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Is High Productivity Growth Returning?

Alexander Cline, James A. Kahn, Robert W. Rich

Productivity growth has shown a notable pickup since the fourth quarter of 2019, and some commentators cite artificial intelligence and other factors as reasons why technological progress can sustain this faster pace. Motivated by this consideration, we use a model designed to detect trend shifts to examine the behavior of productivity growth in the postwar period. The model allows for shifts between high- and low-growth productivity regimes and estimates the probability of being in one regime or the other. We find that recent data provide tentative support for a higher trend growth rate, with the model estimating about a 40 percent probability that the economy is in a high-growth productivity regime.

Topics Econometrics, modeling, and forecasting, Economic growth, Inflation

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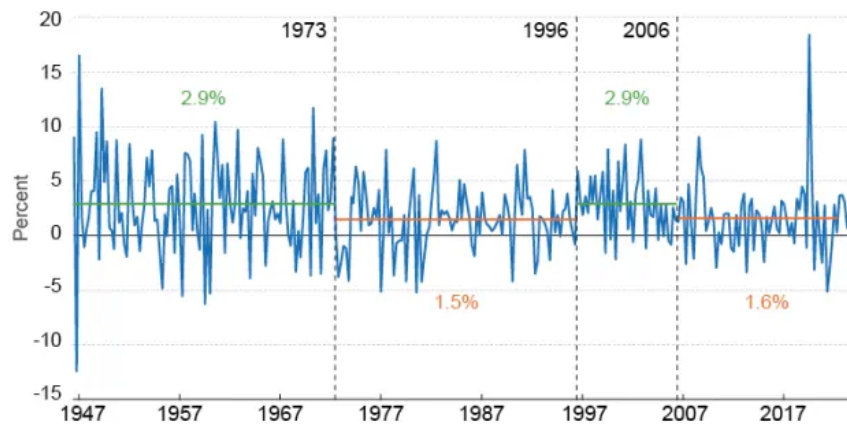
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Introduction

Productivity growth is important because it allows an economy to produce more goods and services with the same amount of labor, serving as the primary source for increases in per capita income and higher living standards over the long term. Since World War II, labor productivity growth in the US nonfarm business sector has averaged 2.2 percent annually, similar to growth in per capita real GDP. However, Figure 1 shows that productivity growth has not been steady, even over periods spanning decades. From 1947 to 1972, it averaged 2.9 percent. It then slowed to just 1.5 percent from 1973 to

1996, followed by a 10-year return to 2.9 percent growth and then another 15-year period through 2022 of 1.6 percent growth.

Figure 1: Nonfarm Business Sector Productivity Growth



Source: US Department of Labor, Bureau of Labor Statistics

Note: The data are expressed as annualized percentage rates.

Productivity growth surged in the last three quarters of 2023, averaging 3.6 percent on an annual basis in the nonfarm business sector, and has triggered speculation that perhaps the US economy was entering a new high-growth phase. Some analysts expressed optimism that rapid advances in artificial intelligence (AI) could be a potential engine of growth in the coming decade.

These swings in productivity trends present a challenge in forecasting productivity growth, particularly in light of shorter-term cyclical fluctuations. The COVID-19 pandemic in 2020 added further complexity, with unprecedented fluctuations in productivity, first when the labor force experienced massive reductions early in 2020 and then again later in 2020 and in 2021 as workers returned to the labor force. Thus, it is difficult to assess whether an acceleration such as occurred in 2023 represents a new trend or merely a transitory blip.

Changes in trend productivity growth also present challenges to policymakers. The slowdown in trend productivity growth in the early 1970s is widely believed to have contributed to inflationary pressures during that decade, as policymakers were perceived to be slow to recognize the change and believed the economy could grow more rapidly without generating inflation than was actually the case. By contrast, the recognition of technology advances in the 1990s prompted policymakers on the Federal Open Market Committee (FOMC) to hold off tightening policy even with strong GDP growth, a condition that would typically prompt a response.

As a tool for separating the “signal” (the longer-term trend in productivity) from the “noise” (shorter-term fluctuations), Kahn and Rich (2007) developed a model to describe and forecast movements in productivity growth. The model focuses on detecting possible changes in productivity growth “regimes” (extended periods of higher- or lower-than-average growth) in real time as new data are released. The model proved adept at detecting, within about two years, the changes in trends that, with hindsight, we can say occurred in 1997 and 2005 (see Kahn and Rich, 2011).

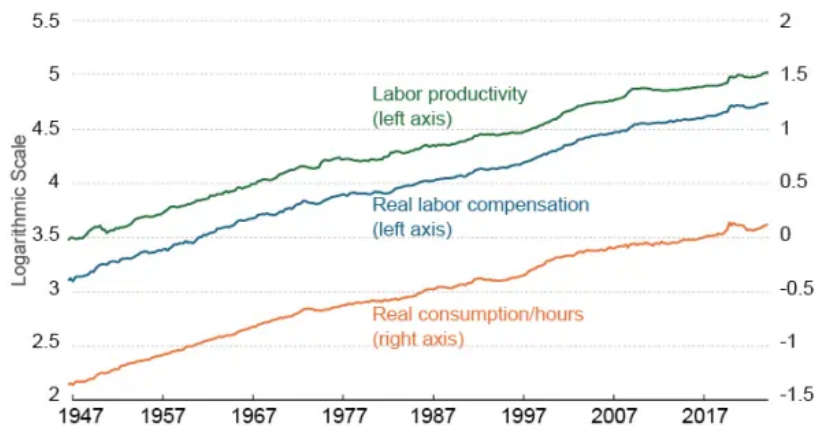
In this *Economic Commentary*, we apply our model to show that the recent data provide some support, albeit limited and preliminary, for the view that productivity growth may have shifted to a higher trend growth rate. The model currently estimates a 41 percent probability that productivity is now in a high-growth regime. We will also address arguments for and against the idea that the recent pickup in productivity growth could be sustained.

A Regime-Switching Model of Productivity Growth

We follow the approach in Kahn and Rich (2006, 2007) and use a regime-switching model to describe the behavior of productivity growth in the United States over the post-World War II period.¹ The regime-switching model differs from traditional time series models by allowing the behavior of a variable to shift between recurring states. The periodic shifts in behavior can relate to the mean, variance, persistence, or some other property of the variable. The evolution of the states is governed by transition probabilities that give the likelihood, conditional on being in one state, of remaining in the same state or switching to another state in the next period.² Lagged values of the variable are also typically assumed to influence its movements over time.

In our current application, the regime-switching model allows productivity to shift between low- and high-growth states. To aid in detecting the current state, the model also includes data on real wages and real consumption (relative to labor hours), because both theory and observation suggest that these variables display similar movements to productivity over the long-run and thereby help to identify changes in the trend.³ Figure 2 plots the three series and shows their parallel movements.

Figure 2: Regime-Switching Model Inputs Move Together over Time



Source: US Department of Labor, Bureau of Labor Statistics

Notes: The series are divided by hours of work in the nonfarm sector. Nominal output and compensation are deflated by the price index for nonfarm output. Nominal consumption is deflated by the price index for personal consumption.

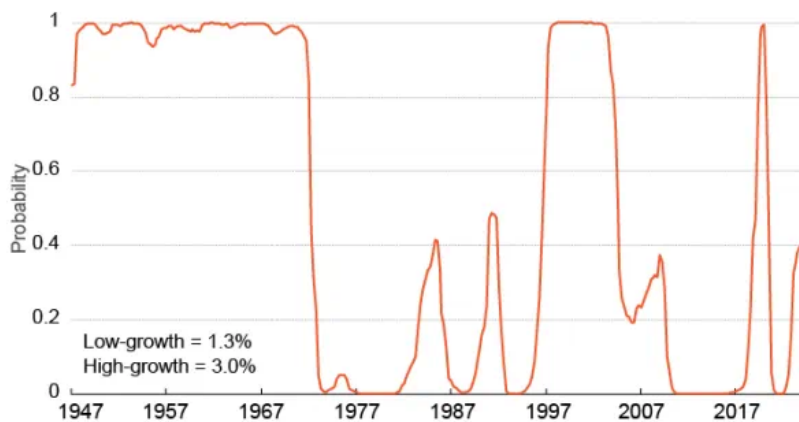
Note that there are periodic changes in the trends that appear to coincide. Specifically, the slopes flatten beginning around 1973:Q1, steepen at around 1997:Q1, and then flatten again after 2005:Q1. Moreover, the slopes of the steeper segments look similar to each other, as do the slopes of the flatter segments. Because the slope of a line plotted on a logarithmic scale measures a growth rate, the data support the choice of the regime-switching model with two growth states.

Another key feature of the model is that the mean growth rates and the incidence of the two growth-regimes are not specified in advance but, instead, are determined through estimation. Specifically, judgement about the realization of the regimes is made from estimated probabilities for productivity being in the low- or high-growth state at any time. One type of assessment—the real-time estimate—gauges the probabilities of the growth states using only the information that was available at the time. A second type of assessment—the retrospective estimate—gauges the probabilities of the growth states using all data through the present. While the real-time estimates assess what could have been known at each point in time, the retrospective estimates make use of subsequent data to provide the most informed assessment of the probabilities with hindsight. A more detailed description of the model and estimation is provided in Kahn and Rich (2006, 2007).⁴

Trend Productivity Growth in the Postwar Period

The data are expressed as quarterly annualized growth rates and cover the period 1947:Q2 through 2024:Q3. Because of the pandemic and the extreme outliers in the data, we use data only through 2019:Q4 for estimation.⁵ However, the model still allows us to estimate probabilities over the full sample period. Figure 3 plots the model's retrospective assessments of trend productivity growth through 2024:Q3.

Figure 3: Probability of Being in High-Growth Productivity Regime in Postwar Period



Source: Authors' calculations

Note: Figure shows November 2024 retrospective estimates.

As shown, the model indicates that productivity growth has displayed occasional shifts between two growth states associated with estimated trends of 1.3 percent and 3.0 percent. The pattern of the estimated probabilities generally points to a clear conclusion about the incidence of the growth states. There is a marked transition to the low-growth regime in 1973 that corresponds closely to the well-documented dating of a growth slowdown in the early 1970s. There was then a reacceleration from 1997 through 2004, coinciding with the information technology (IT) revolution, and this was followed by a second slowdown starting around 2005. The model detects another, albeit relatively short-lived, rebound in productivity growth that we attribute to the unprecedented employment fluctuations during the pandemic.⁶ More recently, because of data revisions going back to 2018 and preliminary data for 2024:Q3, the model has produced a notable increase in the probability that productivity has shifted to higher trend growth, with the most recent reading coming in at 41 percent.

Real-Time Assessments and the Detection of Shifts in Growth Regimes

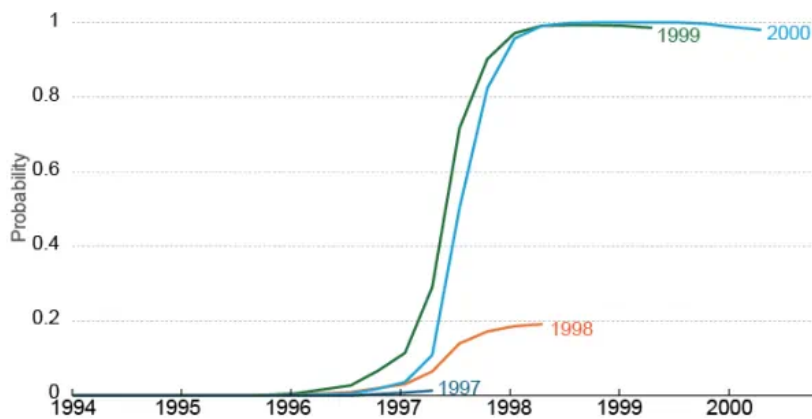
The recent uptick in the model's assessment that the economy is in a high-growth productivity regime should be treated with caution. The model will always display a recognition lag because it requires an accumulation of evidence drawn across the series and over time before concluding that a transition between growth states has taken place. In addition, an uptick in estimated probabilities does not always foreshadow a sustained rise, as evidenced by the mid-1980s and early 1990s during which the model's characterization of these episodes remains ambiguous.

Because of the considerations discussed above, it is natural and important to ask how the model has responded to previous regime shifts. This issue sheds light on the model's usefulness to monitor these events, but it cannot be answered solely from inspection of Figure 3 because (except for the

most recent numbers) the probabilities are based on retrospective estimates that have the benefit of hindsight. To interpret the most recent findings, it is more instructive to examine real-time estimates that are based only on the information that was available at the time. The extent to which the real-time estimates and retrospective estimates align can then inform us whether our model yields reliable estimates in real time. If the model were to detect trend changes only with several years of hindsight, then we would have little confidence in the accuracy of its current assessments.

Figure 4 and Figure 5 focus on the shifts in trend productivity growth in the late 1990s and middle 2000s, respectively. The real-time estimates of the high-growth regime are based on the vintage data sets as they would have appeared in August of each calendar year. Because of publication lags, there is a one-quarter differential between the data vintage and the last observation available. Thus, the August vintage will have data through the second quarter of that year. Figure 4 plots the estimated regime probabilities using data from vintages 1997, 1998, 1999, and 2000. Figure 5 undertakes the same exercise using data from vintages 2005, 2006, 2007, and 2008.

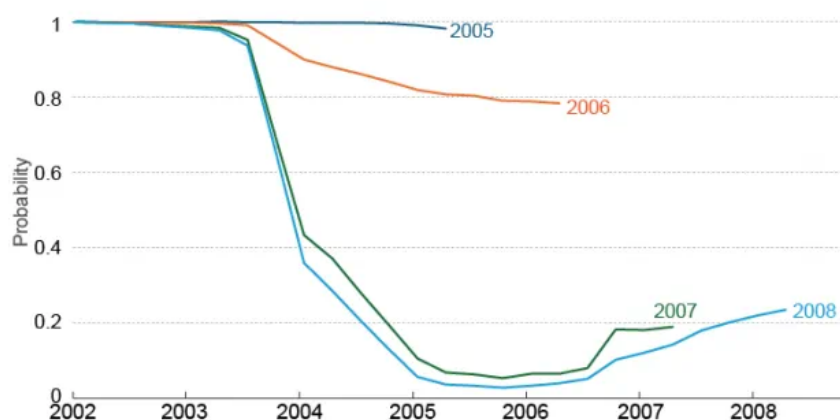
Figure 4: Transition from the Low- to High-Growth Productivity Regime in the Late 1990s



Source: Authors' calculations

Notes: Real-time estimates of the probability of the high-growth productivity regime. Probability estimates are as of August of each year and use data through the second quarter. Each year demarcation indicates the first quarter of that year.

Figure 5: Transition from the High- to Low-Growth Productivity Regime in the Mid-2000s



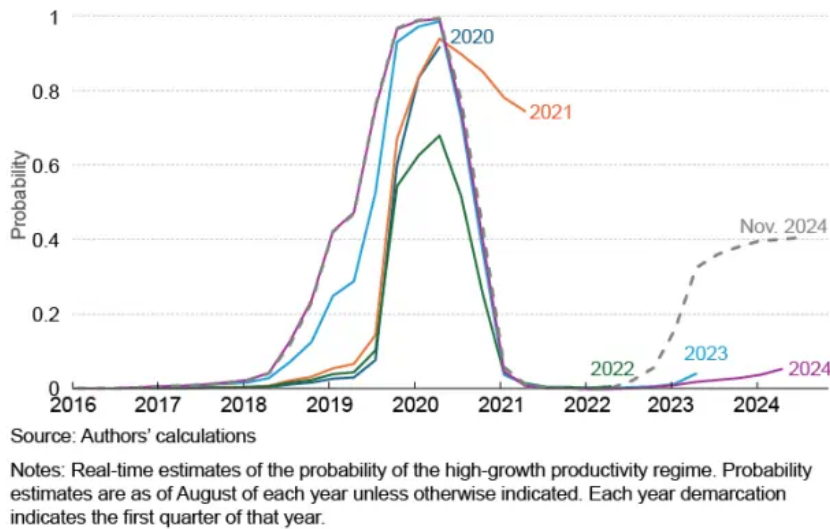
Source: Authors' calculations

Notes: Real-time estimates of the probability of the high-growth productivity regime. Probability estimates are as of August of each year and use data through the second quarter. Each year demarcation indicates the first quarter of that year.

As shown, the timelines for both episodes are quite similar and indicate that the model would have picked up the changes in trend within two years of when they are now known to have occurred. Regarding the late-1990s episode, by 1998 the estimates show a distinct rise in the high-growth regime probability, and by 1999 the probabilities are almost indistinguishable from those estimated retrospectively using data through the present. In the case of the middle-2000s episode, the estimates in 2006 show a distinct decline in the high-growth regime probability, and by 2007 the probabilities are again almost indistinguishable from those estimated retrospectively using data through the present. It is also worth noting that the dating of both regime shifts tends to move back in time during each relevant episode. This movement is likely due a combination of the availability of additional observations and subsequent data revisions.

Figure 6 depicts real-time estimates of the probability of the high-growth regime during the pandemic and its aftermath. Our examination not only provides insights into the behavior of the model in response to the extreme volatility in the data during this episode, but also to the September release of the 2024 comprehensive update of the National Income and Product Accounts (NIPA).

Figure 6: High-Growth Productivity Regime during the Pandemic and More Recently



The 2021 data vintage gives some indication of an upward shift in trend productivity growth, but this indication is based on large outliers in the 2020–2021 data from the pandemic. Even as early as 2022 the model was signaling that the productivity surge during the 2020–2021 period was short-lived. As with the previous episodes from the late 1990s and mid-2000s, in which the initial readings of the model were confirmed by subsequent data, the results through August 2024 continued to indicate that productivity had returned to a low-trend growth path, despite the strong headline productivity numbers in 2023.

There is, however, a notable change when we use data from the November 2024 vintage. This vintage includes the aforementioned NIPA revisions going back to 2018 and preliminary data for 2024:Q3.⁷ While the probability profile from the November 2024 vintage largely tracks that from the (August) 2024 vintage through 2022, the model now finds a higher likelihood, beginning in early 2023, of a shift in the productivity trend; the probability of the high-growth productivity regime is currently estimated at 0.41.

It is evident that the NIPA revision, which resulted in an upward revision of average labor productivity growth by 0.21 percentage points (annualized) since 2019:Q3, underlies the changed assessment of the high-growth regime probabilities over the last two years. However, it is important to note that revisions to the other model inputs were even larger. Growth in real consumption relative to labor hours and growth in real hourly labor compensation were revised up by 0.28 percentage points and 0.35 percentage points, respectively, over the same period. While the upward revisions to productivity growth have received considerable attention and are consistent with a possible shift to a higher trend growth rate, the upward revisions to consumption growth and real compensation growth may be playing an even greater role in the change in our model's assessment of trend productivity growth.

Also notable is that while the initial changes in the high-growth regime probability for the episodes depicted in Figures 4 and 5 were subsequently confirmed with more data, there have also been several instances for which early signs of a change in trend proved illusory. While these supposed false-positive episodes have mainly occurred around major economic turning points such as the 2007–2009 recession, they nonetheless provide additional grounds for refraining from any strong conclusions until more data come in.

The Current Debate about an Imminent Resurgence in Trend Productivity Growth

The resurgence of productivity growth in 2023, together with the strong performance of the stock market and the emergence of generative AI, has led some observers to suggest that the United States has entered a sustained phase of rapid technological advancement similar to that of the late 1990s.⁸ In addition to the potential of generative AI to boost productivity growth, others have pointed to productivity gains from working remotely.⁹ In addition, there is evidence of increased new-business formation and worker reallocation, a reversal of a decline that has been cited as a factor in the productivity slowdown since 2005.¹⁰ Stronger productivity growth has occurred in conjunction with the recovery of prime-age labor force participation and growth in the labor force from immigration. Increased labor supply would normally slow wage and productivity growth, a circumstance that makes the strong productivity numbers over the past 18 months even more impressive.

An important additional argument favoring stronger productivity growth is that technological progress creates measurement problems because of the introduction of new products and the inherent difficulty of measuring quality change in these products. As noted by Hornstein and Krusell (1996), this problem is likely to be especially severe in IT-intensive service industries such as banking and finance. Brynjolfsson et al. (2021) argue that productivity gains from IT have been substantially underestimated since the 1990s because of an understatement of software and complementary intangible capital.¹¹ Their data run through only 2017, so it is likely this undercounting of gains could be even larger in recent years. According to this view, some of the lackluster productivity growth of this era may be attributable to these factors, as actual efficiency gains are missed because quality improvements and intangible capital are underestimated. This would imply that the lack of evidence of a productivity resurgence—and indeed, much of the apparent slowdown of the last 20 years—could simply be that the official output measures are too low.

Even so, there are strong arguments for caution. First, at least some of the strong growth beginning in 2023 may be attributable to the easing of the supply chain disruptions that arose during the pandemic. This source of gains will not persist. Gains in efficiency from working remotely are also inherently transitory, though they may play out over several years as workplaces and technology

evolve. Second, as for increased business formation, it is still too early to judge whether this is a transitory effect of the pandemic or a longer-term trend. Last, given that generative AI is in the early stages of adoption and implementation, it is unlikely to have played a significant role in recent productivity growth. Thus, the hopes for AI rest on predictions about future implementation and efficiency gains. Acemoglu (2024) argues that even the most optimistic assessments suggest very modest effects on productivity growth, on the order of 0.1 percent annually. Goldman Sachs, for example, has tempered its initial enthusiasm, with a June 2024 report expressing skepticism regarding the ultimate payoff from large investments in AI.

Whatever the ultimate potential of AI for enhanced productivity, history suggests that learning and implementation lag for new and disruptive technologies. The information technology revolution that is widely accepted to have begun in the 1970s coincided with a productivity slowdown that lasted more than 20 years, with higher productivity growth only emerging in the late 1990s.¹²

Conclusion

The latest update of our productivity model provides some support for the view that productivity may have shifted to a higher trend growth rate. The most recent estimate puts the probability of being in that regime at about 40 percent, which is a substantial increase compared with pre-pandemic estimates but still less than even odds. Although the model has a good track record at detecting changes in trend growth relatively quickly, it will require at least one, and probably several, more quarters of data to reach a more unambiguous conclusion.

Finally, if productivity growth is consistently understated by the Bureau of Labor Statistics because of mismeasurement of the value of software and intangible capital, then our model would also underestimate its growth. Consistent mismeasurement would not necessarily change the model's conclusions about the timing of changes in trend growth. Our model did pick up a shift to a higher trend growth rate in the 1990s, notwithstanding measurement concerns present at the time; but if the downward bias of the official data has grown since 2005, it is possible that the model has missed a return to stronger growth. We hope to address this question in future work by using alternative measures of our model inputs that correct for any potential downward bias in the data.

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Endnotes

1. The regime-switching model was first introduced in Hamilton (1988). It has gained considerable popularity as a tool to capture the behavior of a wide range of economic and financial variables. [Return to 1](#)
2. The probabilities of staying in the same growth state or switching across growth states are allowed to differ. [Return to 2](#)
3. The model also includes a measure of the growth in detrended hours of work to help identify the influence of the business cycle on movements in the series. [Return to 3](#)
4. Updates to the regime-switching model of productivity growth are made after each “Productivity and Costs” release from the Bureau of Labor Statistics. These updates are posted and archived at

<https://sites.google.com/view/james-a-kahn-economics/home/trend-productivity-update>  [Return to 4](#)

5. We are currently investigating the adoption of techniques proposed by Ng (2021) and Lenza and Primiceri (2022) that can permit model estimation in the presence of the exceptionally large data variation during the pandemic. [Return to 5](#)
6. Although the model now dates the onset of the productivity surge to 2019, a year before the pandemic, we believe that this atypically short high-growth regime is entirely due to the pandemic. [Return to 6](#)
7. Recall that the other vintages are for August and have data through the second quarter of that year. [Return to 7](#)
8. For example, in May 2024 a Goldman Sachs article stated that “AI has the potential to be a major driver of labor productivity growth,” with an estimate of an additional 1.5 percent annual productivity growth. They cautioned, however, that it would be several years before the impact appeared in the data. It should be noted that they subsequently stepped back from this optimistic view, as discussed below. [Return to 8](#)
9. See, for example, Barrero et al. (2021). They estimate a 5 percent increase in efficiency from working remotely. [Return to 9](#)
10. See Decker and Haltiwanger (2023, 2024). [Return to 10](#)
11. Their work specifically examines total factor productivity (TFP). If their argument holds, it would imply that the undermeasurement of labor productivity from the omission of intangible capital would be even larger. TFP adjusts labor productivity for the impact of increased capital inputs. Thus, it partly offsets the positive impact of intangible capital on output by attributing some of the increase to “capital deepening.” Labor productivity would count the additional output without the capital deepening offset. [Return to 11](#)
12. In 1987, Robert Solow famously remarked, “You can see the computer age everywhere but in the productivity statistics.” Thirteen years later, in an interview by Louis Uchitelle (2000), Solow noted that one could “now see computers in the productivity statistics.” [Return to 12](#)

Suggested Citation

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