THE PRODUCTIVITY J-CURVE:
HOW INTANGIBLES COMPLEMENT GENERAL PURPOSE TECHNOLOGIES

By Erik Brynjolfsson, Daniel Rock, Chad Syverson

General purpose technologies (GPTs) such as AI enable and require significant complementary investments, including business process redesign, co-invention of new products and business models, and investments in human capital. These complementary investments are often intangible and poorly measured, even if they create valuable assets for a firm. The model that we developed generates a Productivity J-Curve that shows underestimation of output and productivity in the early years of a new GPT and later--when the benefits of intangible investments are harvested--overestimation of productivity.

Our model can explain the productivity slowdowns that often accompanying the advent of GPTs, as well as the follow-on increase in productivity. We use the model to assess how AI-related intangible capital may be currently affecting measured total factor productivity (TFP) and output using the examples of R&D, software, and computer hardware. We find substantial and ongoing effects of software in particular, and hardware to a lesser extent.

IN THIS BRIEF

- General Purpose Technologies (GPTs) are pervasive, improve over time, and lead to complementary innovation. AI and Machine Learning fall into the GPT category.
- The extensive investment required to integrate GPTs into an organization is often forgotten or underestimated. There is a period, often of considerable length, when measurable resources are committed (and measurable output forgone) to build new, unmeasured inputs that complement the new GPT. Part of the productivity growth slowdown of the past decade may be due to these dynamics.
- Correlating intangible investments with measurable ones can meaningfully change estimates of productivity growth and dynamics. Substantial and ongoing effects of software advancements, in particular, are affecting total productivity.
- The Productivity J-curve explains why a productivity paradox can be both a recurrent and an expected phenomenon when important new GPT technologies are diffusing throughout the economy.

A DECADES-OLD DILEMMA

In the late 1980s, Robert Solow (1987) famously pointed out that "a technological revolution, a drastic change in our productive lives," had curiously been accompanied by a slowing-down of productivity growth. His productivity paradox, that one "can see in the computer age everywhere but in the productivity statistics," named a challenge for economists seeking to reconcile the emergence of exciting technological breakthroughs with tepid productivity growth.

Solow's Paradox was not unique. It was one example of a centuries-old phenomenon resulting from the need for intangible investments in the early stages of new GPTs. GPTs are the defining technologies of their times and can radically change the economic environment. As "engines for growth," GPTs are pervasive, improve over time, and lead to complementary innovation (Bresnahan and Trajtenberg 1995). The transformative economic effects of GPTs in history are legion, starting with the Corliss steam engine and subsequent, widely applied steam power in the British economy during the Industrial Revolution. Other possible GPTs include electrification, mass production, and the factory system.

Economic histories also have related these inventions to the presence of the Productivity Paradox. For example, the technologies driving the British industrial revolution led to "Engels' Pause," a half-century period of capital accumulation, industrial innovation, and wage stagnation (Allen 2009; Acemoglu and Robinson 2013). The later GPT case of electrification lasted a generation as the nature of factory layouts was re-invented (David 1990). Solow was noting a similar phenomenon roughly two decades into the IT era.

GPTs have great potential from the outset, but realizing that potential requires larger, often unmeasured, investments as well as a fundamental rethinking of the organization of production itself. Along with installing more easily measured items like physical equipment and structures capital, firms must create new business processes, develop managerial experience, train workers, patch software, and build other intangibles. The difficulty for productivity measurement arises because intangible investments are not readily tallied on a balance sheet. The invention of a GPT can lead to the creation of entirely new asset classes and the transformation of existing capital varieties. It also presents abundant opportunity for entrepreneurs to discover new ways to deploy existing

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capital and labor. Moreover, these transformations do not occur overnight.

Given all of this, it is easy to see how something like Solow's Productivity Paradox can occur. The extensive investment required to integrate GPTs into an organization is often forgotten. There is a period, often of considerable length, when measurable resources are committed (and measurable output forgone) to build new, unmeasured inputs that complement the new GPT.

THE PRODUCTIVITY J-CURVE

As firms adopt a new GPT, total factor productivity (TFP) growth will initially be underestimated because capital and labor are spent to accumulate unmeasured output in the form of intangible capital stocks. Later, measured productivity growth overestimates true productivity growth because the capital service flows from those hidden intangible stocks and generates measurable output. We call this phenomenon the Productivity J-Curve. The error in measured TFP therefore, follows a J-curve shape, initially dipping while the investment rate in unmeasured capital is larger than the investment rate in other types of capital, then rising as growing intangible stocks begin to affect measured production.

Large capital adjustment costs, correlated intangible investments, and high investment shares of income exacerbate the magnitude of the J-curve effect. In the long run, however, as investment quantities and capital stocks reach their steady-state growth rates, the mismeasurement problem disappears even if the intangible investments continue.

The idea is that the hidden intangibles of GPTs are still captured by market valuations much as they are for smaller, incremental innovations that do not transform productive activity.

We documented the basic idea of the Productivity J-Curve and the Productivity Paradox in the context of artificial intelligence (AI), in Brynjolfsson, Rock, and Syverson (2017). [1] In this paper, we expand on those concepts. AI, and in particular the subfield of AI called machine learning (ML), meet the criteria for a GPT. The complementary innovations necessitated by GPTs motivate our approach: In the GPT context, we expect large-firm investment in unmeasured intangible capital goods. If it were not necessary to transform existing business processes via complementary intangible investments, new GPTs would immediately boost output in straightforward and measurable ways. Therefore, we propose using a set of forward-looking measures derived from stock market valuations to assess the magnitude of intangible investment value. The idea is that the hidden intangibles of GPTs are still captured by market valuations much as they are for smaller, incremental innovations that do not transform productive activity.

Creating complementary innovation introduces implementation lags and also predisposes the new, intangible capital accumulation to mismeasurement. We argued in earlier work that implementation and restructuring lags are a possible explanation for the juxtaposition of optimism about AI's potential and the currently low productivity growth. We focused on mismeasurement: the forgone output due to investment in unmeasured capital goods. Identifying these hidden asset values makes it possible to better measure true productivity growth.
Intangible assets are an increasingly important component of economic activity, especially IT-related intangibles. Recognizing these assets has led to numerous updates to the standard growth accounting frameworks and an emphasis in recent productivity studies on IT's role in productivity dynamics.

MICRO-LEVEL EXAMPLE

The most straightforward way to understand the Productivity J-Curve is to consider foregone output used to produce unmeasured capital goods. Suppose a company wants to become more "data-driven" and reorganize its production processes to take advantage of new machine learning prediction technologies (Brynjolfsson and McElheran 2016). This firm might want, for example, to change its labor mix to build more software and to teach its customers to order products online instead of in person. While the company develops online product ordering applications and business processes for that purpose, it will not use those investment resources to produce more final goods inventory. At the same time, though, the capital assets the firm is building—institutional software knowledge in the company, hiring practices, organization building, and customer retraining to use digital systems—are left unmeasured on the balance sheet.

1.See IDE RB 2018.01: *AI and the Modern Productivity Paradox*

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On the margin, the (present-discounted and risk-adjusted) value of these unmeasured assets equals the costs incurred to produce them. But during the period in which that output is foregone, the firm's traditionally measured productivity will suffer because it will seem as though the company produces proportionately less. Later, when those hidden intangible investments start to generate a yield as inputs, a shift occurs and it will seem as though the measured capital stock and employed workers have spiked and become much more productive. Therefore, in early investment periods productivity is understated, whereas the opposite is true later when investment levels taper off.

The mismeasurement in this example regards a J-curve in productivity levels. That said, a similar J-curve exists for productivity growth rates. (See figure 1). Early in the GPT diffusion process, intangible investment growth is likely to be larger than intangible capital stock growth. With missed output growth dominating, measured TFP growth is lower than true TFP growth. Later in the GPT diffusion process, however, investment growth slows below the growth rate of the installed intangible stock. Eventually the growth rates equalize in steady state, and productivity mismeasurement disappears.

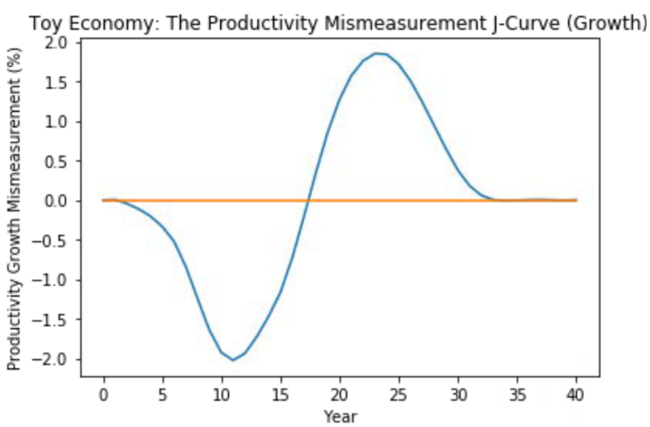

Figure 1

IS THE J-CURVE ALREADY AT PLAY?

Gross Domestic Product in the U.S. in 2017 was $19.5 trillion and in real terms grew at an average annual rate of 2.17% over 2010--2017, down from 2.72% per year from 2000--2007 (the eight years prior to the Great Recession).[2] This implies that unmeasured intangible capital investment from 2010-2017 would need to average $107 billion per year in 2017 dollars to explain the entire slowdown in in GDP growth. How much of this slowdown could be explained by a Productivity J-Curve for investment in AI and related intangibles?

The economy is early in the AI adoption cycle, yet the use of AI and robotics technology has rapidly increased since 2010 (Furman and Seamans 2018). Startup funding for AI has increased from $500 million in 2010 to $4.2 billion by 2016, growing by 40% between 2013 and 2016 (Himel and Seamans 2017). Though concentrated heavily in the IT sector, estimated total measurable corporate investment in AI in 2016 was $26 billion to $39 billion, marking 300% growth since 2013 (Bughin et al. 2017). Similarly, international industrial robot shipments since 2004 have nearly doubled overall and almost quadrupled in the consumer electronics industry (Furman and Seamans 2018).

For AI to account for the 0.55% of "lost" output in 2017 GDP, the quantity of correlated intangible investments per unit of tangible investment must be between roughly 2.7 to 4.1 times the observable investment values (using the Bughin et al. (2017) estimate).[3] This is not implausible. Research from 2002 found that the total market value of measured computer capital investments is as much as $11 per $1 in measured expenditure, with a standard error of $4.03.[4]

No such intangibles' "shadow" value will show up in the productivity statistics. The foregone output cannot be explained by growth in labor or observable capital inputs alone, so the output shortfall will be attributed to slower productivity growth. Further, this investment will later generate a capital service flow that produces measurable output.

Of course, these numbers are just for 2017, when measured AI investment was several times what it was only a few years prior. Thus, AI-associated intangibles are unlikely to explain most of the GDP growth slowdown. Looking forward, however, given that AI investments are likely to continue growing quickly and existing AI capital has a high market valuation, we could well be entering the period in which AI-as-GPT could have noticeable impact on estimates of output and productivity growth.

2. From the Bureau of Economic Analysis GDP statistics.

3. The required forgone output in 2017 was $107 billion. Dividing by the low observed investment figure of $26 billion implies a required intangible investment that was 107/26 = 4.1 times the observed investment. Using the larger $39 billion figure implies intangibles that were 107/39 = 2.7 times observed investment.

4. Brynjolfsson, Hitt, and Yang (2002)

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While the results imply that AI-related intangibles per se have only recently been large enough to affect measured output and productivity, other technology-related investments may have had more substantial effects over greater horizons, creating their own J-curve dynamics.

RESEARCH AND DEVELOPMENT INVESTMENTS

R&D capital provides a useful context for understanding Productivity J-curve dynamics. Corporate R&D leads to the development of new technologies that diffuse over time, and the link between R&D investment and market value is well established (Hall 1993, 2006). Because investment in R&D has persisted for decades, over the long term, we are more likely to find investment in R&D at nearly steady-state levels. This implies that the intangible-related challenges for productivity estimation coming from R&D are likely to be minimal at present. R&D capital investment rates have been steady over the observation period, roughly canceling out the countervailing influences of intangible outputs and intangible inputs.

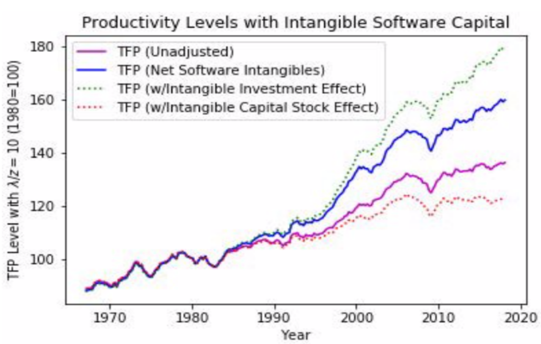

Figure 2: Software-related Intangible Capital-adjusted TFP

Although the net measurement effects of R&D-related intangibles are negligible, the same is not true for software and computer investments. In contrast to the adjustment for R&D-related intangibles, the Productivity J-curves for both software and computer hardware capital have yet to reach positive territory in terms of levels.

SOFTWARE INVESTMENT

Of the three capital varieties, software's J-curve is in the least mature stage. Software investment has grown and continues to grow faster than overall capital investment, and its level is sufficiently large to suggest that productivity growth has been under-measured throughout the history of software investment. Figure 2 shows the software-intangible-adjusted TFP.

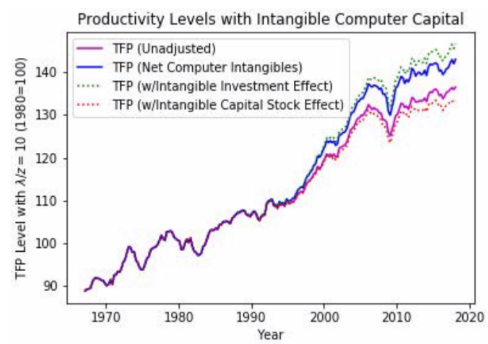

Figure 3: Computer-Hardware-Related Intangible Capital-adjusted TFP

The J-curve dynamics of software investment began in the 1990s and have not waned. Even for lower levels of the multiplier, the productivity level differences are notable and growing.

Paradoxically, the growing rate of software investment is the reason behind the growing understatement of productivity due to software-related intangibles. Aside from brief periods following the dot-com bust and the financial crisis, investment in software has grown significantly. As a result, software-related intangible investment rates are not yet in steady state.

As the analysis shows, when the investment growth rate exceeds the growth rate of the intangible stock, productivity growth is understated. Since 2010, when the productivity growth mismeasurement effect was very nearly zero, annualized quarterly productivity growth underestimation increased to 0.86% by the end of 2016. The implied understatement was even larger at the end of the 1990s, where measured productivity was 1.6% lower than software-adjusted productivity.

HARDWARE INVESTMENT

Figure 3 shows adjusted and measured Total Factor Productivity (TFP) growth and levels for computer hardware-related intangible investment. Again, the divergence between measured and corrected TFP becomes noticeable in the 1990s. We also see where the TFP level would be without adjustment (purple), the net intangible-adjusted series (blue), isolating only the missing

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intangible inputs effect (dotted red), and isolating only the missing intangible outputs effect (dotted green.)

The quantitative patterns for hardware are different from what we found for software. First, the accumulated mismeasurement due to hardware-correlated intangibles is much more modest. Adjusted TFP at the end of 2016 is 4.4% higher than the measured series–a considerably smaller gap than that associated with software-related intangibles. Second, and interestingly, the recent slowdown in the rate of hardware investment has actually caused a small overstatement of productivity growth, and as a result, has started to bring the level difference back toward measured TFP. The reversal followed the dot-com bust, it reverted as computer hardware investment rebounded, and then reversed again at the start of the Great Recession.

CONCLUSION

Our approach has shown how accounting for intangible investments correlated with measurable ones can meaningfully change estimates of productivity growth and dynamics. Both capital inputs and outputs are affected by intangibles. Productivity is underestimated in cases where the growth rate of investment (which contributes to output) exceeds the growth rate of capital services (inputs), and overestimated when the investment growth rate is lower. The first of these effects tends to dominate early in the capital accumulation cycle, when firms and organizations devote resources to building unmeasured intangible capital. The second effect dominates later, when these unmeasured assets generate capital services that increase measured output. Finally, when the capital accumulation reaches steady state, there is no longer any mismeasurement. These dynamics generate what we call the Productivity J-curve.

The introduction of a new GPT often causes a Productivity J-curve to occur because technological improvement often leads to the creation of new capital varieties and necessitates investment in intangible complements. This has been the case for IT-related capital in recent decades, for which our calculations suggest that trillions of dollars of intangibles output has been produced but not counted in national income accounts. There is some evidence that the phenomenon has begun again, very recently, in AI-related intangible investments.

The mere presence of intangible correlate investment is not a guarantee of the existence of the Productivity J-curve. R&D investments are large and are associated with large intangibles, yet we find that mismeasurement related to R&D investments has a negligible effect on the estimation of productivity growth.[5]

On the other hand, computer hardware, and to greater extent software, have a large effect. The difference reflects the fact that R&D is a mature asset type: the difference between the growth rate of R&D investment and the growth rate of capital is not very large. By contrast, the growth rate of newer investments such as software is larger than growth rate of capital overall, so productivity is underestimated in the beginning, We offer a means of adjusting the productivity statistics so that new, seemingly omnipresent GPTs might show up in the productivity statistics.

The J-Curve method also is a possible indicator of whether a new technology is indeed a general-purpose technology. If measures of the investment in a given new technology fail to generate economically significant intangibles, then that particular technology at that moment in time would not qualify as a GPT.

The Productivity J-curve explains why a productivity paradox can be both a recurrent and expected phenomenon when important new technologies are diffusing throughout the economy. Adjusting productive processes to take advantage of new types of capital requires the kind of investments the statistics miss. In the future, after making appropriate adjustments for the Productivity J-curve, we can see new technologies everywhere including the productivity statistics.

The full research paper can be found here http://www.nber.org/papers/w25148

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5. With a minor deviation present in the late 1990s and early 2000s.

THE PRODUCTIVITY J-CURVE:
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