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Understanding and Addressing the Modern Productivity Paradox

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MIT work OF THE FUTURE

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We are in the midst of a technological revolution driven by advances in artificial intelligence (AI). Machines can now accomplish many tasks that only human minds could do as recently as 10 years ago (Perrault et al., 2019), from recognizing images (Russkovsky et al., 2015) and understanding speech (Schmelzer, 2020), to generating plausible text (Brown et al., 2020) and diagnosing diseases as well as or better than human doctors (Esteva et al., 2017). These are not insignificant tasks.

More broadly, the emergence of scalable machine intelligence with a variety of applications is proving to be of first-order importance for solving many economic problems. These technologies have been amplified by an exponential growth of other digital capabilities, including worldwide digital infrastructure that now brings the mobile internet to more than 4 billion people (International Telecommunication Union, 2019). As a result, an ordinary smartphone now delivers information and services that dwarf those available to even a well-connected billionaire of the 1990s.

Yet, in spite of the emergence of these new technologies—with their enormous industrial potential—the rate of productivity growth in recent years has been disappointingly slow. According to official statistics, productivity growth averaged over 2.8 percent per year in the United States in the decade ending 2005, but since then has slowed by half. If U.S. productivity had grown at the same rate from 2005–2019 as it did from 1995–2004, U.S. GDP would have been approximately $4.2 trillion higher at the end of 2019 than it was measured to be.[2] This modern productivity paradox is a redux of the information technology (IT) productivity paradox of the late 1980s (Brynjolfsson, 1993). That earlier divergence between the promise and practice of technology was epitomized by Nobel laureate Robert Solow's pithy remark, "You can see the computer age everywhere but in the productivity statistics."

Paradoxes challenge our assumptions, stimulate innovative research, and lead to improved policy recommendations. On the research side, the current productivity paradox has led to an outpouring of plausible explanations that can be classified into four categories (Brynjolfsson, Rock, and Syverson, 2018).

One possibility is that, despite the excitement of technologists and investors, today's advances simply fall short and will never fulfill their expected economic promise. A second explanation is that the technologies are delivering, but we are failing to measure the growing output of the new economy properly, particularly the explosion of free digital goods, and that is leading to systematic and increasing shortfalls in our tallies of economic activity. A third possibility is that the technologies are privately beneficial, but the social benefits are largely dissipated in zero-sum rent-seeking. The final explanation is the one we find most compelling: new technologies take time to diffuse, to be implemented, and to reach their full economic potential. For a transformative new technology like AI, it is not enough to simply "pave the cow paths" by making existing systems better. Instead, productivity growth from new technologies depends on the invention and implementation of myriad complementary investments and adjustments. The result can be a productivity J-curve, where productivity initially falls, but then recovers as the gains from these intangible investments are harvested.

Fortunately, there are a range of policy interventions that can speed this process, not only boosting productivity, but also fostering shared prosperity. These include (1) increasing investment in R&D, directly as well as via grants and tax credits, (2) increasing human capital by reinventing education and encouraging high-skill immigration, and (3) eliminating the bottlenecks to reorganization and innovation created by burdensome noncompete rules, occupational licensing, inadequate infrastructure, unconstrained monopoly platforms, barriers to entrepreneurship, and unequal taxation of labor and capital. With the right policies, any nation can overcome the modern productivity paradox, boosting both incomes and equity.

Four Reasons for Decelerating Measured Productivity Growth

TODAY'S TECHNOLOGY ISN'T ENOUGH

As noted above, there are four explanations for why productivity growth has not matched the seemingly impressive advances in AI and other technologies. In addition, there are a few interrelated variants of the first hypothesis: that current technological improvements have been inadequate to stimulate meaningful economic change. One perspective is that large and rapid IT-driven growth just prior to 2004 was a onetime dividend from installing computational capabilities across the economy (Gordon, 2015). Related to this view is the assertion that 21st century innovations pale in comparison to the fundamental economic importance of 19th and 20th century innovations in plumbing, mechanization, and electricity (Gordon, 2017). Another perspective is that there are good ideas out there, but they are becoming harder to develop (Cowen, 2011; Jones, 2009). Any of these causes of decreased innovation could induce and be exacerbated by decreased investment and secular stagnation (Rachel and Summers, 2019).

Under this hypothesis, now that the growth prospects of a former technological boom are drying up, productivity growth is returning to its more modest long-term trend. Air conditioning, electricity, and indoor plumbing could only be invented once, yielding large one-time gains but not ongoing growth. Likewise, it is possible that the transformational productivity boost of the computer has mostly run its course. In this view, even AI is merely an example of an additional technological layer on the computational stack, and thus it is not capable of leading to as much complementary innovation as prior technologies.

The underlying cause of poor productivity growth under these hypotheses is a decrease in the rate at which innovations are created, an idea supported by some evidence (Jones, 2009; Bloom et al., 2020). Bloom et al. (2020) document that, at least in some areas, ideas seem to be harder to find on the margins. It appears that research productivity is dropping as the total number of researchers increases. That is, the number of new ideas per researcher has declined.

Bloom et al. (2020) document a number of areas in which the average annual growth rate of research productivity over the past few decades has declined, including research in fields impacted by Moore's Law, research on agricultural outputs like corn and wheat, and investigations into new molecular entities for drugs. The increasing difficulty for researchers of reaching the frontiers of their respective disciplines (the "burden of knowledge") likely serves as one obstacle to innovation. Indeed, research teams are getting larger, and the age of researchers at the time of their first inventions is increasing (Jones, 2009). If research team productivity is more constrained by the least productive members than expanded by the most, then research productivity will decline as greater specialization is required to produce ideas (Ahmadpoor and Jones, 2019). Specialization by type of innovation might also have caused a deterioration in the economy's conversion of research into development. Translational innovation is just as critical as new ideas in the lab. Corporate R&D is needed to convert basic research ideas into products and services, and it is possibly facing increasing friction as scientists specialize more (Arora, Belenzon, and Patacconi, 2015; Arora et al., 2020). This presents yet another burden to alleviate: the bridge between basic and applied research. While there are reasons to be optimistic about meta-innovations (i.e., innovations in tools to provide more innovation) (Cockburn, Henderson, and Stern, 2018), it's not clear these outweigh the factors that have slowed technological progress. If extending the frontiers of knowledge is growing progressively more difficult, then we are going to need ever-better tools and capital-embodied knowledge to maintain the same level of research productivity over time.

Simultaneously, any inventory of existing innovations will tend to be biased toward more mature and obvious technologies and against the incipient and speculative ideas that ultimately may (or may not) create large gains. If technologies follow the typical S-curve for adoption and impact, then older, larger, and more visible innovations will tend to make slower progress than those that are a bit newer, smaller, and less visible. That said, the argument that some of the myriad ideas that are currently only in the early stages of adoption will eventually be productivity game-changers is difficult to falsify until they play out over the next few decades.

WE ARE FAILING TO MEASURE THE NEW ECONOMY

Another possibility is that mismeasurement of new sources of economic activity is to blame for the lackluster productivity growth readings. This is one of Silicon Valley's favored counterarguments to the skeptics' refrain that growth is underwhelming. Syverson (2017) covers the arguments against this hypothesis in detail, noting that an approximately $3 trillion shortfall in GDP arose from slower growth from 2004–2015.[3]

Nevertheless, if the digitally enabled growth of the economy is increasingly difficult to measure, with more of the value created in the economy invisible in such official measures as GDP, then there is a case to be made that mismeasurement is at least partly to blame for slower measured growth. For this argument to explain the slowdown, the problem of mismeasurement would have to be not simply bad, but getting worse over time. If exactly the same proportion of the economy were missed in both past and present official statistics, then growth rates would be unaffected.

There is some evidence that mismeasurement may be getting worse. Consumer valuation of some digital goods, such as search engines and social networks, has grown since the onset of the productivity slowdown (Brynjolfsson, Collis, and Eggers, 2019; Allcott et al., 2020) as free online options have replaced previously marketed goods such as maps and encyclopedias. These effects are not large enough to explain the entirety of the $3 trillion of missing output, but they constitute a meaningful component. Digital channels have radically altered how many goods and services are consumed. If total welfare continues to grow, but an increasing share of output is missed in official measurements due to technological change, the true productivity slowdown may not be as severe as previously thought.

It is also possible that prices are increasingly mismeasured. Price changes are notoriously tricky to measure in the digital space. This is an old problem as well, often related to the difficulty of imputing quality-adjusted price shifts. As described by Moore's Law, computing efficiency increased at an exponential pace, which meant that semiconductor price deflators needed to be calculated separately from other technological inputs (Byrne, Oliner, and Sichel, 2018). More recently, the pace of improvement in general-purpose CPUs may have slowed, but a number of other specialized computational hardware improvements continue at rapid speed. This further complicates the issue of accurately measuring quality improvements in the computational space. If the imputed price deflators over time are "rising too quickly (or falling too slowly) relative to their pre-2004 changes, the result would be that quantity growth as backed out from nominal sales is understated" (Syverson, 2017).

That said, mismeasurement probably cannot explain the entire productivity growth shortfall. This is primarily because mismeasurement has always been an issue for productivity estimation—past innovations from radio and television to antibiotics and vaccines have created large benefits missed by the GDP statistics. The shortfall in recent years is so large that measurement would have to be getting substantially worse to account for it, but mismeasurement still might be an important part of the overall story. It does not seem that the IT revolution is over (Byrne, Oliner, and Sichel, 2013). We certainly are failing to measure parts of the new economy, and our statistical agencies need to be better equipped both to consume and to produce data at larger scales for the public good. Ironically, the same technologies that make the economy difficult to measure with standard techniques and inputs might also offer a way forward to capture their effects. For example, statistical agencies can and should increase their use of cutting-edge big data techniques and machine learning tools.

RENT-SEEKING AND MISALIGNED INCENTIVES

A third possibility is that the innovations are privately beneficial but socially wasteful, leading to rent dissipation. According to this proposition, businesses have been innovating, but in areas that boost their private interests more than the broad social good. One potential example of this is overinvestment in automation technologies relative to the resources spent on inventing new jobs for workers—or, as Brynjolfsson and McAfee write in their book *Race Against the Machine* (2011), using technology to substitute for workers rather than complement them. Either policy might have the same private benefits to the innovator, but society as a whole would be better off with fewer unemployed workers and thus more widely shared benefits from innovation.

Is it possible to incentivize firms to invest in technologies that reduce demand for labor without creating correspondingly large changes in productivity? Acemoglu and Restrepo show that the answer is yes. They analyze a related set of trade-offs and the role of “so-so technologies” in their insightful paper “The Race Between Man and Machine” (Acemoglu and Restrepo, 2018). In their model, firms decide whether to invent and implement technologies that substitute for humans or create new jobs for people. Acemoglu and Restrepo hypothesize that, due to poor incentives, recent innovators have focused on developing technologies that are just better enough than a worker to lower labor demand, but not better enough to free up additional capital for complementing workers. One source of poor incentives are tax policies that subsidize capital over labor. The role of tax policy in incentivizing so-so technologies is explored in Acemoglu, Manera, and Restrepo (2020), who find that a tax system that penalized so-so technologies would boost employment 1-2 percent.

Even more extreme examples of misalignment between private and social incentives on investment in different types of innovation are abundant in “Phishing for Phools” (Akerlof and Shiller, 2016). Some firms pour vast resources into tricking or coercing consumers into purchasing their products. At the economy-wide level, some of the country's brightest minds go into zero-sum specialties in law and high-frequency finance rather than science, engineering, or the arts. Similarly, innovations in matching markets and digital platforms might provide only slight efficiencies while fomenting increasing inequality owing to winner-take-all dynamics. Matchmaking technologies bring the entire world into closer competition. Platform owners and superstar workers and firms may benefit disproportionately from small initial edges through preferential attachment and economies of scale.

While it is certainly the case that private and social incentives to innovate are not perfectly aligned, for this to be the primary driver of the productivity paradox, the misalignment would need to have dramatically worsened over time. As with mismeasurement, the available evidence suggests that the rate of increase in misalignment is large, so its level is not the only issue open to debate.

THE ECONOMIC GAINS ARE YET TO COME

The fourth, and in our view most convincing, resolution to the modern productivity paradox lies in the need for complementary innovations that take time to develop. For a new technology, in particular what economists refer to as a "general purpose technology" (GPT) (Bresnahan and Trajtenberg, 1995; Bresnahan, 2010), to have significant impact, the economy's processes need to be reinvented and reconfigured before the new technology can be effective. This co-invention is expensive and takes time. GPTs are defined by their pervasiveness, ability to improve over time, and capacity to lead to complementary new advances. At the same time, GPTs with great potential create wide gaps between the expectations of progress and the predictions made based on recent measurements of past growth.

Brynjolfsson, Rock, and Syverson (2018) argue that the time needed to accumulate GPT-related capital is a key source of the delay between headline-making innovative progress and aggregate economic statistics. Exacerbating this measurement deviation is the simple fact that the investments must be made, and the technology must diffuse, before any progress can be measured. Many of these investments are intangible in nature. They are not documented on balance sheets, kept in inventory in a warehouse, or easily transferred between firms. Intangible assets include corporate culture, workforce training, business processes, and branding (Haskel and Westlake, 2017), and they are of particular importance for information technology investments (Tambe et al., 2019; Bresnahan et al., 2002; Bloom, Sadun, and Van Reenen, 2012; Cornwell et al., 2019). And, while these assets are intangible, they require real resources to create.

As a result, in the early stages of GPT-related capital accumulation, it can appear that increased tangible costs are required to achieve the same outputs achieved in the recent past. Labor and capital flows seem to vanish from the measured world as they are applied toward producing unmeasured intangible capital output that will only later generate yields. In turn, when the unmeasured capital stock later starts producing returns, measured productivity growth will accelerate because there is a tailwind from the capital and labor investment that created the intangibles. With a long enough time horizon, the benefits from unmeasured capital service flows and the unmeasured costs to create that capital should balance out. This is the "productivity J-curve" (Brynjolfsson, Rock, and Syverson 2020), and it is explained in more detail in the appendix to this paper.

THE CASE FOR OPTIMISM

If, as seems to be the case, current slow productivity growth is due to the buildup of intangible assets, then there is significant room for optimism. Current slow growth may represent the economy digesting a slate of new GPTs. We do not know for sure when (or if) productivity growth is coming. But we can make some educated guesses about the future by looking at changing technologies and what they might mean for economic growth.

There are many ways to make a holistically optimistic case. An obvious point is that, even within the context of the COVID-19 economy, digital goods and services have held up remarkably well. A major proportion of the U.S. workforce has shifted toward remote work (Brynjolfsson et al., 2020; Dingel and Neiman, 2020) since the onset of the pandemic. This growth of digital work is part of an overall acceleration toward software-enabled business now that in-person interactions are more costly and risky. As a result, there is a stark need for new investments in IT infrastructure (e.g., video conferencing technology) that will have durable productivity effects once the crisis has run its course. At the same time, many companies must draw on pre-COVID-19 intangible assets such as corporate culture or team-based routines that are difficult to replenish without in-person interaction. These processes must be rebuilt in new ways. Since this infrastructure is pervasive across the labor market, improves over time, and potentially enables new kinds of business models and innovations, a reasonable case can be made that the remote work technologies proliferating in unusual times today are GPTs in a standard sense (Autor and Reynolds, 2020).

Another example of a budding GPT is artificial intelligence, specifically machine learning (ML) (Brynjolfsson, Rock, and Syverson, 2018; Agrawal, Gans, and Goldfarb, 2018; Cockburn, Henderson, and Stern, 2018; Goldfarb, Taska, and Teodoridis, 2019). ML has wide-ranging applications in business and the economy. ML technologies can help robotic systems navigate environments, provide customer service, perform automated translation, automate administrative tasks, manage traffic, trade financial contracts, reduce energy consumption, and identify people in online photos. Thus, this AI/ML wave may have the potential to trigger broad-based shifts in organizational structure and innovation in the types of tasks people do at work.

Indeed, AI/ML might already be affecting measured productivity statistics (Brynjolfsson, Rock, and Syverson, 2020). Other technologies, including cloud computing and recent advancements in biotechnology, show substantial promise. Goldfarb, Taska, and Teodoridis (2019) offer a method to differentiate between GPTs and other technologies. Their evidence suggests that there is a particularly good case for the potential of ML. Perhaps what is most exciting about new AI systems is their potential to speed up the scientific research and development processes, alleviating some of the aforementioned burden of knowledge. Cockburn, Henderson, and Stern (2018) refer to this idea as inventing a method of innovation. GPTs of this sort occur once every few decades. When they show up, the pervasive opportunities associated with GPTs require enormous reengineering efforts at the level of economic systems. Workplaces are redesigned, new business models are created, and new firms enter the market. We now see a number of technologies with this sort of potential, but we must wait to see if their transformative potential materializes.

A Plan for Equitable Growth

Even if "The Case for Optimism" above is correct, U.S. policymakers can still do much to accelerate the rate of innovation. Increasing productivity can potentially provide more fruits of prosperity for all. But there is no economic law that ensures everyone will benefit. Higher productivity and growth can coexist with decreasing median incomes if most of the gains go to a small group. The proposals we outline below are designed to create not merely prosperity for the few, but shared prosperity for the many.

Here we lay out elements of a plan for equitable growth. That means identifying policies that will boost efficiency while reducing (or at least not exacerbating) inequality. In identifying these policies, we drew on several recent prescriptions. Three particularly useful references are Bloom, Van Reenen, and Williams (2019), Gans and Leigh (2019), and Gruber and Johnson (2019). Readers of these pieces will find much of what we have to say familiar. We organize our recommendations according to the challenges each is meant to address: (1) poorly directed and inadequate research and development efforts, 2) insufficient human capital, and (3) other bottlenecks that constrain growth and promote income inequality.

BOOSTING RESEARCH AND DEVELOPMENT

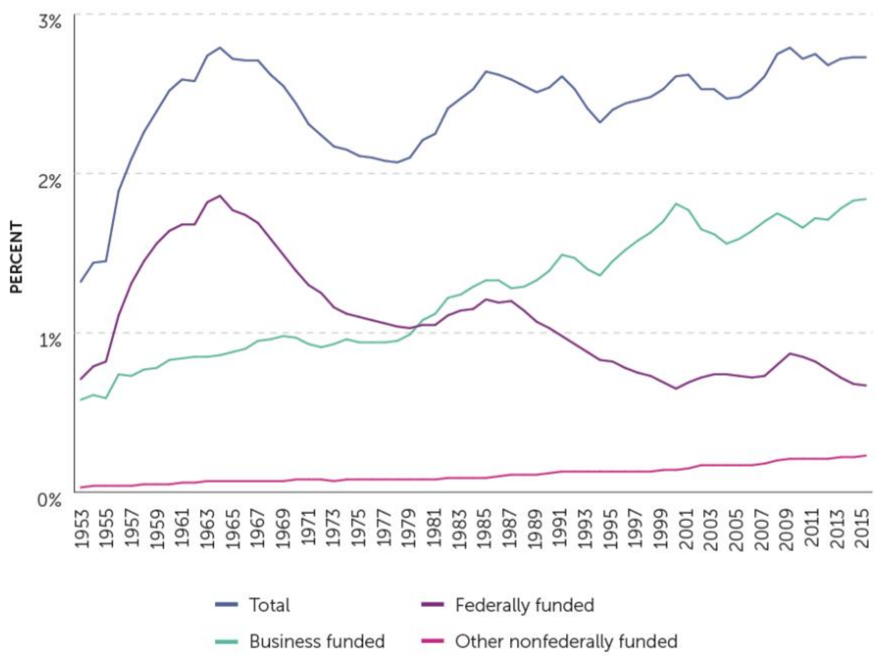
If what we need is more innovation, why don't we just buy some? That is the simple logic behind our first main recommendation: boost the levels of public and private research and development spending. Both public and private R&D should be supported, because different sorts of innovation are often complementary: fundamental science is best funded by governments or nonprofits, while marketable applications work well when privately developed.

The central argument for greater promotion of basic R&D is that it creates positive externalities for firms and governments. In theory, this positive externality can be canceled out by socially wasteful "business stealing," with firms duplicating research expenditures as they race for market share. However, in practice, estimates of gross social returns were more than two times the private return to R&D for spending in the 1980s and 1990s (Bloom, Schankerman, and Van Reenen, 2013). The ratio of social and private returns to marginal spending appears to have grown since then, reaching 4:1 in the 21st century (Lucking, Bloom, and

Van Reenen, 2020). Another study found that the average social benefit from R&D is at least 5.3 times its private costs (Jones and Summers, 2020). Because none of these estimates captures the full consumer surplus benefit of many freely provided digital innovations (see our discussion of mismeasurement above), it's likely they underestimate the size of this incentive misalignment.

Total R&D as a share of the U.S. economy has been fairly flat since the early 1960s, reflecting an increase in business-financed R&D projects offset by falling government-supported R&D. Figure 4, from Bloom, Van Reenen, and Williams (2019), displays R&D in the United States by source of funding. The change in federal spending largely reflects reductions to a handful of major national projects. In 1966, at the peak of the space race, the National Aeronautics and Space Administration (NASA) commanded 4.4 percent of the national budget. In the same year, the Atomic Energy Commission, which was devoted to researching civilian and military uses of fission and fusion power, was assigned 1.79 percent of the federal budget. Over the next decade, both these agencies shrank considerably in nominal terms. By 1975, NASA spending was less than 1 percent of the federal budget, and that year the Atomic Energy Commission was eliminated.[4] Federal R&D funding temporarily reversed its slide in the early 1980s, but then decreased further, reaching current levels after the end of the Cold War.

U.S. Research and Development as a Share of GDP, by Source of Funds 1953–2015



Source: This figure displays data from figure 4-3 of National Science Board (2018), chap. 4. The original data are drawn from the National Science Foundation, National Center for Science and Engineering Statistics, National Patterns of R&D Resources (annual series).
Notes: The figure shows how spending on R&D performed in the United States, presented as a share of GDP, has evolved over time from 1953 to 2015, in total and broken down by source of R&D funding.

Given the social benefits, how should the United States boost R&D expenditures? Three particularly promising current approaches are: government-directed research projects, government grants (e.g., through the National Science Foundation and National Institutes of Health), and tax credits for private business R&D.

The most visible type of government-funded innovation has come from large, government-directed projects. From the Manhattan Project to the Apollo program to the Advanced Research Projects Agency Network, ambitious national projects, funded through a combination of direct government employment and grants, have successfully advanced the frontiers of basic and applied science. These projects have often focused on fundamental scientific discoveries because they cannot be patented and can be difficult to monetize. The economy benefits as new breakthroughs and GPTs create opportunities for businesses to develop applications.

Of course, large government agencies can develop inefficient bureaucracies. NASA is a good example of a once-glorious government project lately plagued by cost overruns and delays.[5] The Defense Advanced Research Projects Agency (DARPA), in contrast, has maintained a better reputation for agility and productivity. One driver of its success may be its reliance on a model in which highly independent project managers are given broad authority to assemble teams and execute on five-year, high-concept, research missions. Over the last several decades, DARPA has been at the cutting edge of developing weather satellites, GPS, personal computers, modern robotics, the internet, autonomous vehicles, voice interfaces, and many other essential dual-use (i.e., useful for both civilian and military applications) technologies.[6] Another reason for DARPA's success may be its broad scope, which enables it to distribute risk among many different categories of projects.

Government-directed research need not be militaristic. Examples such as the Human Genome Project, Large Hadron Collider, and International Space Station show that big science can unite as well as divide. A major new push on GPTs such as artificial intelligence, space travel, genetic engineering, and climate change mitigation could have large benefits.

Large government projects can be undertaken by government employees, as is the case for many NASA projects, or they can be conducted externally through grants, such as those disbursed by DARPA project managers. An advantage of grants is that they can be targeted toward broad goals; the government does not need to know precisely what deliverables it wants. Research grants can be targeted toward areas where spillovers might be greatest or distributed to applicants on the basis of expertise. They can be made either to individual researchers—as is the practice of the National Institute of Health (NIH)—or to private firms, such as the Small Business Innovation Research (SBIR) program. NIH grants have been shown to have a positive effect on applicants' research output (Jacob and Lefgren, 2011) and private-firm patents in the targeted research area (Azoulay et al., 2019). SBIR grants, which inject resources into small, liquidity-constrained, high-tech firms, have been shown to have positive effects on applicants' revenue, venture capital funding, and patenting (Howell, 2017).

Additionally, many governments promote private-sector innovation through R&D tax credits. Since 1981, the United States has increased the proportion of R&D expenses that can be deducted from federal corporate tax liabilities. Currently, state and federal R&D tax credits reduce tax revenues by about $13 billion a year (National Science Board, 2018). These incentives have a good track record of promoting innovation. A literature review suggests that a 1 percent drop in the after-tax price of R&D results in at least a 1 percent increase in R&D, with an overall rate of return only slightly lower than direct federal funding (Van Reenen, 2020). In principle, tax incentives could be restricted to (or enhanced for) industries where positive technology spillovers are more common.

On the other hand, many ostensibly innovation-promoting policies have no empirical support. One example is "patent boxes." These are special tax rates for profits that can be shown to be linked to patented innovations. The idea behind them is to tax profits that are due to innovation at a lower rate than ill-gotten or windfall gains. However, the weight of the evidence shows that these policies have had no effect on aggregate invention across the countries of the European Union that have tried them (Gaessler, Hall, and

Harhoff, 2018). Another approach that has not proven effective is cutting top marginal tax rates. Because the most important innovations reward their inventors and financiers to the point that they are in top tax brackets, it stands to reason that cutting top tax rates will increase the incentive to innovate. However, Bell et al. (2019) show top marginal tax rates are much less important determinants of innovation than factors such as exposure to innovation while young. Whereas Akcigit et al. (2018) find evidence of lower U.S. state income taxes spurring innovation, this effect may be due to interstate movement of innovators rather than increases in their nationwide supply (Moretti and Wilson, 2017).

Bloom, Van Reenen, and Williams (2019) is one of several papers with similar findings that compares the effects of each of the above approaches on boosting innovation. Ultimately, the authors conclude that tax credits have the strongest evidence of providing positive effects and recommend a diversified approach with an emphasis on tax credits. Much as an innovative firm, such as a drug company, invests in investigating several unrelated leads simultaneously to reduce overall risk, the United States should adopt a portfolio of research-boosting policies to guarantee a positive effect from at least one. What's more, these different approaches are likely complementary, with government grants able to fund early stage or large-scale projects that the private sector would not or could not.

Whether research is government-run, or merely government incentivized and regulated, the federal government has a role to play in promoting international cooperation in the innovation arena. International regulation of the military application of technologies could reduce the incentive to engage in military R&D, freeing up military engineers for more socially beneficial work. Sharing dual-use technologies would reduce the redundancy involved in replicating or reverse-engineering others' innovations. Perhaps most importantly, openness and cooperation may prevent nations from incautiously racing to be the first to develop a new technology—which might entail unethical human experimentation, risk environmental disasters, or release a nonaligned artificial intelligence (Bostrom, 2014).

This vision is not utopian. Countries have successfully worked together on restricting and sharing dual-use technologies in the past; key examples include the Chemical Weapons Convention and Biological Weapons Convention. Both of these agreements center on the logic of rewarding countries that ban weapons development with cooperation in the peaceful development of other technologies. Some of this work is already in progress. For example, the Bipartisan Policy Center and Georgetown Center for Security and Emerging Technology (2020) have issued a set of recommendations on AI that include: "[engaging] with China and Russia to define shared concerns in AI safety and related concepts and terminology"; "[involving] allies and partners in U.S. standards-setting initiatives … in order to ensure interoperability"; and "[promoting] multinational collaboration on AI R&D".[7] The Future of Life Institute has been working to raise the status of these efforts, including by giving its 2019 award to molecular biologist Matthew S. Meselson for his work spearheading the international biological weapons ban.[8]

ACCUMULATING HUMAN CAPITAL

One challenge in using R&D spending to boost innovation and productivity growth is the limited stock of scientists and engineers. More money for better lab equipment can only go so far without additional staff to operate it. So, how much human capacity does the United States have for expanding economically useful R&D?

One promising source of short-term domestic scientific capacity is individuals with scientific training who are currently employed doing something other than research. According to a 2014 survey, 39 percent of U.S. PhD workers in science, technology, engineering, and math (STEM) fields are in academia, and 57 percent of the remainder are engaged in private or government R&D as their primary task (Turk-Bicakci et al., 2014). This leaves about 26 percent of the most obvious candidate population open to reassignment to R&D.

To increase the level of human capital, there is some obvious low-hanging fruit. A disproportionate share of America's leaders in science and business are immigrants or the children of immigrants. This reflects the fact that the United States has long been a magnet for talent and a place where that talent could flourish. That strength is being severely undercut by America's recent immigration policies. Boosting the attractiveness of the United States to high-skilled immigrants is the simplest and most important action the country could take today to increase growth. Evidence suggests immigrants do more to expand labor demand than labor supply, creating benefits for native-born researchers as well (Azoulay et al., 2020). The majority of the international students we know, whether undergraduates, graduate students, or postdocs, as well as many of our foreign-born faculty colleagues, tell harrowing stories about the United States' difficult immigration and visa processes. These have prevented people from attending conferences, participating in research projects, and, in far too many cases, driven promising young professionals to Canada, Europe, India, China or elsewhere to continue their research. A more welcoming immigration policy, especially for top talent, would not only be a huge boost for the United States, but also good for the world, because it would make it easier for the best minds to work together.[9] Even immigrants and refugees who do not have university degrees may contribute to productivity growth by expanding market size and providing opportunities for entrepreneurs to serve specialized markets. Furthermore, children of immigrants often become highly educated themselves—in fact, second-generation Americans get bachelor's, master's, and doctoral degrees at a faster rate than the general population (Frostenson, 2016). To overcome current obstacles to migration often requires non-cognitive skills such grit, ambition, and determination that can make even less-educated economic immigrants to the United States important contributors to the nation's economy.

A longer-term, but even more essential, task is to reinvent education to increase the global stock of human capital. Producing more U.S. STEM PhDs is only one part of this challenge. The United States should work to promote the training of scientists abroad as well, both as a potential source of highly skilled immigrants, as well as because R&D conducted abroad, especially fundamental R&D, is likely to produce positive spillovers to the country. Americans have frequently benefited from innovations developed abroad. For instance, the Haber process, which revolutionized agriculture worldwide, was made by a Prussian; penicillin, the first successful antibiotic, was invented by an Englishman; and the computer touchscreen emerged from CERN, a pan-European organization.

Also important is creating a new generation of workers with strong management and organizational skills to complement science and engineering training. Research has shown strong complementarities between social and mathematical skills, suggesting that communicating and implementing innovations in a business organization require humanistic expertise (Deming, 2017). Individuals with these skills can boost productivity by discovering new opportunities to implement emerging technologies and by crystallizing innovative ideas into the kinds of intangible assets discussed earlier (Benzell and Brynjolfsson, 2019).

This is not the first time America has faced a challenge from powerful new general-purpose technologies. In the early 1800s, nearly 90 percent of Americans worked in agriculture; by the end of that century, that figure was only 42 percent (Brynjolfsson and McAfee, 2014). The former farmers didn't simply become unemployed; they were redeployed. They went into manufacturing and services, driving productivity and growth. A big reason why that transition was successful is that America led the world in public education, first via primary schools and later via high schools. This created not only world-leading prosperity, but also one of most equal societies on the planet, with extensive upward mobility.

Goldin and Katz (2008) masterfully document how U.S. educational exceptionalism developed. In the 1930s, the United States was nearly alone in providing universal free secondary schooling; and, with the GI Bill and other reforms, it expanded its lead in higher education in the postwar era. The United States today should boost funding and support for universities. It should also fund new universities either through updating the land-grant process used to create institutions like Rutgers, Louisiana State University, and the University of California, or simply by allocating appropriately sized endowments to be administered by the states. To better prepare children and adolescents for college, the United States should also do more to improve the quality of primary- and secondary-school instruction. A recent literature review of educational field experiments reveals several intriguing paths forward. At the school level, many involve better accountability for teachers. Other ideas center on more intensive instruction: these include extending the length of school days and the school year, offering optional weekend classes, and providing one-on-one math tutoring (Freyer, 2017). Many of these promising interventions were identified from high-performing charter schools, and we are optimistic that charter schools will continue to be a source of—and testing ground for—innovative education methodologies.

Today the United States faces a renewed challenge to prepare students for a changing technological environment. Today's leaders must reinvent education to focus on the types of skills that 21st century machines can't match. This means creating scientists who can discover new ways to see the world, entrepreneurs and artists who can imagine new futures, and engineers and managers who can create new technologies and intangible assets.

It also means new jobs for people with non-STEM skills. Increased wealth and expanded social aid institutions can create opportunities for individuals with interpersonal skills (leadership, teamwork, persuasion, caring, coaching, etc.) to work to keep us connected, directed, and sated. While the burden of knowledge is one force making it harder to develop this kind of education, new conceptual paradigms and educational modularizations can increase the amount of productivity-enhancing insight we can get from each hour of instruction.

BREAKING THROUGH BOTTLENECKS

Scarce human capital is only one of several important bottlenecks holding back U.S. productivity. To create a new era of equitable growth requires breaking through bottlenecks in technological diffusion and industrial organization as well. As research on the productivity J-curve suggests, the benefits of new technologies can be delayed by adjustment costs and lags (Brynjolfsson, Rock, and Syverson, 2020). Technological change increasingly happens at a digital pace, while organizational change is slower.

One way to increase the pace of change would be to eliminate or weaken non-compete clauses that prevent skilled engineers from bringing their talents and insights to competitors. Another would be to enact intellectual property reforms that push more technologies and artistic concepts into the public domain and punish patent trolls. More speculatively, changes in corporate culture that allow for more flexibility and employee input might help with the adoption of new technologies as well.

Countries should also make larger investments in public goods to incorporate more of society into the most productive sectors. New roads, ports, and airports are called for, as well as next-generation public goods such as universal broadband, a 5G mobile network, and expanded publicly accessible (anonymized) datasets. To finance these investments, the government should resist the impulse to cut essential investments in R&D and education. It may be politically appealing to "save" this money, which will pay benefits over a long horizon, to protect taxpayers and mandatory government spending programs, but long-term investments can be debt-financed to better align the costs and benefits over time. The current low-interest-rate environment is a particularly good time to make such public investments.[10]

Bottlenecks also exist at the firm and sectoral levels. Digital platform monopolists can create market power distortions and set prices too high—yet another example of the growing divergence between the social and private incentives for automation. For traditional industries, the rise of superstar firms leads to the concentration and monopolization of power. Acemoglu, Autor and Patterson (2016) show that increased dispersion in productivity gains among suppliers attenuates growth in the rest of the economy.

To correct these issues, the United States should reinvigorate its antitrust and entrepreneurial tools. The Federal Trade Commission, or perhaps a new digital authority, could be empowered to subpoena information needed for better understanding and regulating digital platform monopolies (Scott Morton et al., 2019). Rather than breaking up digital platforms, which might destroy productivity-enhancing network effects, developed countries should encourage or require standards that enable easier entry and interoperability among competitors, much as different telephone systems can interconnect (Aral, 2020). Where this is impossible, regulators should refrain from network effect–killing breakups. Rather, they should focus on tax, regulatory, and collective bargaining tools to ensure the benefits from these platforms are more widely distributed (Weyl and White, 2014; Benzell and Collis, 2020). There should be a high bar for intervention. For non-platforms, more traditional trust-busting is called for after an era of dramatically decreasing antitrust enforcement (Scott Morton, 2019).

There's also scope for interventions to boost entrepreneurship. While stories in the media create an impression of seemingly surging entrepreneurship, the data tell a different story. As documented by John Haltiwanger, Steven Davis, and many others, new business formation is down; fewer people are working in young firms; economic and geographic mobility is down; and almost every measure of business dynamism has declined over the past 20 years (Decker et al., 2014, 2016; Berkowitz, 2019). This has hindered the translation of new technologies into new products and services that benefit the economy. Boosting entrepreneurship will help reverse the stagnation of wages for the people in the bottom half of the income distribution, particularly those groups who have been most adversely affected by automation. Two policies that will directly help with this are reform of occupational licensing and decoupling of healthcare from employment. Each of these will make it easier for people to start new businesses.

Also important is tax policy that encourages the creation of new jobs. The classic research conclusion is that capital is more elastically supplied in the long run than labor and therefore should be taxed at a lower rate than labor (Chamley, 1986; Judd, 1985); this view, which contains some insight, relies on unrealistic assumptions (Straub and Werning, 2020). There is also evidence that the current U.S. tax regime favors capital-intensive automation over the invention of new tasks for labor (Acemoglu, Manera, and Restrepo, 2020). As the share of GDP that goes to labor continues to fall, the United States can create a more level playing field, particularly as AI starts to affect more and more of the labor force. At the international level, countries should cooperate on corporate taxation and tax havens to prevent a "race to the bottom" in the contest to attract capital. Tax competition tends to lower capital taxation for reasons of political economy rather than economics. With such cooperation in place, the world can build a tax policy that rewards firms for creating new jobs, rather than for destroying them.

Conclusion

Productivity growth is the most important single driver of higher living standards, and technological progress is the primary engine of productivity growth. Thus, it is troubling that despite impressive advances in AI and digital technologies, measured productivity growth has slowed since 2005.

While there are many reasons for this, the most important is that technological advances typically don't translate into improvements in productivity unless and until complementary innovations are developed. These include many intangible assets such as new business processes, business models, skills, techniques, and organizational cultures. The need for myriad complementary innovations is substantial, especially in the case of fundamental technology advancements such as AI. Yet, these complementary innovations can take years or even decades to create and implement; in the meantime, measured productivity growth can fall below trends as real resources are devoted to investments in these innovations. Eventually, productivity growth not only returns to normal but even exceeds its previous rates. This pattern is called a Productivity J-Curve.

The good news is that we can further boost productivity, while reducing income inequality, through a series of policy changes: these include increased investment in R&D, increased immigration of high-skilled labor, boosts to our education system, and removal of bottlenecks to entrepreneurship and business innovation. Thus, we are optimistic that the coming decade can and will be one of higher productivity growth and increased equality. Our optimism will be increased in proportion to the success policymakers have in implementing a plan for equitable growth along the lines that we have outlined.

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Appendix: The Mechanics of the Productivity J-Curve

Productivity measurement in the presence of intangible assets poses an unusual challenge. Intangibles are, by their nature, difficult to measure. They are also likely to be growing as a proportion of economic activity as information flows and knowledge-based work increase in importance. There is a well-developed literature in the economics of technology linking intangible capital and productivity (Marrano, Haskel, and Wallis, 2009; Byrne, Oliner, and Sichel, 2013; Byrne, Fernald, and Reinsdorf, 2016; McGrattan, 2017). Recent speculation about new technologies such as AI has followed a broader discussion about IT (Basu et al., 2003) and how IT investments are an increasingly important source of economic growth (McGrattan and Prescott, 2010a, 2010b; Haskel and Westlake, 2017). Accounting for these hidden assets and their influence on key metrics of economic well-being has gained renewed interest as well, including via techniques that infer intangible stocks from stock market valuations (Hall, 2000, 2001; Brynjolfsson, Hitt, and Yang, 2002).[11] With a better understanding of this process, we are able to adjust our measurements of productivity growth to account for the intangible investment generated by GPT-related transformations.

So how does the productivity J-curve work? Broadly, there are four main cases to handle with any productivity growth-measurement apparatus:

1. Measured output created using measured inputs
2. Unmeasured output created using measured inputs
3. Measured output created using unmeasured inputs
4. Unmeasured output created using unmeasured inputs

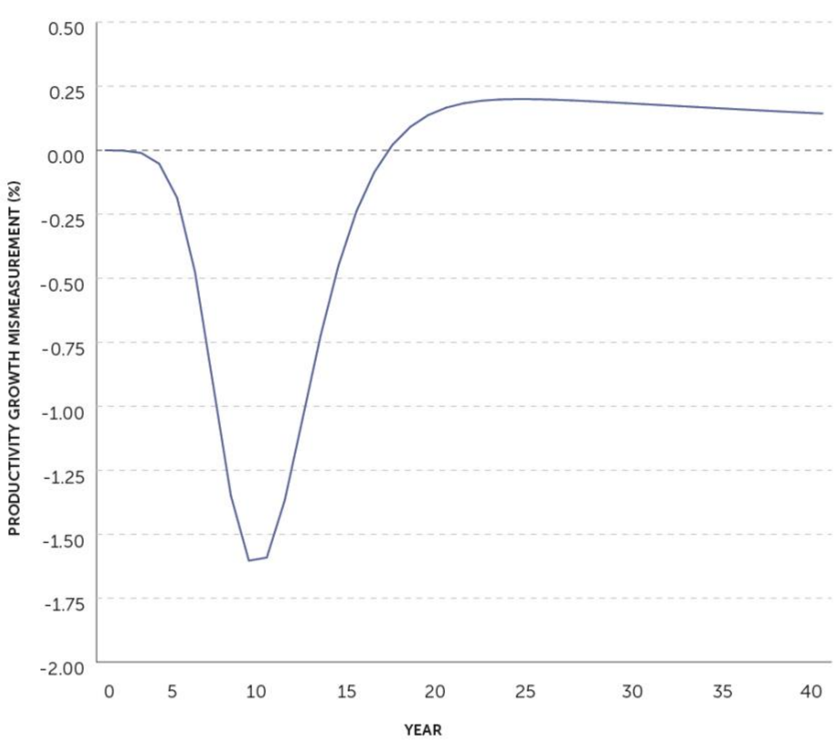
Traditional growth accounting handles the first case well. It handles the last case by completely ignoring it. In traditional growth accounting, productivity growth is the portion of growth that remains after the growth rate of labor and capital services weighted by their respective shares of output has been subtracted. The growth of labor and capital service flows, as well as output shares, are directly measured using national accounts data. The unmeasured accumulation of intangible capital and the contribution to growth of this capital is left out of the standard framework. Thus, the first case is the standard one. Companies buy machines or hire factory workers to produce goods. The fourth case would correspond to building a corporate culture that facilitates retention of specialized knowledge workers. Neither the expenses to generate the culture nor the assets they create are particularly well-documented or measured.

That leaves the second and third cases to be included in a new framework that captures the investment and yield dynamics of GPT-related intangible capital. In case two, the standard measurable capital and labor services are used to create unmeasured or poorly measured intangible assets. Under the lens of traditional growth accounting, case two seems to have some workers, equipment, and (in some cases) measured intellectual property that are put to work doing nothing of *measurable* value. Because the input side of the ledger grows, yet the output side stays stagnant or possibly decreases in this case, measured productivity growth as the residual growth in the standard framework has to decline to make up the difference. This result is deceptive, however, because the composition of the economy's asset base has simply shifted toward unmeasured intangible capital.

Once the intangible investments begin to generate a yield, we will face the third case, in which intangible asset stock generates capital service flows that help generate measurable outputs. In this case we have the opposite issue than in case two: measured output grows faster than the measured inputs would seem to imply, and the productivity growth residual must increase to balance the accounts. Of course, sometimes these investments fail; in other cases, perhaps, they yield more than expected.

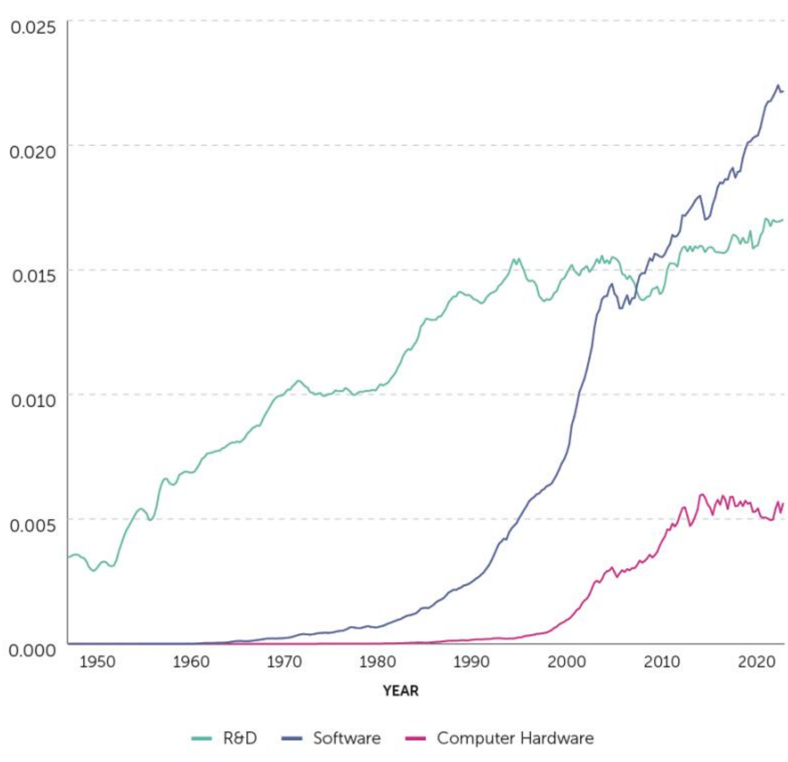
The key measurement idea is that—when innovators, managers, and entrepreneurs are rational—the expenses, in present value terms, are roughly the same as the long-run accumulated risk-adjusted returns when averaged across the entire economy. The figure below, from Brynjolfsson, Rock, and Syverson (2020), shows one possible evolution of the J-curve for a simulated toy economy. When the curve drops below zero, the effects of case two dominate. Above zero, case three's effects are larger.

Toy Economy: The Productivity Growth Mismeasurement J-Curve Calculation of Capital as Share as 1-(wL/y)



So far, we have said little about how to recover relatively accurate approximations of the intangible economy. One answer, with the help of a few assumptions, comes from stock market valuations (Hall, 2000; Brynjolfsson, Hitt, and Yang, 2002; McGrattan and Prescott, 2010). While the official government statistics might not account for mismeasured intangible assets, private markets seek to recognize their value. That means the standard Q-theory of investment can serve as a guide for correcting the official statistics (Tobin, 1969; Hayashi, 1982; Hayashi and Inoue, 1991). In cases where corporate assets are exposed to public markets, researchers and analysts can recover the "shadow" quantity of intangibles per unit of observable capital with some relatively basic assumptions. For some types of IT-related capital, a dollar of observable investment might correspond to as much as $12 of total capital inclusive of unmeasured intangible investment (Brynjolfsson, Hitt, and Yang, 2002; Brynjolfsson, Rock, and Syverson, 2020; Rock, 2019). For R&D assets, a measured dollar on the balance sheet might reflect $1.50 to $2.84 in total assets. Overall R&D investment has been increasing as a share of GDP since the 1950s, and IT investment has accelerated even more rapidly since the end of the 1980s.

Investment Share of Measured Output



These shares are important because they directly affect the size of the gap between official measurements of productivity growth and intangible-adjusted productivity growth. In the simplest terms, the adjusted productivity measurement is a weighted combination of the measured productivity growth and the difference between the growth rate in intangible capital investment and the growth rate of the measured capital stock. The weights are the proportion of true output accounted for by the measured component of economic activity and the proportion of true output accounted for by hidden intangibles, respectively (summing to one). In other words, if all economic activity is properly measured, the official statistics are perfectly accurate.

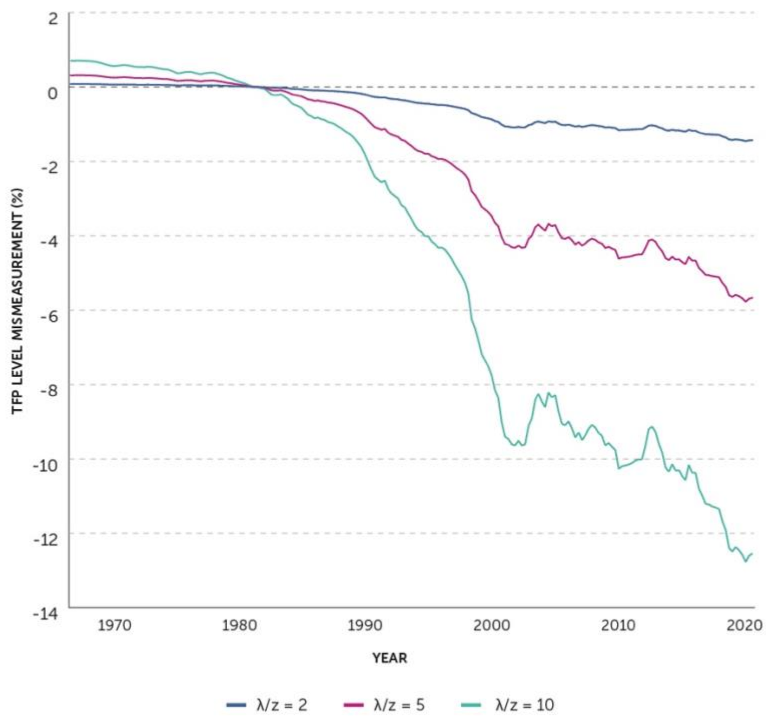
Armed with updated measurements, the adjusted productivity growth statistics offer a new look at growth in the modern economy. Can intangibles explain the productivity slowdown since 2005? According to Brynjolfsson, Rock, and Syverson (2020), it turns out that, after accounting for intangibles related to IT and R&D, total factor productivity growth since 2005 averages about 0.71 percent each year instead of about 0.40 percent. The good news is that the productivity level is higher by about 15.9 percent, but that fails to explain the puzzle of how productivity growth is slowing down. But the adjustment method applies equally to the prior boom period, implying that the productivity slowdown in percentage terms was actually *worse* in the recent past than had previously been thought. Adjusted productivity grew at 2.20 percent annually from 1995 to 2004 instead of the measured benchmark of 1.63 percent.

By more accurately incorporating intangibles into productivity growth measurement, we gain a better understanding of the magnitudes of economic trends. Our measures of the economy's overall productivity level are substantially higher with intangibles included, even though the growth slowdown paints a more dire picture with intangibles than without them.

The biggest source of these differences within the set of intangible assets comes from software investment. The digital economy is growing as a proportion of overall economic activity, and software investment is at the core of this shift. Cloud computing, remote work, customer relationship management systems, inventory management systems, data science, and artificial intelligence are all feeding a boom in software's centrality to businesses and organizations. Software investment continues to accelerate as a share of GDP.

Because software investments must be coupled with so much additional intangible investment to be viable (Tambe and Hitt, 2012; Tambe et al., 2019), the acceleration of these types of investments makes the productivity measurement problem worse over time. The figure below, from Brynjolfsson, Rock, and Syverson (2020), shows the effect of software intangible investments for different multipliers (a multiplier of two, for example, means that a dollar of observable investment corresponds to two dollars of total investment).

TFP Level Mismeasurement Percentage with Software Intangibles (Measured – Corrected TFP)



The cumulative effects of software on the mismeasurement of productivity levels may have been as much as 12 percent by the end of 2017. Shifts in the economy caused by the COVID-19 pandemic likely accelerated this change. More of the economy came to rely on software infrastructure to facilitate both remote work and remote consumption. Additionally, the availability of many goods and services has either been transformed or, in some cases, drastically curtailed in the COVID-19 economy.

Consumption has also changed as a result (Baker et al., 2020), shifting economic activity toward digital goods. Because the proportion of overall economic activity represented by the digital economy grew following the onset of the COVID-19 pandemic, some mismeasurement issues may have been exacerbated. This affects both the workforce and the bundle of goods and services that consumers purchase. Some goods, such as movie theater tickets, exercise equipment, and toilet paper, became harder to obtain. Many in-person services likewise became unavailable. At the same time, digital goods (such as movie downloads), digital channels for physical goods (e.g., online ordering from grocery stores), and remote work via online communication became increasingly important. Changes of these types require the creation of new routines and intangible capital too. If digital activity is relatively poorly captured by our statistical infrastructure, then the mismeasurement problem will have grown in the recent past.

Endnotes

1 This is a research brief for the MIT Work of the Future Task Force. Special thanks to Kevin Xu Shen for valuable research assistance and to David Autor, Liz Reynolds, and David Goldston for useful guidance and valuable comments on the draft.

2 At the end of 2019, counterfactual TFP would have been 1.276 (= 1.00407^(4*15)) times its level at the end of 2004, in which 0.407 percent was the average quarterly TFP growth over 1995–2004. Measured TFP was instead 1.068 times larger. Assuming observed labor and capital inputs remained as observed, counterfactual GDP at the end of 2019 would thus have been 1.195 (= 1.276/1.068) times larger than the observed value of $21.75 trillion. The difference, $4.24 trillion, is 19.5 percent of $21.75 trillion. See Syverson (2017) and Brynjolfsson, Rock, and Syverson (2020) for a similar calculation through earlier years.

3 The shortfall is even larger when unmeasured intangible investment is included. See Brynjolfsson, Rock, and Syverson (2020).

4 See "Nasa Budgets: U.S. Spending on Space Travel since 1958" (2010), *Guardian Datablog*, https://www.theguardian.com/news/datablog/2010/feb/01/nasa-budgets-us-spending-space-travel#data, and Buck, Alice (1983) "The Atomic Energy Commission," https://www.energy.gov/sites/prod/files/AEC History.pdf. After the Atomic Energy Commission (AEC) was abolished, some of its responsibilities and budget were transferred to the Department of Energy and Nuclear Regulatory Commission. However, in the decade before the AEC was abolished, its expenditures had been in significant decline.

5 See Thompson, Andrea, "Delays and Cost Overruns Epidemic at NASA, Former Official Charges," (December 5, 2008), *Space.com*, https://www.space.com/6200-delays-cost-overruns-epidemic-nasa-official-charges.html, and U.S. Government Accountability Office, *NASA Human Space Exploration: Persistent Delays and Cost Growth Reinforce Concerns over Management of Programs* (2019), GAO-19-377, Washington, DC, https://www.gao.gov/products/GAO-19-377.

6 See Reinhardt, Ben (2020), "Why Does DARPA Work?" https://benjaminreinhardt.com/wddw.

7 In lieu of such international cooperation, long-term-focused nations should shift military expenditures from equipment acquisition toward R&D projects. In addition to creating positive innovation spillovers for civilians, the intangible assets created by such research today will be more useful in a conflict 20 years from now than a soldier's salary paid today or a rusting 2010s-vintage weapons system (Fettweis, 2008).

8 See Gronlund, Kirsten, "Dr. Matthew Meselson Wins 2019 Future of Life Award" (April 9, 2019), *Future of Life Institute*, https://futureoflife.org/2019/04/09/dr-matthew-meselson-wins-2019-future-of-life-award/.

9 See *Artificial Intelligence and the Future of Work: Hearing before the Committee on Science, Space, and Technology, House of Representatives,* 116th Cong. (2019), (statement of Erik Brynjolfsson), https://www.congress.gov/116/meeting/house/109981/witnesses/HHRG-116-SY15-Wstate-BrynjolfssonE-20190924.pdf.

10 In contrast, there is a legitimate debate as to whether debt financing of transfer payments to the current elderly reduces output and welfare for future generations (Blanchard, 2019; Kotlikoff et al., 2020).

11 See Brynjolfsson, Rock, and Syverson (2020) for a more detailed discussion of this literature.