mid-20th century, decelerated slightly around 1970, and finally decelerated much more noticeably after 2005. The magnitude of the slowdown will therefore look different based on exactly which years are being compared. Vollrath (2020) provides useful numbers to fix ideas and keep things simple: economic growth averaged about 2.25% per year over the second half of the 20th century and has slowed to around 1.0% per year during the 21st century, a decline of 1.25 percentage points.

It is important to keep in mind that this slower growth does not mean the economy is shrinking or that living standards are getting lower. With the exception of recession years like 2008 and 2009, each year the U.S. is still producing more of the things that people want to consume than it did the year before. In fact, because the growth rate is measured from an increasing base, the absolute growth in GDP—that is, the total value of goods and services added to the economy in a given year—has not seen a meaningful slowdown (Vollrath 2020, p. 14-15). In other words, 1.0% growth in 2020 adds about as many real goods and services to the economy as 4.0% growth in 1950, because the economy has quadrupled in size over that time.

Though the slowdown in economic growth does not mean that living standards are getting lower, it does still point to a missed opportunity. If the U.S. economy had kept growing after 2000 at the same pace it did during the 1990s, real GDP per capita would be about 23% higher today than it actually is (Vollrath 2020, p. 24). The cost of slower growth is this gap between the economy as it is now and the economy that could have existed with faster growth.

If innovation is a large driver of economic growth, and growth has been slowing over recent years, does that mean that innovation has also slowed? One possibility is that growth hasn't actually slowed because measured GDP does not capture the value of new innovations. Feldstein (2017) explains two key difficulties in measuring GDP related to innovation. First, improvements to the quality of goods and especially services are difficult to measure and to incorporate into the official GDP statistics. For example, in some cases the Bureau of Labor Statistics uses information on the marginal cost producers incur to produce a higher-quality product to infer the value of the quality improvement. But with this method, an innovation that improved quality without increasing costs would not be counted as an improvement at all. If the first problem is measuring improvements to existing products, the second is valuing the introduction of entirely new products. New products are not included in the price indexes used to calculate GDP until they reach a significant level of expenditures. Once they are included in the price indexes, they can contribute to real GDP growth, but the value to consumers of their initial introduction is never truly captured.

These difficulties with incorporating new and better products into GDP are important, but for them to account for the growth slowdown it must be the case that mismeasurement is getting worse over time. At first glance, it does seem plausible that the nature of innovation in the 21st century could be making mismeasurement worse. Wikipedia, Google, and Facebook, for example, provide valuable services at no cost to their users. But as Cowen and Southwood (2019) explain, this does not imply that these services are distorting GDP measurements. Users may not pay to use Wikipedia directly, but they do pay for the devices and data plans that allow them to access Wikipedia. Additionally, the fact that the internet makes some goods and services cheaper is no different than any other innovation that has the same effect. Consumers spend or invest the money they save elsewhere, which is then captured by GDP. More to the point, several studies that have measured the size of the underestimation of GDP have found that it is just not large enough to explain a meaningful share of the growth slowdown (Byrne, Fernald and Reinsdorf 2016; Nakamura, Samuels and Soloveichik 2016; Syverson 2017).

2.1.1 The importance of demographics

The evidence suggests that the slowdown in economic growth is a real phenomenon and not just an artifact of measurement error. To understand whether this implies a slowdown in innovation, then, it is important to first break down economic growth into its component parts. In general, economists think of goods and services as being produced by two primary inputs: human capital (or labor) and physical capital. Human capital consists of the number of people in the labor force, the hours that they work, and their skill level. Physical capital refers to the machines, buildings, and other physical equipment used in production. When the economy's output of goods and services increases, this can be due to an increase in physical capital, an increase in human capital, or an increase in productivity—how effectively the physical capital and human capital are combined to produce the output.

Vollrath (2020) does some basic accounting to show that the bulk of the growth slowdown—at least 0.80 percentage points of the 1.25 percentage point drop in growth from 2.25% to 1.0% per year—can be attributed to a slowdown in human capital growth. In particular, the baby boom generation and the increase in women joining the labor force led to large increases in the number of people working throughout much of the second half of the 20th century. But the baby boomers had relatively few children themselves. Following Becker (1960), the rising incomes of the baby boomers and subsequent generations increased the opportunity cost of having children, leading them to choose smaller family sizes than their parents had.

The consequence of those choices is a declining labor force participation rate today, as baby boomers retire and are replaced by smaller cohorts of young workers. As mentioned above, human capital is a function of how many workers there are in the labor force, how many hours they work, and their skill level. There were small changes to the trends in hours worked and skill level between the 20th and 21st centuries, but they appear mostly irrelevant compared to the massive shift in labor force participation. In sum, the declining labor force participation rate decreases the growth rate of human capital, which in turn slows the economic growth rate. Much of the growth slowdown is thus due to demographic trends that have nothing to do with innovation.

Following Vollrath's (2020) accounting, changes in physical capital growth did not contribute meaningfully to the growth slowdown. The remaining piece of the growth slowdown, then, stems from a slowdown in productivity growth, to which we now turn.

2.2 Total Factor Productivity growth

Since the development of national growth accounting in the 1930s and 1940s, it has been recognized that growth in human capital and physical capital cannot explain all output growth (Hulten 2010). In a seminal contribution, Solow (1957) tied this unexplained output growth to a shift in the aggregate production function. Thus the "Solow residual," also called Total Factor Productivity (TFP) or Multi-Factor Productivity, captures how effectively an economy can combine the inputs at its disposal to produce the outputs that its people want. Because increases in this effectiveness are usually thought to come from new ideas, TFP growth is commonly taken as a measure of innovation in an economy, industry, or firm.

As with GDP growth, the noisiness of the data makes trends difficult to identify and cutoffs between different periods somewhat arbitrary. In general, TFP growth was highest during the 1930s through 1950s, decelerated sharply after 1950, and slowed throughout most of the second half of the 20th century (Gordon 2010). There was a revival in TFP growth from about 1995 to 2004 before another deceleration around 2005. Focusing on the more recent slowdown and sticking with Vollrath's (2020) accounting for simplicity, TFP growth averaged 1.51% from 1950 to 2000 and has slowed to 1.26% in the 21st century, a 0.25 percentage point decline.

It is important to note that TFP growth is truly a residual (as the "Solow residual" moniker implies) and is not measured directly; all output growth that cannot be explained by increases in inputs is necessarily captured as TFP growth. As such, TFP growth captures innovations that allow the economy to produce more with less, but it also captures improvements that don't fit into the typical idea of innovation. As Cowen and Southwood (2019) discuss, innovation is usually thought of as pushing forward the technological frontier, but an inefficient firm merely catching up to the technological frontier will boost measured productivity.

Another difficulty in thinking of TFP growth as a measure of innovation is that there is not a clear distinction between standard capital accumulation and innovation-driven technological change. Hulten (2010) discusses three main conceptual issues. First, the R&D expenditures that lead to innovation are often understood and accounted for as investments in (knowledge) capital, blurring the line between capital accumulation and innovation. Second, endogenous growth models (see e.g., Romer 1990) predict that capital accumulation leads to spillover effects that increase TFP, and the increase in TFP in turn induces increased capital accumulation. This positive feedback makes it difficult, both conceptually and in practice, to determine how much of the resulting growth should be attributed to innovation. Finally, product innovation by one industry may provide capital goods for other industries. This capital-embodied technological change would appear in the statistics as capital investments by the adopting industries, but again the line between capital accumulation and innovation is blurred.

As with the difficulties in measuring GDP, these issues may bias estimates of the level of TFP, but they only bias estimates of TFP growth if the measurement problems are changing over time. Cowen and Southwood (2019) note that there is some reason to suspect that the measurement issues could be worsening: as societies increasingly invest in intangible capital and education, it is possible that more innovation is being embodied in physical and human capital. However, if the only change happening were a shift from innovation being counted as TFP growth to being counted as capital accumulation, we would expect to see an increase in the growth rate of capital corresponding to the drop in TFP growth. This is not what we observe in the data, suggesting that there is real slowdown occurring.

2.2.1 Technology adoption lags and costs

A further difficulty in using TFP as a measure of innovation is that new technologies are not immediately and universally adopted when they become available. Instead, technologies often take decades to diffuse through the population of potential users. Even when the technology is adopted, it may take additional investments of time and money for the technology to be fully incorporated into the production processes. As Cowen and Southwood (2019) note, this means that TFP growth today may reflect innovations from two or more decades in the past, making it difficult to infer anything about the current rate innovation from the current rate of TFP growth.

A key feature of technology adoption is that it often involves significant sunk costs (Hall 2003). These sunk costs include the monetary costs of purchasing and installing the technology, of course, but they also include the intangible costs of learning how to use the technology and incorporate it into the user's environment. Sunk costs may contribute to the long lags in technology diffusion by creating a high bar that a new technology must clear before a firm finds it profitable to adopt. Once the technology is adopted, the learning costs associated with incorporating the new technology into the production environment may continue for quite some time.

Recent studies have made the case that the nature of innovation over the last few decades has magnified the effects of the lags and costs in technology adoption (Brynjolfsson, Rock and Syverson 2019; Brynjolfsson, Benzell and Rock 2020; Brynjolfsson, Rock and Syverson 2021). These studies argue that recent developments in information and communication technology, from computers to remote work technology to artificial intelligence, are new forms of general purpose technologies (GPTs), which are technologies characterized by their "pervasiveness, inherent potential for technical improvements, and 'innovational complementarities'" (Bresnahan and Trajtenberg 1995). GPTs are in a sense the foundational technologies upon which the economy is built.

This foundational position means that fully incorporating new GPTs into the economy takes a significant amount of time and investment in complementary capital. Much of the complementary capital needed to realize the benefits of GPTs is intangible capital like corporate culture and new workflows and processes. These investments in intangible capital can lead to a temporary decline in productivity followed by a long-run increase, which Brynjolfsson, Rock and Syverson (2021) have called a productivity J-curve. When the investments are made, real resources are put to use creating the intangible assets needed to benefit from the new GPTs. Productivity falls because these investments increase the firm's costs without providing any immediate benefits to production. However, eventually the intangible capital, in combination with the GPT, begins to produce returns, causing a large increase in measured productivity growth as output increases without any apparent increase in physical or human capital. Productivity growth is therefore underestimated early in the GPT's lifecycle and overestimated later in the lifecycle, forming the productivity J-curve.

When accounting for the role of this intangible capital in production, Brynjolfsson, Rock and Syverson (2021) find that TFP growth since 2005 has averaged 0.71% per year instead of the 0.40% per year growth measured without taking intangibles into account. However, accounting for intangible capital from 1995 to 2004 increases TFP growth during that period from 1.63% per year to 2.20% per year. Thus, the TFP growth slowdown since 2005 actually increases from 1.23 percentage points to 1.49 percentage points (note that these numbers are different than Vollrath's (2020) because of the different cutoff dates used) when accounting for the intangible capital needed to incorporate new GPTs.

2.2.2 The shift from goods to services

The discussion above suggests that the slowdown in TFP growth points to a real productivity slowdown and is not an artifact of measurement or intangible capital. However, this does not necessarily mean that innovation is slowing. Vollrath (2020) points out that the shifting makeup of U.S. GDP has had a large impact on measured TFP growth. Since at least 1970, the share of GDP accounted for by goods-intensive industries like agriculture, mining, and manufacturing has declined, while the share accounted for by service-intensive industries like healthcare and professional services has increased. Because the goods industries generally have historically had higher TFP growth than the service industries, this shift in the composition of GDP mechanically decreases the TFP growth of the full economy.

It is possible to imagine that this shift from goods to services was due to a failure of innovation, but Vollrath (2020) explains that this is not the case. An industry's share of GDP depends on both its real value-added production, which measures the quantity of output minus the intermediate inputs used in production, and its relative price. In general, the real value-added production of all industries has increased over time—even for the goods industries whose GDP shares have decreased. The real value-added production of the goods industries has increased more slowly than some of the service industries, but it has increased more quickly than some others. The relative prices of the service industries, on the other hand, have generally increased much more quickly than the goods industries across the board. The trends in real value-added production thus may play a small role in GDP's shift from goods to services, but the main driver of the shift has been the trends in relative prices.

This rise in the relative prices of services can be explained by a phenomenon articulated by Baumol (1967), now often referred to as *Baumol's cost disease* or the *cost disease of services*. The premise of the cost disease is that productivity growth in services is inherently more difficult than productivity growth in the production of goods. When people purchase goods like an air conditioner or refrigerator, they generally don't know and don't really care how much labor went into making the product. But when they purchase services, the labor itself is often what is being purchased. For example, cutting an hour of a live performance or tutoring down to half an hour does not improve productivity because the time and attention of the service provider are the real product being exchanged. This key difference in the potential for productivity growth leads to the cost disease of services. As productivity in the goods sector increases more quickly than in services, the relative costs of producing goods compared to services falls. Or, put another way, the relative cost of services increases, just as we see in the data.

The cost disease of services does not, however, fully explain GDP's shift from goods to services. If services are getting more expensive, we might expect the quantity of services demanded to decline. But as discussed above, the trends in real value-added production do not bear this out. Real value-added production of services was generally increasing in absolute terms, and for some services the real value-added production even increased relative to the main goods industries. The last mechanism causing the shift from goods to services, then, is that demand for services is relatively income elastic, while demand for goods is relatively income inelastic. This means that as a person's income increases, they will spend an increasing share of their income on services and a decreasing share on goods, which is precisely what we see in the aggregate with the shifting composition of GDP.

Recent evidence on the shift from goods to services adds some nuance to the narrative of Baumol's cost disease. Young (2014) essentially questions Baumol's assumption that the productivity of goods production will grow more quickly than the productivity of services. The key idea is that slow productivity growth in services may not be an inherent feature, as Baumol suggested, but rather a result of the growing demand for services and employment in the service industries. Young (2014) develops a Roy (1951) model of self-selection, where workers choose to work in the industry (goods or services) where they have a comparative advantage. Importantly, absolute advantage and comparative advantage are assumed to be positively correlated. This positive correlation means that as the service industry grows, it will pull in workers who are less and less productive when working in the service industry. Meanwhile, the workers who remain in the goods-intensive industry will be only those who are the most productive there. This effect will mechanically drive the growing service industry to have slower productivity growth and the shrinking goods industry to have faster TFP growth, even if the true rate of productivity growth based on technological change is exactly the same in the two industries.

Young (2014) empirically estimates the size of this self-selection effect on measured productivity growth. The estimates are imprecise, but they suggest that the rate of true productivity growth based on technological change in services could possibly be just as high as or even higher than true productivity growth in goods production. What this means for overall productivity growth, however, is unclear. On the one hand, it suggests that TFP growth in services industries is not necessarily doomed to forever be slow. On the other hand, Young (2014) finds that the aggregate effect of the self-selection is that true productivity growth in the U.S. was actually slower from 1987 to 2010 than the official measured TFP growth rate over that time. However, this effect is not universal; true productivity growth in Europe was faster than the official measured TFP growth.

In the end, Young's (2014) research does not negate the ideas behind Baumol's cost disease. Baumol's (1967) insight that demand for services is income elastic while demand for goods is income inelastic is still critical to explaining why we keep purchasing more services even as their prices rise. As TFP increases, we become wealthier as a society, and we use that wealth to buy more services, even if their relative prices have increased. This shift in the makeup of GDP, combined with the slower productivity growth in services—whether that is an inherent feature of services or a result of the self-selection of workers—is responsible for as much as 0.20 percentage points of the 0.25 percentage point drop in TFP growth after 2000 (Vollrath 2020).

2.2.3 Innovation and TFP growth

TFP growth is probably the best economy-wide measure of innovation available. By measuring our ability to do more with less—to produce more of the goods and services we want using fewer resources—TFP growth captures our ability to innovate more directly than GDP growth. However, as the preceding discussion highlights, TFP growth is influenced by many factors that have little to do with innovation. Firms increasing their productivity by merely catching up to the technological frontier and GDP's shift from goods to services get dumped into the measurement of TFP growth, while the ambiguity between technology and capital blurs the line between TFP growth and capital accumulation. Furthermore, when real innovation does occur, as in the case of the introduction of a new GPT, its role in TFP growth can be obscured by adoption lags and investment in intangible capital.

Because of these issues, the slowdown in TFP growth is not conclusive evidence of an innovation slowdown. To get a more complete picture of the state of innovation, we need to complement TFP growth with more direct measures of innovation. These measures can help us to understand if the trend in TFP growth is caused by a real slowing of innovation or by the other factors that impact TFP. We now turn to these more direct measures of innovation.

3. Direct measures of technological progress

3.1 Patent statistics

By granting firms the right to exclude others from using their innovation, patents provide a way for firms to appropriate the value of the innovation and earn a return on the investment needed to develop it. Like TFP growth, patents are therefore an outcome of innovation. In many ways patent data may provide a more reliable measurement of innovation than TFP growth. The connection between innovation and patents is more direct, with fewer confounding factors between the conception of the innovation and the measured outcome. Additionally, patents themselves are directly observable, unlike the residual TFP growth.

However, patent data has its own set of limitations. First, not all innovations are patented. Cohen, Nelson and Walsh (2000) survey U.S. manufacturing firms about their use of various mechanisms firms use to protect their intellectual property. For both product innovations and process innovations, the firms rate patents as the fifth most important mechanism out of six, behind secrecy, lead time, complementary manufacturing, and complementary sales, and ahead of only "other legal." The reasons firms give for not using patents to protect their innovations include the ease of inventing around the patent, the difficulty of demonstrating novelty, and the amount of information disclosed in the patent application. Fontana et al. (2013) find under 10% of R&D Magazine's annual "top 100 innovations" awards are protected by a patent.

These survey results show that firms have alternative mechanisms available to them to protect their intellectual property and appropriate the value of their innovations, and that they weigh the perceived costs and benefits of a patent before applying. Because of this, raw patent numbers can be a misleading indicator of innovation. The number of patents in a given year depends not only on the rate of innovation at that time but also on the economic incentives to patent the innovations.

The fact that raw patent numbers depend partly on the economic incentives to file for a patent points to the second major limitation of patent data: not all patents are equally innovative or valuable. In the most extreme cases, some patents appear to have zero or even negative social value and are used only as a tool for rent extraction by the patenting firm. Using data from Japan, Motohashi (2008) finds that around half of all active patents are not used by firms either internally or for external licensing. Furthermore, over half of the unused patents are classified by Motohashi (2008) as blocking patents because the firm has no intention of using or licensing the patent. These blocking patents are apparently kept either for the purposes of blocking a competitor from using the technology or as leverage for future licensing negotiations with other firms (Nagaoka, Motohashi and Goto 2010).

Various measures have been proposed to go beyond raw patent counts and capture the actual value of the patent. These measures vary based on what aspect of the patent's value they try to capture: its scientific value or its private economic value. A patent's scientific value measures the knowledge spillover it creates and its technological influence on subsequent patents. Its private economic value measures the financial value of the patent to the firm that owns it. Both scientific value and private economic value are important measures of the innovation embedded in a patent. Scientific value reflects how technologically innovative the patent is and its influence on future technological progress. The private economic value reflects, to some extent, how much value society places on the innovation. More precisely, it captures how much of the social value of the innovation that the inventor is able to appropriate through the use of the patent. A measure of the full social value of the innovation would in many cases be ideal, but for now measures of scientific value and private economic value are the best proxies available. In practice, the scientific value and private economic value are positively correlated, but they do contain independent information (Kogan, et al. 2017; Kelly, et al. 2021).

3.1.1 Forward citations

Patents include citations to prior patents in order to identify the prior art and demonstrate their novelty and inventive step (Nagaoka, Motohashi and Goto 2010). A patent's forward citations—the number of subsequent patents that cite it as prior art—is therefore a measurement of its technological and scientific influence. Forward citations may reflect the private economic value of the patent to the innovating firm to some extent, perhaps through capturing the potential for licensing the patent. But the forward citations measure is more often intended to be an indicator of the scientific value of the patent, ideally capturing knowledge spillovers from one inventor to another.

Even under the best of circumstances, forward citations may be limited in their use as measure of innovation. For example, more recent patents suffer from a truncation problem because they have not had enough time to accumulate citations, and the propensity to cite patents varies widely across fields (Nagaoka, Motohashi and Goto 2010). More concerningly, Kuhn, Younge and Marco (2020) provide evidence that calls into question the ability of forward citations to measure knowledge spillovers and innovation altogether. They document that citations are becoming systematically less informative about the technological similarities between patents over time. Aggregate forward citation counts are increasingly driven by patents that cite over 100 other patents. These citations appear to be added for strategic reasons, likely by patent attorneys or other actors rather than by the inventors themselves. The citations of these extreme citation-count patents provide very little information about actual knowledge spillovers or scientific value, and the increase in such extreme patents is causing aggregate forward citation measures to lose their informative value. Despite these limitations, forward citations have been one of the most common ways of measuring the innovative value of patents for several decades (Kuhn, Younge and Marco 2020; Nagaoka, Motohashi and Goto 2010) and have shown—in the past—to be correlated with other measures of the value of patents.

3.1.2 Textual analysis

Recognizing the limitations of forward citations, Kelly et al. (2021) propose a method for measuring the scientific value of a patent based on textual analysis of patent documents. Using natural language processing, their measure quantifies the similarity of a patent's textual content to the patents that were filed within a given timeframe before and after it. Important patents are identified as those whose content is different from previous patents but similar to subsequent patents. These patents are thought to be both novel, since they are distinct from previous patents, and influential, since they are similar to subsequent patents. The importance is measured simply by the ratio of the patent's forward similarity (similarity to subsequent patents) to its backward similarity (similarity to previous patents).

Kelly et al. (2021) demonstrate that this measure performs better than forward citations at capturing historically important patents identified by organizations like the U.S. Patent and Trademark Office. The measure is highly correlated with forward citations, but generally needs fewer years of data than forward citations to determine a patent's scientific importance and is not subject to the limitations inherent in counts of forward citations.

Arts, Hou and Gomez (2021) use additional natural language processing techniques to capture the scientific value of a patent. They explore a measure of forward and backward similarity similar to that of Kelly et al. (2021) as well as several measures based on the use of scientific keywords. For example, they determine a patent's novelty based on whether it is the first patent to use any scientific keyword or a unique pair of keywords. Similarly, they determine a patent's impact based on the number of subsequent patents that use keywords or keyword combinations that the patent originated. Arts, Hou and Gomez (2021) show that their measures of textual novelty and impact generally perform better than citation-based measures at discriminating between award-winning patents, average patents, and rejected patents.

3.1.3 Stock market response

Kogan et al. (2017) propose a measure of a patent's private economic value based on firms' stock price movements after a patent is granted. They show that stock trading volumes and price volatility are significantly higher for a firm within a two-day window following the firm being granted a patent. This suggests that the patent grant contains valuable information for the market's valuation of the stock. They then measure the stock's return in the two-day window after a patent grant, filtering out stock price movements that are unrelated to the patent grant using assumptions on the distribution of stock returns.

Kogan et al. (2017) demonstrate that their measure of private economic patent value is positively correlated with scientific patent value as measured by forward citations. However, their measure contains independent information and is able to provide insights that forward citations do not. For example, economically valuable innovation, as measured by stock market response, by a firm's competitors leads to a decline in the firm's profits, output, capital investment, and employment. The authors interpret these declines as signs of the creative destruction of innovation. On the other hand, scientifically valuable innovation, as measured by forward citations, is not associated with creative destruction because the scientifically valuable innovation leads to knowledge spillovers that the firm can benefit from.

3.1.4 Aggregate innovation indexes

Both Kelly et al. (2021) and Kogan et al. (2017) propose an index of aggregate innovation based on their measures of patent value. Kelly et al. (2021) construct their index by measuring the number of "breakthrough" patents per capita each year, which they define as patents in the top 10% of importance as determined by the ratio of forward similarity to backward similarity. Kogan et al. (2017) construct their index by aggregating the total economic value of patents granted in each year, deflated by that year's GDP.

Both indexes are positively correlated with TFP growth, suggesting that they do in fact capture important aspects of innovation. A one-standard-deviation increase in the Kelly et al. (2021) scientific value index is associated with 0.5% to 2% higher TFP growth over the next ten years. A one-standard-deviation increase in the Kogan et al. (2017) economic value index is associated with a 0.6% to 3.5% increase in TFP growth over the next five years.

Adding further validity to the indexes is the fact that they both appear to capture periods of rapid innovation, particularly the 1930s and 1990s, as Figure 2 shows. Interestingly, both indexes show innovation reaching its highest point around 2000 and falling throughout the 21st century. However, according to both indexes the decline is relatively small compared to the large increase in innovation throughout the 1990s, and so innovation remains at a high level historically, even if it has fallen somewhat from its peak.

3.2 Non-patent measures

Patent statistics are not the only possible direct measures of technological progress. One way to measure technological progress directly is to look at narrow areas where the idea of progress is well-defined. In an influential recent paper, Bloom et al. (2020) examine innovation in

Figure 2

Aggregate innovation indexes based on U.S. patent data. Panel A shows the Kelly et al. (2021) index: the number of breakthrough patents per 1000 people in each year. Panel B shows the Kogan et al. (2017) index: the log of the total private value of patents deflated by GDP in each year. Panel C shows the log of the raw number of patents per year for comparison to the two indexes. Note that Panel A covers a longer timespan than Panels B and C.

(A) Breakthrough patent index
Source: Kelly et al. 2021

(B) Patent value index, log scale
Source: Kogan et al. 2017

(C) Patent per capita, log scale
Source: Kogan et al. 2017

various fields. They focus on fields where the rate of technological progress is relatively tangible and well-defined and can thus be measured directly. Specifically, they use Moore's Law and the doubling of the number of transistors on an integrated circuit every two years as a measure of progress in computing; the growth rate of crop yields as a measure of progress in agriculture; and the number of new molecular entities (a basis for new drugs) and years of life saved from declining mortality as a measure of progress in healthcare.

The drawback of these types of measures is that they are field-specific and difficult to combine into any sort of aggregate rate of innovation or progress for the economy as a whole. Furthermore, many areas of the economy are not amenable to such direct measurements of progress, which is why residual TFP growth is so commonly used to capture innovation. Nevertheless, the trends in these field-specific measures of progress can still be informative, especially when the trends from multiple fields seem to point to the same conclusion. Bloom, et al. (2020) find that the rate of progress in the three specific fields they study has remained roughly constant over time.

Another non-patent measure of innovation involves textual analysis of reports on public companies. Bellstam, Bhagat and Cookson (2020) apply topic modelling tools to analyst reports covering S&P500 companies. They develop a measure of companies' innovation based on the topics discussed in the text of these reports. Their measure correlates with valuable patents for patentable product innovations, but it also captures valuable process innovations and other non-patented innovations. They also demonstrate that their measure predicts future company performance, suggesting that they are capturing the private economic value of the company's innovation.

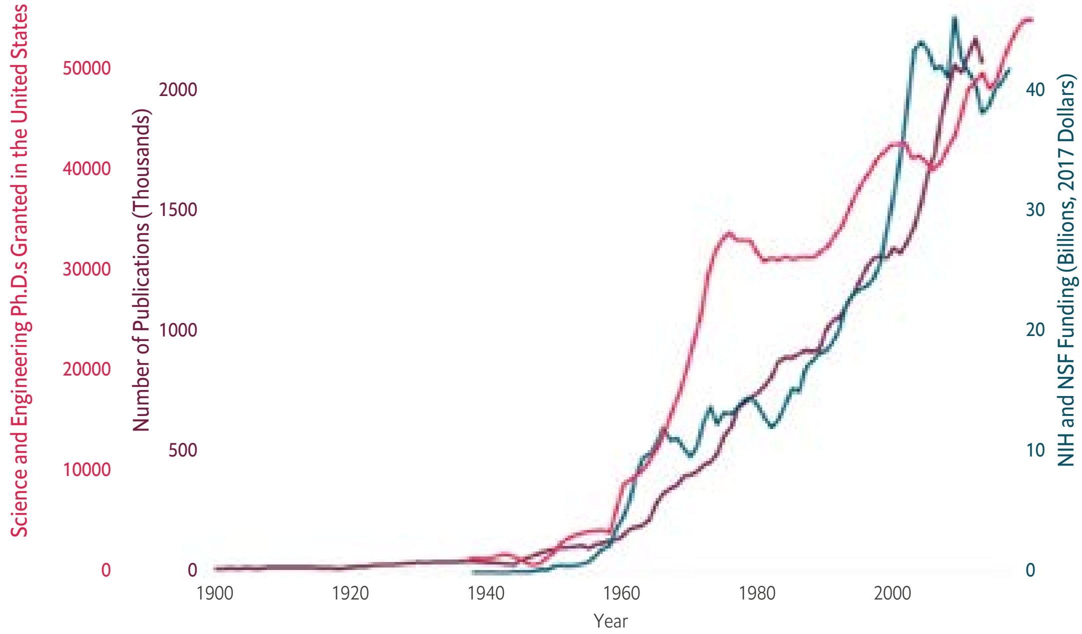
A final potential way to measure technological progress over time is to simply count the number of important innovations made each year. Meisenzahl and Mokyr (2011) use this sort of method, constructing a database of 759 British innovators and their contributions to innovation during the Industrial Revolution. This method is subject to some clear limitations. Determining what counts as an important innovation is subjective, and it will be especially subjective for more recent innovations that have had less time to prove their worth. Compounding this issue is the fact that the impact of specific innovations will tend to decline as the economy becomes more specialized, which Howes (2020) has called the "paradox of progress." For example, an agricultural innovation from several centuries ago, when agriculture accounted for 40% of the economy, is bound to have a greater impact and seem much more important than a similar innovation today, when the largest single sector (finance) accounts for just 22% of GDP.

4. Direct measures of scientific progress

Because innovation depends to a large extent on the ideas discovered by basic and applied science, measures of scientific progress provide another potential measure of innovation. In general, it appears that directly measuring scientific progress is even more difficult than directly measuring technological progress, and relatively few measures of scientific progress have been developed. That said, a few promising measures do exist.

A good place to begin is with the raw inputs and outputs of the scientific process, which have been increasing drastically over time. As Figure 3 shows, the number of scientists, the funding for science, and the number of scientific publications have all increased exponentially since the mid- 20th century (Collison and Nielsen 2018). However, these trends do not tell us much about the rate of actual scientific progress. The number of scientists and the amount of science funding are both inputs to science; we hope increasing these inputs will increase progress, but there is

Figure 3
Trends in the number of scientists, funding for science, and the number of publications.



Source: Collison and Nielsen (2018).

no guarantee that this will be the case. Scientific publications are an output of science, but as we saw with patents, the raw count of publications is not a reliable indicator of the social value of the output or its impact on innovation because not all publications are equally valuable or impactful.

A potential measure of a publication's value and impact might be its forward citations. At a given time within a given field, forward citations may be a reliable indicator of a publication's quality. However, forward citations are likely not a good measure of how science progresses over time. If the information value of patents' forward citations has been changing over time, the increasing number of scientific publications and changing citation practices are likely to change the information value of forward citations in science as well. Additionally, the forward citations in science will be subject to the same issues of truncation and differences across fields as we saw with the forward citations of patents.

Wu, Wang and Evans (2019) study scientific progress using the structure of a publication's citations rather than a simple count of forward citations. For each publication, they measure how often an article that cites the focal publication also cites a reference that the focal publication itself cites. The idea is that a publication with forward citations that don't also cite its own references is more disruptive to science, representing a new idea or a paradigm shift. Conversely, a publication with forward citations that do cite its own references is developing science by answering acknowledged questions and refining methods. Both types of science are important, but major breakthroughs, like Nobel Prize-winning work, tend to be disruptive rather than developing science.

Wu, Wang and Evans (2019) use their measure of disrupting or developing science to examine the difference in the science produced by small and large scientific teams. They find that large teams tend to develop science, while small teams are more likely to disrupt science. Combining this with evidence showing that the size of scientific teams is increasing (see Wuchty, Jones and Uzzi 2007), these findings suggest that science may be becoming less disruptive and dynamic over time.

Another promising approach uses the text of scientific articles. Iaria, Schwarz and Waldinger (2018) attempt to measure changes in the quality of scientific publications during World War I by counting the number of new words that appear in journal titles, as well as the number of new words that subsequently appear in patents. Milojevic (2015) develops a measure of the cognitive extent of science based on the lexical diversity of the titles and abstracts of published research articles. The lexical diversity of a scientific field is essentially the number of unique phrases with scientific meaning that are used in a given number of articles. The idea is that if the number of unique scientific phrases in a field is increasing, this must represent an expansion of the cognitive territory covered by the field. Milojevic (2015) finds that the cognitive bounds of physics, astronomy, and biomedicine are all increasing linearly over time, as opposed to the exponential increase in publication volume in each of these fields. This result thus suggests that scientific progress is advancing, though not at the rate that publication volumes would suggest.

Milojevic (2015) also finds that individuals and smaller teams cover larger cognitive territory than large scientific teams. Like the results of Wu, Wang and Evans (2019), this suggests that the observed increase in scientific team sizes may be a drag on scientific progress.

With a much different approach to assessing scientific progress, Collison and Nielsen (2018) survey scientists working in physics, chemistry, and medicine about the importance of Nobel Prize-winning contributions over time in their respective fields. They find that physicists generally rate the discoveries of the 1920s as the most important, with the importance of discoveries generally declining since then. Discoveries in chemistry and medicine, on the other hand, are judged to be generally improving slightly in importance over time. These findings, however, have many of the same drawbacks as counting major innovations: subjectivity, difficulty in assessing the value of recent advances, and decreasing overall impact due to specializations within the field and the paradox of progress.

5. Potential drivers of an innovation slowdown

The direct measures of innovation provide mixed evidence for an innovation slowdown. Even without conclusive evidence that innovation is slowing, it is worthwhile to consider the mechanisms that could be driving such a slowdown.

Bloom et al. (2020), discussed earlier for their direct measures of technological progress in various fields, study the trends in research productivity in each of those fields, as well as in the corporate business sector using firm-level microdata. They note that endogenous growth models (e.g., Romer 1990) predict that an input of a constant number of researchers should be able to produce an output of a constant rate of innovation and productivity growth for the economy. They measure the research productivity of each field by dividing its rate of progress by its effective number of researchers, which they calculate as the R&D expenditures in the field deflated by the wage for high-skilled workers in the economy. Importantly, they point out that previous studies of R&D productivity typically used R&D expenditures as the denominator instead of effective researchers. However, endogenous growth models actually predict that the ratio of innovation to R&D expenditures will decline; therefore, this empirical finding is not actually informative about innovation and endogenous growth. Bloom et al.'s (2020) use of innovation per effective researcher, on the other hand, is motivated by economic theory and thus provides an informative test.

Bloom et al. (2020) find that research productivity is declining in all the areas they study. They focus on the U.S., but Boeing and Hunermund (2020) replicate their results in the corporate business sector using Chinese and German firm-level data, and Miyagawa and Ishikawa (2019) replicate the same results using Japanese data, suggesting that the decline in research productivity is a global phenomenon.

Jones (2009) provides theory and evidence that this declining research productivity may be due to the "burden of knowledge." This idea is based on two simple observations. First, people are not born on the knowledge frontier, and it takes time for them to acquire the human capital needed to get to the frontier. Second, because knowledge is cumulative, reaching the knowledge frontier becomes more difficult over time. Together, these facts imply that it becomes more difficult for each successive generation to contribute to innovation. Jones (2009) shows that this leads innovators to invest in more education and to narrow their focus so that they can reach the knowledge frontier in a more specific area. The burden of knowledge has thus led to an increase in the age at first invention, specialization, and teamwork among inventors.

Several studies have suggested that the burden of knowledge is also increasing the amount of effort needed to make innovative contributions to scientific research. Jones (2010) documents that the age at which Nobel Prize winners make their prize-winning discovery is increasing, and that their lack of productivity in their early years is not offset by increased productivity later in life. Wuchty, Jones and Uzzi (2007) show that scientific research is increasingly done in teams across science and engineering, social sciences, and arts and humanities. They also note that teams produce research that receives more citations and are more likely to produce highly influential research as measured by extremely high citation counts. Agrawal, Goldfarb and Teodoridis (2016) provide evidence that the increase in scientific teamwork is indeed caused by the burden of knowledge and not other potential mechanisms, such as changing norms or declining communication costs. Using the fall of the Iron Curtain as a natural experiment, they show that the influx of Soviet mathematicians into Western science pushed the knowledge frontier outward and led directly to an increase in scientific teamwork.

These findings suggest that the amount of effort and resources required to innovate is increasing over time, but whether they show that innovation is slowing down is open to interpretation. In each area they study, Bloom et al (2020) find that the rate of innovation has remained roughly constant over time, but that the effective number of researchers has increased drastically, leading to the sharp decrease in research productivity. The endogenous growth models that Bloom et al. (2020) test predict that we can achieve a constant rate of productivity growth with a constant number of researchers. Bloom et al. (2020) find that we generally can and do achieve that constant rate of productivity growth within each field, but we just use an increasing number of researchers to do so.

It is unclear what these results means for the future of innovation—will we be able to continue to increase the resources we put toward innovation quickly enough to overcome the burden of knowledge and keep innovation constant? For now, the decline in research productivity and the burden of knowledge are not necessarily evidence of an innovation slowdown in themselves, but they do shed light on the mechanisms that would be likely to drive a slowdown.

6. Discussion

Because of innovation's key role in economic growth, the recent slowdown in economic growth has prompted worries that we are losing our ability to innovate. However, as discussed here and more thoroughly in Vollrath (2020), much of the slowdown in economic growth is due to factors that have nothing to do with innovation. Human capital growth has slowed due to demographic trends, and TFP growth has slowed largely due to GDP's shift from goods to services. But this does not mean that innovation is not slowing down; it just means that we need additional measures of innovation to help answer the question.

More direct measures of technological and scientific progress present a mixed view of the current state of innovation. The patent-based innovation indexes developed by Kelly et al. (2021) and Kogan et al. (2017) do show a drop in innovation since about 2000, but still show the current level of innovation as reasonably high by historical standards. Measures of progress in specific fields show little to no decline in total, though the research productivity in each field is declining sharply (Bloom, et al. 2020). Measuring scientific progress is even more difficult than measuring technological progress, and the measures we do have do not seem to paint a clear picture of the trends in science. Taken as whole, evidence from GDP growth, TFP growth, and the more direct measures of progress suggest that it may be possible that innovation is slowing on a per capita basis but remaining roughly constant in total.

As we continue to develop new measures to better understand the true rate of innovation in the economy, it is important to note that TFP growth remains the benchmark measure of innovation. As we saw with the innovation indexes derived from patent statistics (Kelly, et al. 2021; Kogan, et al. 2017), a test of their validity is how well they correlate with TFP growth. Bloom et al (2020) and Jones (2009) relate their findings on R&D productivity and the burden of knowledge to TFP growth. Understanding the TFP growth measure and the issues associated with its ability to quantify innovation, especially the shift from goods to services, is therefore critical when using the more direct measures of innovation to understand the slowdown of economic growth and its relation to the pace of innovation.

Finally, it is often important to view measurements that capture different aspects of economic growth and innovation in order to understand the full context. For example, the per capita growth rate is the standard measure of economic growth, but because the economy is growing from a larger base this can obscure the fact that the value of goods and services added to the economy is still about as large as it has ever been. Similarly, Cowen and Southwood (2019) point out that per capita statistics can be misleading indicators of progress. Part of the reason that per capita economic growth is decreasing is due to the increasing denominator—that is, the increasing population. But this is its own sign of progress, as it reflects our success in sustaining more people and increasing their life expectancy. How one weighs the different pictures painted by different measures is largely subjective, but it is important to keep these different viewpoints in mind when studying growth and innovation.

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