Journal of Economic Perspectives—Volume 31, Number 2—Spring 2017—Pages 165–186

Challenges to Mismeasurement Explanations for the US Productivity Slowdown

Chad Syverson

The flow and ebb of US productivity growth since World War II is commonly divided into four periods: 1947–1973, 1974–1994, 1995–2004, and 2004–2015. After labor productivity growth averaged 2.7 percent per year from 1947–1973, it fell in a much-studied-but-still-debated slowdown to 1.5 percent per year over 1974–1994. Another fast/slow cycle has followed. Productivity growth rose to a trajectory of 2.8 percent average annual growth sustained over 1995–2004. But since then, the US economy has been experiencing a slowdown in measured labor productivity growth. From 2005 through 2015, labor productivity growth has averaged 1.3 percent per year (as measured by the nonfarm private business labor productivity series compiled by the US Bureau of Labor Statistics).

This slowdown is statistically and economically significant. A *t*-test comparing average quarterly labor productivity growth rates over 1995–2004 to those for 2005–2015 rejects equality with a *p*-value of 0.008. If the annualized 1.5 percentage point drop in labor productivity growth were to be sustained for 25 years, it would compound to an almost 50 percent difference in income per capita.

The productivity slowdown does not appear to be due to cyclical phenomena. Fernald (2014a) shows that the slowdown started before the onset of the Great Recession and is not tied to "bubble economy" phenomena in housing or finance. This work, along with the analysis in Byrne, Oliner, and Sichel (2013), ties the slowdown to a reversal of the productivity accelerations in the manufacturing and utilization

■ *Chad Syverson is J. Baum Harris Professor of Economics, University of Chicago Booth School of Business, Chicago, Illinois, and Research Associate, National Bureau of Economic Research, Cambridge, Massachusetts. His email is chad.syverson@chicagobooth.edu.*

† For supplementary materials such as appendices, datasets, and author disclosure statements, see the article page at
https://doi.org/10.1257/jep.31.2.165 doi=10.1257/jep.31.2.165

of information and communication technologies that drove the more rapid pace of productivity from 1995–2004. While one cannot rule out persistent, less-direct channels through which the Great Recession might have long-lived influences on productivity growth, it is clear that measured labor productivity in the United States has not awakened from its slowdown as the Great Recession recedes.

The debate about the causes of the productivity slowdown is ongoing. Gordon (2016) points to multiple possible explanations and ties the current slowdown to the one in 1974–1994, viewing the 1995–2004 acceleration as a one-off aberration. Cowen (2011) shares these views and enumerates multiple reasons why innovation—at least the kind that leads to changes in measured productivity and income—may slow. Tarullo (2014) suggests that the slowdown in US business dynamism documented by Decker, Haltiwanger, Jarmin, and Miranda (2014) and Davis and Haltiwanger (2014) may have a role. Some have argued that there are reasons to be optimistic that the slowdown may reverse itself. Baily, Manyika, and Gupta (2013) point to potential innovation opportunities in multiple sectors. Syverson (2013) notes that the productivity growth from electrification and the internal combustion engine—a prior diffusion of a general purpose technology—came in multiple waves, implying that the 1995–2004 acceleration need not be a one-time event.

However, these arguments all accept that the measured decline in productivity growth is meaningful. A separate set of explanations for the slowdown in measured productivity put forward by several parties is that it is substantially illusory (for example, Brynjolfsson and McAfee, 2011, 2014; Mokyr 2014; Alloway 2015; Byrne, Oliner, and Sichel 2015; Feldstein 2015; Hatzius and Dawsey 2015; Smith 2015). The theme of these arguments is that true productivity growth since 2004 has not slowed as much as official statistics may suggest—and perhaps productivity growth has even accelerated—but that due to measurement problems, the new and better products of the past decade are not being captured in official productivity metrics.

There is a prima facie case for this assertion, which for brevity I refer to as the "mismeasurement hypothesis." Many of the fastest-diffusing technologies since 2004—like smartphones, online social networks, and downloadable media—involve consumption of products that are time-intensive but do not impose a large direct monetary cost on consumers. If one considers the total expenditure on such products to be both the monetary price *and* the value of time spent consuming them, a revealed preference argument would suggest they deliver substantial utility (Becker 1965). At the same time, the fact that these new products are not particularly expensive (at least relative to consumers' supposed interest in them) could result in a relatively modest portion of their delivered consumption benefit to be reflected in GDP.

This mismeasurement hypothesis could take one of two related forms. One possibility is that a smaller share of the utility that these products provide is embodied in their prices than was the case for products made before 2004. If this were true, measured output growth would slow even as growth of total surplus continued apace. The second possibility is that if the price deflators of these new technology products are rising too fast (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.[1]

In this study, I explore the quantitative plausibility of the mismeasurement hypothesis. One fact dominates the discussion: had the measured productivity slowdown not happened, measured GDP in 2015 would have been, conservatively, $3 trillion (17 percent) higher than it was. This is $9,300 for every person or $24,100 for every household in the United States. For the mismeasurement hypothesis to explain the productivity slowdown, the losses in measured incremental gains from the new technologies would need to be at or around this level. Thus, to explain even a substantial fraction of the productivity slowdown, current GDP measures must be missing hundreds of billions of dollars of incremental output (and moreover with no accompanying employment growth).

I start with a computation of the missing output lost to the productivity slowdown. I then turn to discussion of four patterns in the data, each looking at the mismeasurement hypothesis from different directions, which pose challenges for the hypothesis.

First, the productivity slowdown is not unique to the United States. It has occurred with similar timing across at least two dozen other advanced economies. However, the magnitude of the productivity slowdown across countries (of which there is nontrivial variation) is unrelated to the relative size of information and communication technologies (ICT) in the country's economy, whether this "ICT intensity" is measured in consumption or production terms.

Second, a research literature has attempted to measure the consumer surplus of the internet. These efforts are based on the notion that many of the newer technologies that could create large surplus with little revenue require internet access, which makes purchase and use of internet access a metric for the gains from such technologies. However, most of the estimates of the value of internet-linked technologies are at least an order of magnitude smaller than the trillions of dollars of measured output lost to the productivity slowdown. As I will discuss, even the largest estimate, which explicitly accounts for the time people spend online and is computed with very generous assumptions about the value of that time, totals only about one-third of the missing output.

Third, if the mismeasurement hypothesis were to account entirely (or almost so) for the productivity slowdown, and if the source of this mismeasurement is predominantly in certain industries that make and service digital and information

[1] These issues have arisen before. Diewert and Fox (1999) discuss related productivity measurement problems in the context of an earlier slowdown, arguing that there were several plausible sources of mismeasurement. The price-deflator-based interpretation of the measurement problem evokes the Boskin Commission report (US Congress 1996), which argued that the Consumer Price Index methodology at the time overstated inflation and therefore understated growth. Many of the commission's suggested changes, including those specifically aimed at better measurement of new products and technologies, were implemented before 2004 (Klenow 2003). The issues raised by the Boskin Commission report were discussed in a six-paper symposium on "Measuring the CPI" in the Winter 1998 issue of this journal, and a follow-up report by the National Academy of Sciences was discussed in a three-paper symposium on the "Consumer Price Index" in the Winter 2003 issue.

and communication technologies, then the implied change in real revenues of these industries would be five times their measured revenue change. Incremental real value added would have been six times the observed change, and true labor productivity in these industries would have risen 363 percent over 11 years.

Fourth, gross domestic income (GDI) and gross domestic product (GDP) are conceptually equivalent, but because they are computed with different source data, they are not actually equal. Since 2004, GDI has outstripped GDP by an average of 0.4 percent of GDP per year. This pattern is consistent with workers being paid to produce goods that are being given away for free or sold at steep discounts, which is consistent with the mechanism behind the mismeasurement hypothesis. However, I show that GDI began to be larger than GDP in 1998—several years before the productivity slowdown and, indeed, in the midst of a well-documented productivity acceleration. Additionally, a breakdown of GDI by income type shows that GDI growth over the period has been driven by historically high capital income (like corporate profits), while labor income has actually fallen. This is opposite the implication of a "workers paid to make products sold free" story.

In isolation, none of these four patterns are dispositive. But taken together, they challenge the ability of the mismeasurement hypothesis to explain a substantial part of the productivity slowdown.

Calculating the Missing Output

Whether the mismeasurement of productivity hypothesis is presumed to act through output gains disproportionately flowing into consumer surplus rather than GDP or through incorrect price deflators, the implication is the same: US consumers benefited from this missing output, but it just was not reflected in measured GDP. Any evaluation of the hypothesis needs to put estimates of productivity mismeasurement in the context of measures of this hypothetically missing output.

I first compute the implied lost output due to the productivity slowdown. Using quarterly labor productivity data from the US Bureau of Labor Statistics for the entire nonfarm business sector, I calculate average quarterly productivity growth over four post-WWII periods: 1947–1973, 1974–1994, 1995–2004, and 2005–2015 (period averages are inclusive of endpoint years). Past research has shown that average productivity growth has inflection points at or around the transitions between these periods, and work on both the most recent and prior productivity slowdowns has used these periods (for example, Byrne, Oliner, and Sichel 2013). Table 1 shows average productivity growth rates along with their annualized values for each period. As is clear in the table, measured labor productivity growth after 2004 fell by more than half from its 1995–2004 average.[2]

[2] Related productivity measures testify to the spread and depth of the slowdown. Sector-specific labor productivity growth slowed over the same period for each of the six two-digit NAICS industries with available data (mining, utilities, manufacturing, wholesale, retail, and accommodation and food services).

Table 1
Average Quarterly Labor Productivity (LP) Growth by Period

Period	*Average quarterly LP growth (%)*	*Annualized LP growth (%)*
1947–1973	0.681	2.73
1974–1994	0.386	1.54
1995–2004	0.712	2.85
2005–2015	0.317	1.27

Note: These values are taken from the Bureau of Labor Statistics nonfarm private industry labor productivity growth series. Annualized growth values are simply four times quarterly growth.

Labor productivity is defined as the ratio of real output to labor inputs, so it is straightforward to compute what counterfactual output would have been after 2004 had productivity growth not slowed. The drop in average quarterly labor productivity growth between 1995–2004 and 2005–2015 is 0.395 percentage points (= 0.712 – 0.317). Thus, counterfactual output in 2015 would thus have been 19 percent higher ($1.00395^{44} = 1.189$) than observed output in that period. Note that this exercise does not change labor inputs. Counterfactual output still reflects the observed movements in labor inputs over the period, like the considerable decline during the Great Recession. This exercise therefore does not assume away the employment downturn of the slowdown period.[3]

Nominal GDP in 2015 was $18.037 trillion. If I apply the counterfactual extra productivity growth of 19 percent to this value, the amount of output "lost" due to the productivity slowdown is $3.43 trillion per year.[4]

Notably, these sectors might vary in their inherent "measurability." Total factor productivity growth also slowed. The Bureau of Labor Statistics measure of multifactor productivity fell from 1.4 percent per year during 1995–2004 to 0.5 percent per year over 2005–2015. The utilization-corrected total factor productivity measures of Fernald (2014b) also saw similar decelerations, by 2.5 percent per year in the equipment and consumer durables producing sectors and 1.1 percent per year for makers of other outputs.

[3] An implication of the mismeasurement hypothesis is that the reported output deflator does not reflect true price changes and should have grown more slowly than what was measured. It is therefore instructive to compare the average growth rates of the implicit price deflator for the Bureau of Labor Statistics productivity series in the 1995–2004 and 2005–2015 periods. The deflator grew an average of 0.36 percent per quarter from 1995–2004 and 0.41 percent per quarter from 2005–2015. Compounded over the 44 quarters of the latter period, the deflator grew a cumulative 2.3 percent more than had it remained at its earlier trajectory. To the extent that this acceleration might reflect real output mismeasurement (and the fact that it did accelerate does not imply that it shouldn't have), it would only explain about one-eighth of the measured slowdown.

[4] The calculations here and throughout this paper use 2015 as an endpoint because several of the data sources I use extend only through that year. The implied "lost" output would be even larger than the reported values if I used the labor productivity data through 2016 (the latest available numbers as of this writing). This is for two reasons. First, average labor productivity growth during 2016 was even slower than the 2005–2015 average. Second, the slowdown would be compounded over another year of GDP growth. Conducting similar calculations to those above using the 2016 data imply values of lost output that are 14 percent larger than those reported here.

However, it is not immediately obvious if GDP is the correct base to which to apply the counterfactual growth rate. The Bureau of Labor Statistics labor productivity series that I use here applies to nonfarm business activity, which excludes farming, government, nonprofits, and paid employees of private households. The reason given is that the outputs of these sectors in GDP "are based largely on the incomes of input factors. In other words, the measure is constructed by making an implicit assumption of negligible productivity change" (http://www.bls.gov/lpc/faqs.htm). The value of owner-occupied dwellings is left out "because this sector lacks a measure of the hours homeowners spend maintaining their home." Together, these factors jointly account for about one-quarter of GDP. If labor productivity growth in the excluded activities didn't slow as much as in nonfarm business productivity growth, then the "lost" output could be smaller than $3.43 trillion per year; conversely, if productivity in the excluded activities slowed more, then the "lost" output could be larger. As long as productivity growth did not actually accelerate in these excluded sectors—which seems a fair assumption—a very conservative estimate of lost output would apply the 19 percent slowdown only to the three-fourths of GDP that the labor productivity series covers directly. This lower bound implies at least $2.57 trillion of lost output.

Some additional data can refine this lower bound estimate. First, the Bureau of Labor Statistics does compute a productivity series that adds the farming sector (which accounts for about 1 percent of GDP) to the set of covered industries. This series experienced an even larger productivity slowdown than the nonfarm business series, falling from an average growth per quarter of 0.741 percent over 1995–2004 to 0.310 percent for 2005–2015. This implies a larger amount of "missing" output—$3.80 trillion applied to GDP or a lower bound of about $2.89 trillion when applied only to the directly covered sectors. Second, I combined an unpublished Bureau of Labor Statistics series of total economy aggregate hours through 2015 with the real GDP index from the Bureau of Economic Analysis to compute a total economy labor productivity measure.[5] This metric indicates a drop in productivity growth between 1995–2004 and 2005–2015 of 0.369 percentage points per quarter. Applying this to all of GDP (which, here, the productivity metric spans) implies lost output due to the productivity slowdown of $3.21 trillion per year.

Thus, the amount of output lost to the productivity slowdown ranges somewhere between $2.57 trillion and $3.80 trillion per year. Going forward, I will analyze the case for the mismeasurement hypothesis using $3 trillion as the implied value of output "lost" because of the productivity slowdown. This measure is conservative in the sense that it leaves less total lost output for the hypothesis to explain than would applying the BLS measured productivity slowdown to all of GDP. Based on 2015 US Census estimates of a US population of 321 million living in 125 million households, this works out to output that is lower because of the productivity slowdown by $9,300 per capita and $24,100 per household.

[5] I thank Robert Gordon for sharing the hours data.

Thus, to explain the entire productivity slowdown as a figment of measurement problems implies that every person in the United States in 2015 enjoyed an average additional surplus of $9,300 that did not exist in 2004.

It is important to recognize that the question is *not* whether the average consumer surplus in 2015 is $9,300 per capita. GDP does not measure, nor ever has measured, consumer surplus. Nominal GDP values output at its market price; consumer surplus is the extent to which willingness to pay is above the market price. There surely was consumer surplus in both 2004 and 2015, and it was probably substantial in both years. The question instead is whether it is plausible that technological growth between 2004 and 2015—and in particular the advent and diffusion of digitally oriented technologies like smartphones, downloadable media, and social networks that have been the most cited examples—created $9,300 per person in *incremental and unmeasured* value above and beyond any consumer surplus that already existed in goods and services present in 2004 and was brought forward to 2015.

The Extent of the Productivity Slowdown Is Not Related to Digital Technology Intensity

Several studies have noted recent productivity slowdowns in economically advanced countries (for example, Mas and Stehrer 2012; Connolly and Gustafsson 2013; Pessoa and Van Reenen 2014; Goodridge, Haskel, and Wallis 2015). As in the US economy, these slowdowns began before the 2008–2009 financial crisis and recession (Cette, Fernald, and Mojon 2015).

Given the relatively technology-heavy profile of US production (and citation of digital technologies produced by US-based multinationals as prime examples of the sources of mismeasurement), one might argue that the fact that a productivity slowdown has occurred across a number of economies makes a measurement-based explanation for the slowdown less likely. Still, similar measurement problems could have arisen in multiple advanced economies. I test if there is any systematic relationship between the extent of a slowdown in a country and the importance of information and communications technology (ICT), whether on the production or consumption side, to that country's economy. The logic of this test is, if information and communication technologies have caused measured productivity to understate true productivity, the mismeasurement hypothesis would imply that the *measured* slowdown in productivity growth should be larger in countries with greater "ICT intensity."

I conduct this test using OECD labor productivity growth data, which contains yearly percentage changes in real GDP per worker-hour. Growth rates are reported for about three dozen countries in 2015—the latest year for which data are available—but only 30 have data going back to 1995 as needed to directly compare to the US slowdown. I combine this productivity growth data with two measures, also from the OECD, of the intensity of an economy in information and communications technology. The consumption-side measure is the fraction of a country's households with broadband internet access. My data are taken from 2007, the year in which this data was most widely available, and cover 28 countries, 25 of which overlap with those for which I can compute the change in average annual productivity growth between 1995–2004 and 2005–2015.[6] Obviously broadband access has increased since this time, but here I am interested in the much more stable cross-sectional variation. The production-side intensity metric is the share of the country's value added accounted for by industries related to information and communications technology. This data is only available for 2011. It spans 28 countries, 24 of which overlap with my productivity slowdown sample.

The ubiquity of the productivity slowdown is readily apparent in the data. Labor productivity growth decelerated between 1995–2004 and 2005–2015 in 29 of the 30 countries in the sample (Spain is the only exception). Labor productivity growth across the sample's countries fell on average by 1.2 percentage points per year between the periods, from 2.3 percent during 1995–2004 to 1.1 percent over 2005–2015. There was substantial variation in the magnitude of the slowdown, with a standard deviation of 0.9 percent per year across countries. While the crisis years of 2008–09 saw unusually weak productivity growth—these were the only two years with negative average productivity growth across the sample—the slowdown does not merely reflect the crisis years. Calculating later-period average productivity growth excluding 2008–2009 still reveals slowdowns in measured productivity growth in 28 of 30 countries (excepting Spain and Israel), with an average drop of 0.9 percentage points per year (a decline in annual rates from 2.3 to 1.4 percent). Similarly, computing the prior period average productivity growth using only 1996–2004 data in order to allow for an expanded sample gives the same results: productivity growth slows between the periods in 35 of 36 countries (Spain is again the exception).

To consider the covariance between the size of a country's slowdown and its information and communications technology (ICT) intensity, Figure 1A plots each country's change in average annual labor productivity growth between 1995–2004 and 2005–2015 against the share of the country's households that have broadband access. There is no obvious relationship to the eye, and this is confirmed statistically. Regressing the change in labor productivity growth on broadband penetration yields a coefficient on broadband of -0.0003 (s.e. = 0.009). The point estimate implies that a one standard deviation difference in broadband penetration is associated with less than a one-hundredth of a standard deviation difference in the magnitude of the slowdown.

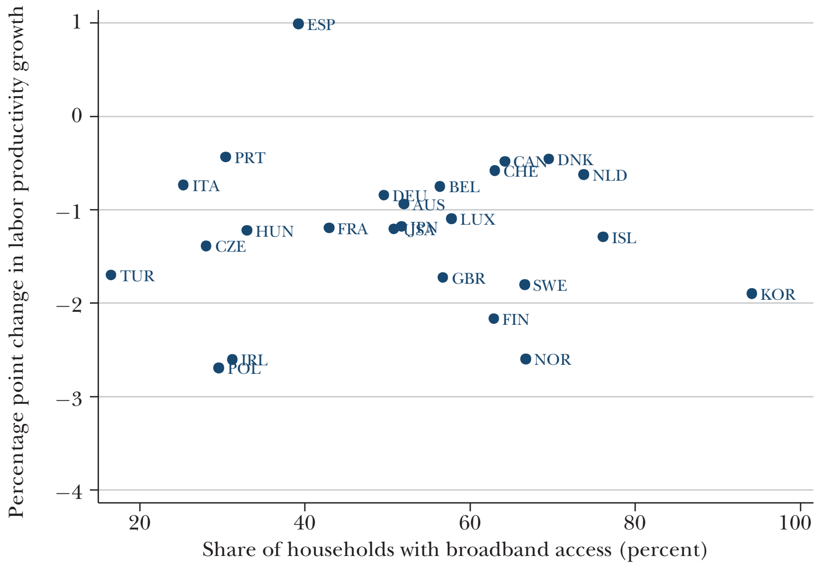
On the production side, Figure 1B plots the change in average annual labor productivity versus the share of a country's value added due to its ICT industries. Here the visual is less obvious, but as with the previous panel, a regression yields a statistically insignificant relationship. The coefficient on intensity of production

[6] Two countries, Iceland and Turkey, did not have 2015 data available, so I instead use 2005–2014 as the later period. I also use 2005–2014 for Ireland because reported labor productivity growth in 2015 was 22.5 percent, an astonishing number and one that is likely due to tax-driven corporate inversions (for example, Doyle 2016). That said, the results are not sensitive to these substitutions.

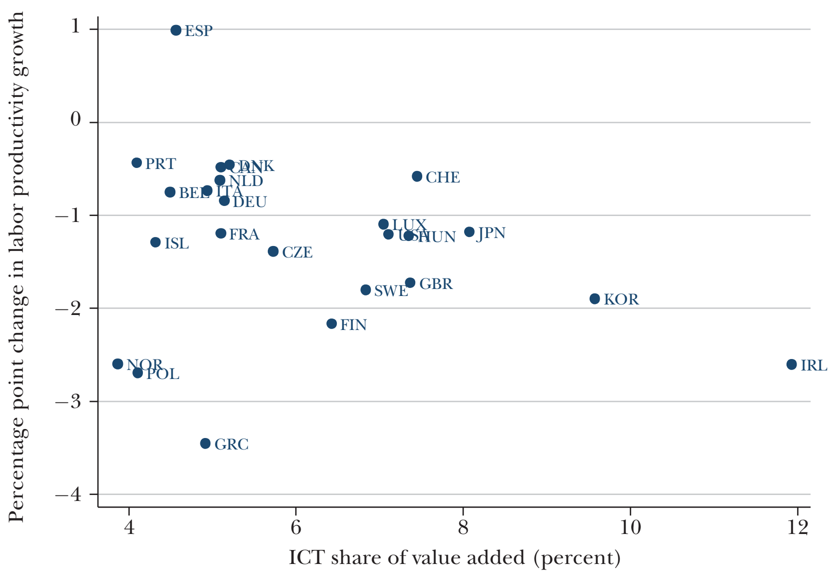
Figure 1

Change in Labor Productivity Growth versus Information and Communication Technology (ICT) Intensity

A: Labor Productivity Growth Change between 1995–2004 and 2005–2015 versus Share of Households with Broadband Access (*N* = 25 OECD countries)



B: Labor Productivity Growth Change between 1995–2004 and 2005–2015 versus ICT's Share of Value Added (*N* = 24 OECD countries)



Source: Data for both figures are from OECD. See text for details.

in information and communications technology is −0.123 (s.e. = 0.101). To the extent any relationship exists, it is due completely to the outlier Ireland, which has a value-added share in information and communications technology of 11.9 percent, double the sample average. Removing Ireland from the sample yields a statistically insignificant coefficient of −0.054 (s.e. = 0.133). This point estimate correlates a one standard deviation difference in share of value added from information and communications technology to one-eleventh of a standard deviation change in the magnitude of the productivity slowdown.

Similar results obtain both qualitatively and quantitatively if I instead measure the productivity slowdown using later-period growth rates that exclude 2008–2009 or the larger sample with 1996–2004 as the early period. This is not surprising given that the correlations between the three productivity slowdown measures are all above 0.9.

Overall, the size of the productivity slowdown in a country does not seem to be systematically related to measures of the intensity of consumption or production of information and communications technology in that country. These results echo and complement the findings of Cardarelli and Lusinyan (2015), who show that differences in the slowdown in total factor productivity growth across US states are uncorrelated with measures of state-level intensity of information and communication technologies, both as inputs and outputs in production.

Estimates of Surplus from Internet-Linked Technologies

Several researchers have attempted to measure the consumer surplus of newer technologies like those discussed in the context of the mismeasurement hypothesis. While not always explicitly motivated by the post-2004 measured productivity slowdown (some of these studies predated the recognition of the productivity slowdown among scholars), these analyses were impelled by a similar notion: certain newer technologies, those tied to internet access in particular, may have an exceptionally high ratio of consumer surplus to observed expenditure. Several studies that seek estimates of these values, which I update here, offer insight into the potential for such technologies to explain the productivity slowdown.

Greenstein and McDevitt (2009) estimate the consumer surplus created by broadband access. They choose broadband because, as an access channel, its price at least partially embodies the surplus created by otherwise unpriced technologies (for example, internet search, some downloadable media, social networking sites, and others). As Greenstein (2013) notes, "Looking at broadband demand, which does have a price, helped capture the demand for all the gains a user would get from using a faster form of Internet access." They estimate that the new consumer surplus created by households that switched from the earlier technology (dialup) was between 31–47 percent of broadband's incremental revenue over dialup. At the end of their analysis sample in 2006, this consumer surplus totaled $4.8–6.7 billion. In 2015, total US broadband revenues are estimated to be $55 billion (see The Statistics Portal, http://www.statista.com/statistics/280435/fixed-broadband-access-revenues-in-the-united-states).

Supposing broadband's overall ratio of consumer surplus to revenues is the same in 2015 as Greenstein and McDevitt (2009) estimated, this implies that the consumer surplus of broadband was $17–26 billion in 2015. Some of this value is likely priced into GDP indirectly through broadband's use by producers as an intermediate input, and as such should not be considered part of the missing output due to the productivity slowdown. But even absent any such adjustment, this surplus is two orders of magnitude smaller than the $3 trillion of missing output.

Dutz, Orszag, and Willig (2009) apply demand estimation techniques to household data on internet service take-up and prices. They estimate a consumer surplus from broadband (again relative to dialup) on the order of $32 billion per year in 2008. To scale up this value for the growth in broadband since then, I use the fact that their estimates implied the same consumer surplus was $20 billion in 2005. Assuming this robust 60 percent growth over three years (a compounded annual growth rate of 17 percent) held until 2015, consumer surplus in 2015 would be $96 billion. While this is notably larger than the Greenstein and McDevitt (2009) valuation, it is still only 3.2 percent of $3 trillion.

In another attempt to measure broadband's consumer surplus, Rosston, Savage, and Waldman (2010) use a different methodology and dataset. Their estimate is $33.2 billion in 2010. I bring this forward to 2015 using their assessment that this surplus had doubled or perhaps even tripled between 2003 and 2010, which implies a compound annual growth rate between 10.4 and 17.0 percent (which as it happens is on the order of the growth rate in Dutz, Orszag, and Willig 2009). This extrapolation implies consumer surplus was in the range of $54–73 billion in 2015. Once again, this is miniscule compared to the lost output.

Nevo, Turner, and Williams (2015) use household-level data on broadband purchases to estimate a dynamic model of broadband demand. They find an average consumer surplus among households in their data between $85 and $112 per month ($1,020–1,344 per year) in 2012. Applying this to the 80 percent of US households that had broadband access in 2015, this totals at most $132 billion—larger than the estimates above, but again less than 5 percent of the $3 trillion in missing GDP.[7]

Goolsbee and Klenow (2006) take a different approach. They use the time people spend online as an indicator of "full expenditure" on internet-based technologies. In their methodology, consumption of a good generally involves expenditure of both income and time. Therefore, even if financial expenditures on a good are relatively small, the good can deliver substantial welfare if people spend a lot of time consuming it. They argue this is a realistic possibility for the internet, which in their data (for 2005) has a time expenditure share 30 times greater than its income

[7] They also use their estimates to infer the total surplus (revenues plus consumer surplus) of access to 1 Gb/s networks, which is currently unavailable in most locations. This extrapolation implies a total surplus of $3,350 per year. Some of this would surely be captured as revenues of downstream firms and thus measured in GDP. A conservative price for this service would be $900 per year, so consumer surplus per household would be around $2,450. Even if service were obtained by every household in the country that has broadband, this adds up to $241 billion of consumer surplus, which is 8 percent of $3 trillion.

expenditure share. Applying their theoretical framework to data, they find that the consumer surplus of internet access could be as large as 3 percent of full income (the sum of actual income and the value of leisure time). This surplus would be $3,000 annually for the median person in their dataset. Brynjolfsson and Oh (2012) extended this analysis with updated data. They pay particular attention to incremental gains from free internet services, valuing these at over $100 billion (about $320 per capita) annually.

To extend the Goolsbee and Klenow (2006) value-of-time analysis to the question of the mismeasurement hypothesis, I must first compute total income in 2015. Disposable personal income totaled $13.52 trillion, about $42,100 per capita, in 2015. For the value of leisure time, I start with the fact that according to the American Time Use Survey (ATUS), the average person in 2014 spent 10.8 hours a day on non-work-related, non-personal-care activities. (Personal care includes sleep, so sleep is not included in the 10.8 hours.) I make the (very) generous assumptions that all of these 10.8 hours are leisure time and that people value them at the average after-tax wage of $22.08, regardless of employment status and whether the hours are inframarginal or marginal. This value of time is based on the estimate by the Bureau of Labor Statistics that average pre-tax hourly earnings for all nonfarm private business employees were $25.25 over the final quarter of 2015. To impute an after-tax wage, I multiply this value by the ratio of that quarter's disposable personal income ($13.52 trillion) to total pre-tax personal income ($15.46 trillion), reflecting an average tax rate of 12.5 percent. This yields a total annual value of leisure time of about $87,000 per person. Adding this to personal income gives a total income equal to $129,100 per capita.

Applying the Goolsbee and Klenow (2006) top-end estimate that it is 3 percent of total income, I end up with a measure of the consumer surplus from the internet in 2015 of around $3,900 per capita.[8] Assuming this surplus accrues mainly to the 80 percent of people with broadband access in their household, the aggregate benefit is $995 billion. Going through the same set of computations with 2004 data (when broadband penetration was about 12 percent according to OECD data) and subtracting the result so as to estimate incremental gains from broadband-based technologies yields a post-2004 incremental surplus from broadband of $863 billion.[9]

[8] As noted in the text, the 3 percent value is determined in part from Goolsbee and Klenow's (2006) time use data. It is plausible that the ratio of the internet's time expenditure share to its income expenditure share could have risen in the intervening decade, thereby raising this number. However, comparable contemporaneous data necessary to check this is difficult to find. The ATUS does not offer a separate item for online activity save for an email category that accounts for a tiny share of time. Many commercially available data products do not separate online leisure from online work time (the latter being an input into production rather than a final output) and allow multitasking, so a day can be filled with more than 24 hours of activity. In absence of specific guidance, I keep the original 3 percent value here.

[9] The specific figures for 2004 are $9 trillion of nominal disposable income ($30,700 per capita given a population of 293 million), 11 hours of leisure time per day, and $18.19 per hour after-tax nominal hourly earnings (based on Bureau of Labor Statistics earnings data for 2006, the start of the all-worker-compensation series). This implies a total nominal income of $103,800 per capita. Applying the 2004–2015 GDP deflator ratio of 1.21 and multiplying by the Goolsbee–Klenow estimate of 3 percent

The Goolsbee–Klenow time-based estimate is by far the highest valuation of the internet in the literature, essentially an order of magnitude larger than the other estimates. Time-of-use valuation approaches can produce large numbers; there are always 24 hours in a day to allocate and value, and it is hard to estimate the monetary value of a minute. Indeed, one could have used a similar logic to argue that productivity numbers in the 1950s and 1960s—the height of the post-World War II productivity acceleration—were missing the allegedly massive social gains of families' fast-increasing TV viewing. I stick with common practice and apply a (generous) wage-related valuation here, but in principle the wage only applies to the unit of time on the margin of work. Inframarginal leisure time should be valued by the incremental surplus relative to the next-best use of that time: for example, the extra amount someone is willing to pay to be online as opposed to, say, watch television. This increment could be much smaller than the person's wage, and the increment and wage may be uncorrelated across people, making the $863 billion figure a large overstatement. Even given these measurement issues, the implied valuation from the time-of-use approach is still less than one-third the $3 trillion of lost income from the productivity slowdown.

Most of the technologies cited by proponents of the mismeasurement hypothesis require internet access of some sort, so these estimates of the surplus delivered by that gateway should embody the surplus of the technologies that are not priced on the margin. It is possible that some post-2004 technologies that deliver a high ratio of consumer surplus to revenue do not require internet access. The numbers above indicate, however, that to explain the bulk of the productivity slowdown in quantitative terms, these products would need to deliver surplus that is both somehow not priced either directly or through complementary goods and services, and that is as large as or larger than the biggest estimates of the surplus of internet-linked products.

What If the "Missing" Output Were Measured?

Yet another calculation of the quantitative plausibility of the mismeasurement hypothesis relates the $3 trillion of missing GDP to the value-added of the specific products associated with post-2004 technologies. I take an expansive view of which products include such technologies, in an attempt to construct something of an upper bound of the lost output that can be explained by the hypothesis.

The first step in this calculation is to select the set of technologies that would be most implicated in the mismeasurement, if GDP mismeasurement results from the migration of value from output to consumer surplus since 2004. I include the

yields a benefit of $3,800 per capita in 2015 dollars. This is very close to the 2015 figure, so almost all incremental surplus from broadband by this calculation comes from diffusion of broadband to a larger population. This increase in population with broadband is (0.8 x 321 million) – (0.12 x 293 million) = 222 million.

following sectors in this group: computer and electronic products manufacturing (NAICS 334), the entire information sector (NAICS 51), and computer systems design and related services (NAICS 5415). The first and last are self-explanatory. The information sector includes the following four subindustries: publishing (including software), except internet; motion picture and sound recording; broadcasting and telecommunications; and data processing, internet publishing, and other information services. Both internet service providers and mobile telephony carriers are in this sector (in particular, NAICS 517, telecommunications).

These industries comprise the segments of the economy most likely to produce the technologies that are the focus of claims of the mismeasurement hypothesis. They also doubtlessly contain some activity that has *not* seen considerable technological expansion over the past decade (or even the past couple of decades, for that matter). As will be clear, this overexpansive definition of the output tied to the mismeasurement hypothesis is conservative in the sense that it will tend to overestimate the missing output of these industries for which technological developments in these industries might account.

The value added of these industries in 2015 were as follows: computer/electronics manufacturing, $278 billion; information, $840 billion; computer systems design and services, $266 billion. This totals $1,384 billion.

At the precipice of the productivity slowdown in 2004, nominal value added of the sectors was $945 billion ($202 billion in computer/electronics manufacturing, $621 billion in information, and $123 billion in computer systems design and services). Applying the Bureau of Economic Analysis value-added price indices of the three sectors yields 2004 value-added expressed in 2015 dollars: $813 billion.[10]

These industries therefore saw measured real value added growth between 2004 and 2015 of about $571 billion (that is, $1,384 billion – $813 billion). If measurement problems in the products of these industries are to account for the lion's share of $3 trillion in missing GDP, the incremental consumer surplus these industries would have created would need to be over six times their measured incremental value-added. Or to put this another way, if the incremental consumer surplus implied by the mismeasurement hypothesis would in fact have been captured as measured value added (and therefore the productivity slowdown observed in the data never materialized), the real value added of the industries would actually have increased by 440 percent (($1.384 trillion + $3 trillion)/$813 billion), over six times the 70 percent growth ($1.384 trillion/$813 billion) that was actually observed in

[10] This method divides the industries' summed nominal value added in 2004 by a Tornqvist price index I constructed for the combined industries. This index is equal to the average-share-weighted sum of the log changes in each of the three components' price indexes from 2004 to 2015. Note that all three industries saw drops in their value-added price indices over the period, which is why the figure in 2015 dollars is smaller than the 2004 figure. An alternative approach of deflating each industry's 2004 nominal value added by the industry-specific deflator and summing the result implies 2004 real value added in 2015 dollars of $829 billion. The difference in the methods mostly reflects the effect of the 36 percent decline in the computer equipment manufacturing price index during the period. Note that using this latter figure for 2004 value added in the calculations below would make the "missing" output of the mismeasurement hypothesis even larger in terms of the industries' measured incremental value added.

the data. This implies an enormous amount of mismeasurement. Even to account for just one-third of the missing output, by far the largest estimate of surplus from internet-related products discussed in the prior section, the industries' "correct" value added would have had to have grown by 190 percent from 2004–2015, almost triple the measured growth.

Looking at the dual to this calculation—that is, not how much larger the "real" output would need to be, but how much larger the price deflator would need to be—is also instructive. The (Tornqvist) value-added price index for this bundle of industries fell 14 percent over 2004–2015, a compound annual growth rate of −1.4 percent. If real GDP growth has been misstated because deflators have improperly accounted for quality changes in these products, the true deflator would be that which raises measured real value added growth by the extra \$3 trillion. This deflator would have a compound annual growth rate of −9.9 percent, sustained over 11 years—seven times the magnitude of the official deflator. Prices would have fallen not by 14 percent since the productivity slowdown began, but by 68 percent instead.

Some of the outputs of these industries are intermediate inputs used to make other products. Therefore, they do not directly deliver surplus to final demanders. It is possible that some of the gains from the new technologies might arise as (again mismeasured) productivity gains in the production of goods for which they are used as inputs. For example, in the 2015 input-output tables for the national income and product accounts, 83 percent of computer equipment manufacturing output was used as an intermediate in the production of another commodity. The corresponding values for information and computer services are 46 and 42 percent, respectively. The total "multiplier" effect of technological progress through input use is captured by the industry's ratio of gross output (revenues) to its value added (Domar 1961; Hulten 1978). Incremental revenues capture the gains associated not just with the industry's products per se but also any embodied productivity gains obtained through their use as inputs. To gauge the potential influence of this usage, I repeat the calculations above using revenues—that is, gross output—in place of value added.

The nominal gross output of the three sectors in 2015 was \$2.29 trillion (\$387 billion in computer/electronics manufacturing, \$1,550 billion in information, and \$353 billion in computer systems design and services). The corresponding values in 2004 were \$1.67 trillion (\$392 billion, \$1,080 billion, and \$195 billion). Again applying the Bureau of Economic Analysis price deflators (this time for gross output) to express these values in 2015 dollars yields a real gross output of \$1.61 trillion.

Incremental real gross output (that is, real revenue) for this set of industries was therefore about \$680 billion. A full accounting for the mismeasurement hypothesis would imply an increment to consumer surplus that is five times as large as this. Had such a surplus been captured in revenue figures, the industries' real revenues would have more than tripled over 2004–2015, rather than risen 42 percent as observed in the data. The dual calculation implies a mismeasurement-corrected deflator with a compound average growth rate of −7.3 percent over 2004–2015 instead of the official gross output price index compound average growth rate of −0.3 percent, for a total price decline of 57 percent rather than 3 percent.

These calculations reveal how severely one must believe the measured growth of these industries understates their true growth if measurement problems are to explain the overall productivity slowdown for the entire US economy. What was measured and what would have actually had to happen would be multiples apart.

A final set of calculations reinforces this point. If the data miss industry output growth, they of course also miss productivity growth. In this case, it would need to be a lot of missing productivity. These industries, combined, saw their total employment rise 3.2 percent over 2004–2015 (from 5.58 million to 5.76 million, about 0.3 percent annually). Assuming they actually produced all of the output lost to the productivity slowdown, real value added per worker, properly measured, would have risen by 415 percent over those 11 years, an astounding rate of productivity growth. For example, it is notably larger than the 83 percent productivity growth seen in durable goods manufacturing during the productivity acceleration of 1995 to 2004, when durables had the fastest labor productivity growth of any major sector and they were a primary driver of the acceleration (Oliner, Sichel, and Stiroh 2007).

Perhaps these numbers are not that surprising when one considers that these digital-technology industries accounted for only 7.7 percent of GDP in 2004. A full accounting of the productivity slowdown by the mismeasurement hypothesis requires this modest share of economic activity to account for lost *incremental* output that in 2015 is about 17 percent of GDP—over twice the 2004 size of the entire sector.

One should be mindful that it is possible that unmeasured incremental gains are being made in industries outside these. For example, more intensive use of information technologies has been a recent focus of attention (including public policy efforts) in the sizeable health-care sector. Yet evidence on the productivity benefits of specific technologies in the sector has been mixed (for example, Agha 2014; Bhargava and Mishra 2014). There does not appear to be a clear case for large missing gains in the sector. Moreover, further balancing this out is the fact that, as discussed above, the digital-product-focused industries here are defined expansively. It is unlikely that every segment in this grouping (as one example, radio broadcasting) experienced similarly rapid technological progress.

National Income versus National Product

In national income accounting, it is an identity that gross domestic product (GDP) is equal to gross domestic income (GDI)—the sum of employee compensation, net operating surplus, net taxes on production and imports, and consumption of fixed capital (that is, depreciation). However, GDP and GDI are never equal in practice, because different data are used to construct each—expenditure data on the one hand and income information on the other.

In recent years, the gap between GDI and GDP—the so-called "statistical discrepancy"—has widened, with GDI on average outpacing GDP. Table 2 shows

Table 2
Gross Domestic Income versus Gross Domestic Product

				Percent of GDI going to			
Year	*GDI ($ billions)*	*GDP ($ billions)*	*GDI–GDP gap ($ billions)*	*Labor income*	*Net operating surplus*	*Net taxes*	*Depreciation*
1995	7,573.5	7,664.1	–90.6	55.5	22.7	6.9	14.8
1996	8,043.6	8,100.2	–56.6	55.0	23.6	6.8	14.6
1997	8,596.2	8,608.5	–12.3	54.9	24.0	6.7	14.4
1998	9,149.3	9,089.2	60.1	55.5	23.5	6.6	14.3
1999	9,698.1	9,660.6	37.5	55.9	23.2	6.5	14.4
2000	10,384.3	10,284.8	99.5	56.5	22.6	6.4	14.6
2001	10,736.8	10,621.8	115	56.4	22.4	6.2	14.9
2002	11,050.3	10,977.5	72.8	55.7	22.8	6.5	15.0
2003	11,524.3	11,510.7	13.6	55.3	23.1	6.6	15.0
2004	12,283.5	12,274.9	8.6	54.9	23.5	6.7	14.9
2005	13,129.2	13,093.7	35.5	54.1	24.2	6.7	15.1
2006	14,073.2	13,855.9	217.3	53.4	24.7	6.7	15.2
2007	14,460.1	14,477.6	–17.5	54.7	22.9	6.8	15.7
2008	14,619.2	14,718.6	–99.4	55.3	21.7	6.8	16.2
2009	14,343.4	14,418.7	–75.3	54.4	22.4	6.7	16.5
2010	14,915.2	14,964.4	–49.2	53.4	23.9	6.7	16.0
2011	15,556.3	15,517.9	38.4	53.2	24.3	6.7	15.8
2012	16,358.5	16,155.3	203.2	52.7	25.3	6.6	15.5
2013	16,829.5	16,691.5	138	52.6	25.2	6.6	15.6
2014	17,651.1	17,393.1	258	52.5	25.4	6.5	15.6
2015	18,290.3	18,036.6	253.7	53.1	25.0	6.5	15.5

Note: Data are from the US Bureau of Economic Analysis, national income accounts Table 1.10.

GDI, GDP, and the gap between them in annual data for 1995–2015.[11] Over 2005–2015, a cumulative gap of $903 billion (nominal) grew between GDI and GDP. This is an average gap of about 0.5 percent of GDP per year, though not every single year saw domestic income exceed domestic product. One could argue that this gap reflects workers being paid to make products (whose labor earnings are included in GDI) that are being given away for free or at highly discounted prices relative to their value (reducing measured expenditures on these products and therefore GDP in turn). This would be an indicator of the forces surmised by the mismeasurement hypothesis.

A closer examination of the data, however, strongly suggests that the GDI–GDP gap is not a sign of the mismeasurement hypothesis.

First, the gap started opening before the productivity slowdown. GDI was larger than GDP in each of the seven years running from 1998 to 2004, all of which were a time of fast productivity growth. The average annual gap was 0.6 percent of GDP, even larger than in the slowdown period.

Second, a closer look at the composition of national income reveals patterns inconsistent with the "workers paid for making free (or nearly free) products" story.

[11] The US Bureau of Economic Analysis defines the statistical discrepancy as GDP minus GDI, so a negative reported value implies that GDI is larger than GDP. I am focusing on the extent to which GDI is greater than GDP, so I am discussing the behavior of the negative of the statistical discrepancy.

The four right-most columns in Table 2 follow the evolution of the shares of GDI paid to each of the four major income categories that comprise it. Between 2004 and 2015, employee compensation's share of GDI *fell* by 1.8 percentage points, while net operating surplus grew by 1.5 percentage points. The net taxes share fell by 0.2 percentage points and depreciation rose by 0.6 percentage points. Thus, the GDI gains over the period were tied to payments to capital that came at the expense of labor income.[12] Nor is this link between GDI and capital income only manifested in long differences; the correlation in annual data from 1995 to 2015 between the GDI–GDP percentage gap and labor's share is –0.35, while it is 0.58 for net operating surplus.

Growth in domestic income measures relative to measured domestic product therefore seems to reflect increases in capital income rather than labor income. "Abnormally" high measured income relative to measured expenditures is positively related to growth in businesses' profitability and negatively related to payments to employees. This is inconsistent with—and indeed implies the opposite of—the "pay people to build free goods" story.

Conclusion

What I have termed the "mismeasurement hypothesis" argues that true productivity growth has not slowed (or has slowed considerably less than measured) since 2004, but recent gains have not been reflected in productivity statistics, either because new goods' total surplus has shifted from (measured) revenues to (unmeasured) consumer surplus, or because price indices are overstated. My evaluation focuses on four pieces of evidence that pose challenges for mismeasurement-based explanations for the productivity slowdown that the US economy has been experiencing since 2004. Two patterns—the size of the slowdown across countries is uncorrelated with the information and communications technology intensities of those countries' economies, and the GDI–GDP gap began opening before the slowdown and in any case reflects capital income growth—are flatly inconsistent with the implications of the mismeasurement hypothesis. Two others—the modest size of the existing literature's estimates of surplus from internet-linked products and the large implied missing growth rates of digital technology industries that the mismeasurement hypothesis would entail—show the quantitative hurdles the hypothesis

[12] These income share changes are a reflection of the trends that other researchers have been exploring in other contexts (for example, Elsby, Hobijn, and Şahin 2013; Karabarbounis and Neiman 2014). An alternative decomposition of income yields the same implications as those described here. This alternative divides national income (gross domestic income adjusted for international transfers minus depreciation) into employee compensation, proprietor's income, capital income (the sum of rental income, corporate profits, and net interest), and a residual category that is the sum of net taxes on production and imports plus business transfer payments plus the surplus of government enterprises. As with the results above, labor's share fell as capital's share rose over 2004–2015. Employee compensation's share of national income fell by 2.1 percentage points while capital income grew by 2.5 percentage points. (Proprietors' income share fell by 0.3 percentage points and the share of taxes fell by 0.1 percentage point over the period.)

must clear to account for a substantial share of what is an enormous amount of measured output lost to the slowdown (around $9,300 per person per year).

These results do not definitively rule out the possibility that productivity measurement problems may have developed over the past decade for specific products or product classes. However, the combined weight of the patterns presented here makes clear that the intuitive and plausible empirical case for the mismeasurement hypothesis faces a higher bar in the data, at least in terms of its ability to account for a substantial portion of the measured output lost to the productivity slowdown.

In addition to the quantitative analyses above, several qualitative points further bolster the case for skepticism about the mismeasurement hypothesis.

As briefly mentioned above, concerns about GDP mismeasurement preceded the recent slowdown, particularly regarding GDP's disconnect with social welfare. Perhaps, the argument goes, even if true productivity growth has slowed, it need not be the case that welfare growth has. I agree that GDP does not measure social welfare; it was not designed to do so. But the GDP-welfare disconnect is not a recent phenomenon. The mere fact that GDP is an imperfect measure of welfare is insufficient as evidence for the measurement hypothesis; instead, to support the hypothesis one must argue that a *break* in the GDP-welfare disconnect somehow developed around 2004. None of the evidence presented above indicates this. In fact, the estimates of the benefits of internet-linked technologies are measures of consumer surplus, which by definition are not in GDP. In other words, even if all of that surplus (recall the largest estimate is $863 billion) were somehow captured in GDP—which is not typically the case—it would still fall considerably short of making up for the GDP lost because of the productivity slowdown.

A second point is that my four analyses took as given the possibility that, as the mismeasurement hypothesis asserts, many new goods post-slowdown are missed in GDP because of low or zero prices. However, it is not clear at all that this baseline assertion is correct. To enjoy all these free goods—Facebook, the camera on your phone, Google searches, and so on—one must purchase complementary goods: a smart phone, an iPad, broadband access, mobile telephony, and so on. If companies that sell those complements know what they are doing, they ought to be pricing the value of those "free goods" into the price of the complementary products. Their value ought to be captured in the product accounts through the prices of the complementary products that are required to consume them. As an example, at least one of these complementary goods sellers, Apple, has been famously profitable during the slowdown.

Finally, in parallel with this study, other researchers have been conducting independent work that also looked at the mismeasurement hypothesis. Their approaches used different methods and data than mine, yet they came to the same conclusion. I mentioned earlier the work by Cardarelli and Lusinyan (2015), which shows that the differing rates of productivity slowdown across US states are not related to variations in the intensity of information and communications technology production across states. Nakamura and Soloveichik (2015) estimate the value of advertising-supported internet consumer entertainment and information. They apply the existing procedures for valuing advertising-supported media content in GDP, and find that accounting for free-to-consumers content on the internet raises GDP growth by less than 0.02 percent per year. Byrne, Fernald, and Reinsdorf (2016) offer two main arguments. First, they readily admit that information technology hardware is mismeasured since 2004, but they argue that the mismeasurement was even larger in the 1995–2004 period. Moreover, more of the information technology hardware was produced in the United States in the 1995–2004 period. Taken together, these adjustments imply that the slowdown in labor productivity since 2005 looks worse, not better. The second main point is that consumers are using many information and communications technologies to produce service for their nonmarket time, which means that consumers benefit, but gains in nonmarket production (which in any event are small) do not suggest that market sector productivity is understated.

If the theory that new products caused the productivity slowdown is to be resurrected, it may well need to take on a different form. For example, one very speculative mechanism that would tie a *true* productivity slowdown to people spending a large share of their time on zero-to-low-marginal-price activities would be if workers substituted work effort for technology consumption—for example, spending time while they are at work on social networking sites. This pattern would heighten consumer surplus in a way largely unmeasured by standard statistics while at the same time reducing output per hour—that is, measured labor productivity. Of course, to explain a slowdown in annual labor productivity growth, this substitution would need to be occurring in ever-greater magnitudes over time.

The empirical burdens facing the mismeasurement hypothesis are heavy, and more likely than not, much if not most of the productivity slowdown since 2005 is real. Whether that slowdown will end anytime soon remains an open question.

■ *I thank Erik Brynjolfsson, Dave Byrne, Austan Goolsbee, Bob Gordon, Jan Hatzius, Pete Klenow, Rachel Soloveichik, Hal Varian, and the JEP editors for comments. I have no financial interests relevant to this study.*

References

Agha, Leila. 2014. "The Effects of Health Information Technology on the Costs and Quality of Medical Care." *Journal of Health Economics* 34: 19–30.

Alloway, Tracy. 2015. "Goldman: How 'Grand Theft Auto' Explains One of the Biggest Mysteries of the U.S. Economy." Bloomberg, May 26. http://www.bloomberg.com/news/articles/2015-05-26/goldman-how-grand-theft-auto-explains-one-of-the-biggest-mysteries-of-the-u-s-economy.

Baily, Martin Neil, James Manyika, and Shalabh Gupta. 2013. "U.S. Productivity Growth: An Optimistic Perspective." *International Productivity Monitor* 25(Spring): 3–12.

Becker, Gary S. 1965. "A Theory of the Allocation of Time." *Economic Journal* 75(299): 493–517.

Bhargava, Hemant K., and Abhay Nath Mishra. 2014. "Electronic Medical Records and Physician Productivity: Evidence from Panel Data Analysis." *Management Science* 60(10): 2543–62.

Brynjolfsson, Erik, and Andrew McAfee. 2011. *Race Against the Machine: How the Digital Revolution Is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*. Lexington, MA: Digital Frontier Press.

Brynjolfsson, Erik, and Andrew McAfee. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W.W. Norton & Company.

Brynjolfsson, Erik, and JooHee Oh. 2012. "The Attention Economy: Measuring the Value of Free Digital Services on the Internet." *Proceedings of the International Conference on Information Systems*, Orlando. http://aisel.aisnet.org/cgi/viewcontent.cgi?article=1045&context=icis2012.

Byrne, David M., John G. Fernald, and Marshall B. Reinsdorf. 2016. "Does the United States Have a Productivity Slowdown or a Measurement Problem?" *Brookings Papers on Economic Activity*, Spring, 109–182.

Byrne, David M., Stephen D. Oliner, and Daniel E. Sichel. 2013. "Is the Information Technology Revolution Over?" *International Productivity Monitor* 25(Spring): 20–36.

Byrne, David M., Stephen D. Oliner, and Daniel E. Sichel. 2015. "How Fast Are Semiconductor Prices Falling?" NBER Working Paper 21074.

Cardarelli, Roberto, and Lusine Lusinyan. 2015. "U.S. Total Factor Productivity Slowdown: Evidence from the U.S. States." IMF Working Paper 15/116.

Cette, Gilbert, John Fernald, and Benoît Mojon. 2015. "The Pre-Global-Financial-Crisis Slowdown in Productivity." Unpublished Paper.

Connolly, Ellis, and Linus Gustafsson. 2013. "Australian Productivity Growth: Trends and Determinants." *Australian Economic Review* 46(4): 473–82.

Cowen, Tyler. 2011. *The Great Stagnation: How America Ate All the Low-Hanging Fruit of Modern History, Got Sick, and Will (Eventually) Feel Better.* New York: Dutton.

Davis, Steven J., and John Haltiwanger. 2014. "Labor Market Fluidity and Economic Performance." NBER Working Paper 20479.

Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda. 2014. "The Role of Entrepreneurship in US Job Creation and Economic Dynamism." *Journal of Economic Perspectives* 28(3): 3–24.

Diewert, W. Erwin, and Kevin J. Fox. 1999. "Can Measurement Error Explain the Productivity Paradox?" *Canadian Journal of Economics* 32(2): 251–80.

Domar, Evsey D. 1961. "On the Measurement of Technological Change." *Economic Journal* 71(284): 709–29.

Doyle, Dara. 2016. "Ireland's Economists Left Speechless by 26% Growth Figure." *Bloomberg*, July 12, 2016.

Dutz, Mark, Jonathan Orszag, and Robert Willig. 2009. "The Substantial Consumer Benefits of Broadband Connectivity for U.S. Households." Commissioned by the Internet Innovation Alliance. https://internetinnovation.org/files/special-reports/CONSUMER_BENEFITS_OF_BROADBAND.pdf.

Elsby, Michael W. L., Bart Hobijn, and Ayşegül Şahin. 2013. "The Decline of the U.S. Labor Share." *Brookings Papers on Economic Activity*, Fall, pp. 1–63.

Feldstein, Martin. 2015. "The U.S. Underestimates Growth." *Wall Street Journal*, May 18.

Fernald, John G. 2014a. "Productivity and Potential Output Before, During, and After the Great Recession." NBER Working Paper 20248.

Fernald, John G. 2014b. "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity." Working Paper 2012-19, Federal Reserve Bank of San Francisco (updated March 2014).

Goodridge, Peter, Jonathan Haskel, and Gavin Wallis. 2015. "Accounting for the UK Productivity Puzzle: A Decomposition and Predictions." Imperial College London Discussion Paper 2015/02.

Goolsbee, Austan, and Peter J. Klenow. 2006. "Valuing Consumer Products by the Time Spent Using Them: An Application to the Internet." *American Economic Review* 96(2): 108–13.

Gordon, Robert J. 2016. *The Rise and Fall of American Growth: The U.S. Standard of Living since* *the Civil War*. Princeton University Press.

Greenstein, Shane. 2013. "Measuring Consumer Surplus Online." *Economist*, March 11.

Greenstein, Shane, and Ryan C. McDevitt. 2009. "The Broadband Bonus: Accounting for Broadband Internet's Impact on U.S. GDP." NBER Working Paper 14758.

Hatzius, Jan, and Kris Dawsey. 2015. "Doing the Sums on Productivity Paradox v2.0." *Goldman Sachs U.S. Economics Analyst*, No. 15/30.

Hulten, Charles R. 1978. "Growth Accounting with Intermediate Inputs." *Review of Economic Studies* 45(3): 511–18.

Karabarbounis, Loukas, and Brent Neiman. 2014. "The Global Decline of the Labor Share." *Quarterly Journal of Economics* 129(1): 61–103.

Klenow, Peter J. 2003. "Measuring Consumption Growth: The Impact of New and Better Products." *Federal Reserve Bank of Minneapolis Quarterly Review* 27(2): 10–23.

Mas, Matilde, and Robert Stehrer, eds. 2012. *Industrial Productivity in Europe: Growth and Crisis*. Northhampton, MA: Edward Elgar.

Mokyr, Joel. 2014. "Secular Stagnation? Not in Your Life." Chap. 6 in *Secular Stagnation: Facts, Causes and Cures,* edited by Coen Teulings and Richard Baldwin. London: CEPR Press.

Nakamura, Leonard, and Rachel Soloveichik. 2015. "Valuing 'Free' Media across Countries in GDP." Federal Reserve Bank of Philadelphia Working Paper 15-25.

Nevo, Aviv, John L. Turner, and Jonathan W. Williams. 2015. "Usage-Based Pricing and Demand for Residential Broadband." Available at SSRN: http://ssrn.com/abstract=2330426.

Oliner, Stephen D., Daniel E. Sichel, and Kevin J. Stiroh. 2007. "Explaining a Productive Decade." *Brookings Papers on Economic Activity* no. 1, pp. 81–152.

Pessoa, João Paulo, and John Van Reenen. 2014. "The UK Productivity and Jobs Puzzle: Does the Answer Lie in Wage Flexibility?" *Economic Journal* 124(576): 433–52.

Rosston, Gregory L., Scott J. Savage, and Donald M. Waldman. 2010. "Household Demand for Broadband Internet in 2010." *B.E. Journal of Economic Analysis & Policy: Advances* 10(1): 1–45.

Smith, Noah. 2015. "The Internet's Hidden Wealth." *Bloomberg View,* June 10, 2015. http://www.bloombergview.com/articles/2015-06-10/wealth-created-by-the-internet-may-not-appear-in-gdp.

Syverson, Chad. 2013. "Will History Repeat Itself? Comments on 'Is the Information Technology Revolution Over?'" *International Productivity Monitor* 25: 37–40.

Tarullo, Daniel K. 2014. "Longer-Term Challenges for the American Economy." Speech given to 23rd Annual Hyman P. Minsky Conference: Stabilizing Financial Systems for Growth and Full Employment, Washington, D.C., April 9, 2014.

US Congress. 1996. "Toward a More Accurate Measure of the Cost of Living." Final Report to the Senate Finance Committee from the Advisory Commission to Study the Consumer Price Index. (The Boskin Commission Report.) 104th Congress, 2nd sess., S.Prt. 104-072. http://www.ssa.gov/history/reports/boskinrpt.html.

This article has been cited by:

1. Philippe Aghion, Antonin Bergeaud, Timo Boppart, Peter J Klenow, Huiyu Li. 2023. A Theory of Falling Growth and Rising Rents. *The Review of Economic Studies* **109**. . [Crossref]
2. F. J. Escribá-Pérez, M. J. Murgui-García, J. R. Ruiz-Tamarit. 2023. Endogenous capital stock and depreciation in the United States. *Journal of Public Economic Theory* **25**:1, 139-167. [Crossref]
3. Ryuichiro Nishioka, Takashi Tatsuse, Michikazu Sekine, Masaaki Yamada. 2023. Association of Sleep, Work Environment, and Work–Life Balance With Work Performance. *Journal of Occupational & Environmental Medicine* **65**:2, e61-e67. [Crossref]
4. Christos A. Makridis, Erin McGuire. 2023. The quality of innovation "Booms" during "Busts". *Research Policy* **52**:1, 104657. [Crossref]
5. Paul Dolfen, Liran Einav, Peter J. Klenow, Benjamin Klopack, Jonathan D. Levin, Larry Levin, Wayne Best. 2023. Assessing the Gains from E-Commerce. *American Economic Journal: Macroeconomics* **15**:1, 342-370. [Abstract] [View PDF article] [PDF with links]
6. Georg Duernecker, Miguel Sanchez-Martinez. 2023. Structural change and productivity growth in Europe — Past, present and future. *European Economic Review* **151**, 104329. [Crossref]
7. Roberta Capello, Camilla Lenzi, Giovanni Perucca. 2022. The modern Solow paradox. In search for explanations. *Structural Change and Economic Dynamics* **63**, 166-180. [Crossref]
8. Roberto Camagni, Roberta Capello, Giovanni Perucca. 2022. Beyond productivity slowdown: Quality, pricing and resource reallocation in regional competitiveness. *Papers in Regional Science* **101**:6, 1307-1330. [Crossref]
9. David R Baqaee, Ariel Burstein. 2022. Welfare and Output With Income Effects and Taste Shocks. *The Quarterly Journal of Economics* **116**. . [Crossref]
10. Arthur Grimes, Shine Wu. 2022. Sustainable consumption growth: New Zealand's surprising performance. *New Zealand Economic Papers* **76**, 1-15. [Crossref]
11. Alexander S. Kritikos, Alexander Schiersch, Caroline Stiel. 2022. The productivity shock in business services. *Small Business Economics* **59**:3, 1273-1299. [Crossref]
12. Xiaomeng Zhang, Chu Wei. 2022. The economic and environmental impacts of information and communication technology: A state-of-the-art review and prospects. *Resources, Conservation and Recycling* **185**, 106477. [Crossref]
13. Gantungalag Altansukh, Denise R. Osborn. 2022. Using structural break inference for forecasting time series. *Empirical Economics* **63**:1, 1-41. [Crossref]
14. Toyoichiro Shirota. 2022. The cost-of-living index in a cash and credit goods economy. *Macroeconomic Dynamics* **10**, 1-14. [Crossref]
15. Fatih Guvenen, Raymond J. MataloniJr., Dylan G. Rassier, Kim J. Ruhl. 2022. Offshore Profit Shifting and Aggregate Measurement: Balance of Payments, Foreign Investment, Productivity, and the Labor Share. *American Economic Review* **112**:6, 1848-1884. [Abstract] [View PDF article] [PDF with links]
16. Muxin Zhai, Ruby P. Kishan, Dean Showalter. 2022. Social capital and suicidal behaviors: Evidence from the United States counties. *Journal of Behavioral and Experimental Economics* **98**, 101856. [Crossref]
17. Evguenia Bessonova, Anna Tsvetkova. 2022. Do Productivity Laggards Ever Catch Up With Leaders? †. *Review of Income and Wealth* **68**:S1. . [Crossref]
18. Jasper Hepp. 2022. Being small at the right moment: Path dependence after a shift in the technological regime. *Industrial and Corporate Change* **31**:2, 464-499. [Crossref]

19. Sam Peltzman. 2022. Productivity, Prices, and Concentration in Manufacturing: A Demsetzian Perspective. *The Journal of Law and Economics* **65**:S1, S121-S153. [Crossref]
20. Francesco Venturini. 2022. Intelligent technologies and productivity spillovers: Evidence from the Fourth Industrial Revolution. *Journal of Economic Behavior & Organization* **194**, 220-243. [Crossref]
21. Ekkehard Ernst. Artificial Intelligence: Productivity Growth and the Transformation of Capitalism 149-181. [Crossref]
22. Benjamin Bridgman. 2022. IS PRODUCTIVITY ON VACATION? THE IMPACT OF THE DIGITAL ECONOMY ON THE VALUE OF LEISURE. *Macroeconomic Dynamics* **26**:1, 127-148. [Crossref]
23. Abe Dunn, Anne Hall, Seidu Dauda. 2022. Are Medical Care Prices Still Declining? A Re-Examination Based on Cost-Effectiveness Studies. *Econometrica* **90**:2, 859-886. [Crossref]
24. Victoria Sevcenko, Lynn Wu, Aleksandra (Olenka) Kacperczyk, Sendil Ethiraj. 2022. Surplus Division between Labor and Capital: A Review and Research Agenda. *Academy of Management Annals* **16**:1, 334-390. [Crossref]
25. Felix Roth. The Productivity Puzzle: A Critical Assessment and an Outlook on the COVID-19 Crisis 1-16. [Crossref]
26. Steffen Elstner, Svetlana Rujin. 2021. The consequences of US technology changes for productivity in advanced economies. *Macroeconomic Dynamics* **15**, 1-25. [Crossref]
27. Glenn Hubbard. "The $64,000 Question": Living in the Age of Technological Possibility or Showing Possibility's Age? 115-131. [Crossref]
28. Erik Brynjolfsson, Wang Jin, Kristina McElheran. 2021. The power of prediction: predictive analytics, workplace complements, and business performance. *Business Economics* **56**:4, 217-239. [Crossref]
29. Yingying Lu, Yixiao Zhou. 2021. A review on the economics of artificial intelligence. *Journal of Economic Surveys* **35**:4, 1045-1072. [Crossref]
30. Christopher Biolsi. 2021. Labor productivity forecasts based on a Beveridge–Nelson filter: Is there statistical evidence for a slowdown?. *Journal of Macroeconomics* **69**, 103321. [Crossref]
31. Tsutomu Miyagawa, Konomi Tonogi, Takayuki Ishikawa. 2021. Does the productivity J-curve exist in Japan?-Empirical studies based on the multiple q theory. *Journal of the Japanese and International Economies* **61**, 101137. [Crossref]
32. Giovanni Dosi, Richard B Freeman, Marcelo C Pereira, Andrea Roventini, Maria Enrica Virgillito. 2021. The impact of deunionization on the growth and dispersion of productivity and pay. *Industrial and Corporate Change* **30**:2, 377-408. [Crossref]
33. Giovanni Dosi, Dario Guarascio, Andrea Ricci, Maria Enrica Virgillito. 2021. Neodualism in the Italian business firms: training, organizational capabilities, and productivity distributions. *Small Business Economics* **57**:1, 167-189. [Crossref]
34. Alessandro Mistretta, Francesco Zollino. 2021. Recent Trends in Economic Activity and TFP in Italy with a Focus on Embodied Technical Progress. *Italian Economic Journal* **7**:1, 79-107. [Crossref]
35. Emmanuel Dhyne, Jozef Konings, Jeroen Van den bosch, Stijn Vanormelingen. 2021. The Return on Information Technology: Who Benefits Most?. *Information Systems Research* **32**:1, 194-211. [Crossref]
36. Erik Brynjolfsson, Daniel Rock, Chad Syverson. 2021. The Productivity J-Curve: How Intangibles Complement General Purpose Technologies. *American Economic Journal: Macroeconomics* **13**:1, 333-372. [Abstract] [View PDF article] [PDF with links]
37. Ufuk Akcigit, Sina T. Ates. 2021. Ten Facts on Declining Business Dynamism and Lessons from Endogenous Growth Theory. *American Economic Journal: Macroeconomics* **13**:1, 257-298. [Abstract] [View PDF article] [PDF with links]

38. Chihiro Watanabe, Yuji Tou, Pekka Neittaanmäki. Introduction 1-17. [Crossref]
39. Andrew Koch, Marios Panayides, Shawn Thomas. 2021. Common ownership and competition in product markets. *Journal of Financial Economics* **139**:1, 109-137. [Crossref]
40. Ekaterina Prytkova. 2021. ICT's Wide Web: a System-Level Analysis of ICT's Industrial Diffusion with Algorithmic Links. *SSRN Electronic Journal* **19**. . [Crossref]
41. Spyridon Gkikopoulos, Edward Lee, Konstantinos Stathopoulos. 2021. Does Corporate Tax Avoidance Affect Firm Productivity?. *SSRN Electronic Journal* **83**. . [Crossref]
42. Yuta Takahashi, Naoki Takayama. 2021. Tech-Driven Secular Low Growth: Cross-Country Evidence. *SSRN Electronic Journal* **116**. . [Crossref]
43. Nicola Bianchi, Matteo Paradisi. 2021. Countries for Old Men: An Analysis of the Age Wage Gap. *SSRN Electronic Journal* **67**. . [Crossref]
44. Sabrina T Howell, Jason Rathje, John Van Reenen, Jun Wong. 2021. Opening up Military Innovation: Causal Effects of 'Bottom-Up' Reforms to U.S. Defense Research. *SSRN Electronic Journal* **88**. . [Crossref]
45. Georg Duernecker, Miguel Sanchez-Martinez. 2021. Structural Change and Productivity Growth in Europe - Past, Present and Future. *SSRN Electronic Journal* **2**. . [Crossref]
46. Seidu Dauda, Abe Dunn, Anne Hall. 2021. A Systematic Examination of Quality-Adjusted Price Index Alternatives for Medical Care Using Claims Data. *SSRN Electronic Journal* **30**. . [Crossref]
47. Josh Lerner, Amit Seru, Nick Short, Yuan Sun. 2021. Financial Innovation in the 21st Century: Evidence from U.S. Patents. *SSRN Electronic Journal* **119**. . [Crossref]
48. A. A. Tatarinov. 2020. Measuring the Value of Data and Their Treatment in Macroeconomic Statistics. *Voprosy statistiki* **27**:6, 5-25. [Crossref]
49. Milojko Arsić. 2020. Impact of Digitalisation on Economic Growth, Productivity and Employment. *Economic Themes* **58**:4, 431-457. [Crossref]
50. Riccardo Pariboni, Pasquale Tridico. 2020. Structural change, institutions and the dynamics of labor productivity in Europe. *Journal of Evolutionary Economics* **30**:5, 1275-1300. [Crossref]
51. Stefan Schweikl, Robert Obermaier. 2020. Lessons from three decades of IT productivity research: towards a better understanding of IT-induced productivity effects. *Management Review Quarterly* **70**:4, 461-507. [Crossref]
52. Temitayo Shenkoya. 2020. Social change: A comparative analysis of the impact of the IoT in Japan, Germany and Australia. *Internet of Things* **11**, 100250. [Crossref]
53. Sheida Teimouri, Joachim Zietz. 2020. Coping with deindustrialization: A panel study for early OECD countries. *Structural Change and Economic Dynamics* **54**, 26-41. [Crossref]
54. Mardi Dungey, Denise R. Osborn. 2020. The Gains from Catch-up for China and the USA: An Empirical Framework. *Economic Record* **96**:314, 350-365. [Crossref]
55. Jon Bokrantz, Anders Skoogh, Cecilia Berlin, Thorsten Wuest, Johan Stahre. 2020. Smart Maintenance: an empirically grounded conceptualization. *International Journal of Production Economics* **223**, 107534. [Crossref]
56. David Autor, David Dorn, Lawrence F Katz, Christina Patterson, John Van Reenen. 2020. The Fall of the Labor Share and the Rise of Superstar Firms*. *The Quarterly Journal of Economics* **135**:2, 645-709. [Crossref]
57. Joseph A. Clougherty, Tomaso Duso, Jo Seldeslachts, Lorenzo Ciari. 2020. Transformational Strategies and Productivity Growth: A Transformational-Activities Perspective on Stagnation in the New-Normal Business Landscape. *Journal of Management Studies* **57**:3, 537-568. [Crossref]

58. Joze Damijan, Jozef Konings, Aigerim Yergabulova. 2020. Increasing market power in Slovenia: Role of diverging trends between exporters and non-exporters. *The World Economy* **43**:5, 1327-1345. [Crossref]
59. Giovanni Dosi, Maria Enrica Virgillito, Xiaodan Yu. 2020. The wage-productivity nexus in the world factory economy. *World Development* **129**, 104875. [Crossref]
60. Tauqir Ahmed, Arshad Ali Bhatti. 2020. MEASUREMENT AND DETERMINANTS OF MULTI-FACTOR PRODUCTIVITY: A SURVEY OF LITERATURE. *Journal of Economic Surveys* **34**:2, 293-319. [Crossref]
61. Alfred Kleinknecht. 2020. The (negative) impact of supply-side labour market reforms on productivity: an overview of the evidence1. *Cambridge Journal of Economics* **44**:2, 445-464. [Crossref]
62. Hunt Allcott, Luca Braghieri, Sarah Eichmeyer, Matthew Gentzkow. 2020. The Welfare Effects of Social Media. *American Economic Review* **110**:3, 629-676. [Abstract] [View PDF article] [PDF with links]
63. Cristiano Antonelli, Christophe Feder. 2020. The new direction of technological change in the global economy. *Structural Change and Economic Dynamics* **52**, 1-12. [Crossref]
64. Robert Inklaar, Marianna Papakonstantinou. 2020. Vintage Effects In Human Capital: Europe Versus The United States. *Review of Income and Wealth* **66**:1, 1-25. [Crossref]
65. Peter Fernandez. 2020. Automation, the 4th industrial revolution and libraries. *Library Hi Tech News* **37**:3, 23-26. [Crossref]
66. Ester Camiña, Ángel Díaz-Chao, Joan Torrent-Sellens. 2020. Automation technologies: Long-term effects for Spanish industrial firms. *Technological Forecasting and Social Change* **151**, 119828. [Crossref]
67. Nicholas Crafts, Terence C. Mills. 2020. IS THE UK PRODUCTIVITY SLOWDOWN UNPRECEDENTED?. *National Institute Economic Review* **251**, R47-R53. [Crossref]
68. Stephen J Redding, David E Weinstein. 2020. Measuring Aggregate Price Indices with Taste Shocks: Theory and Evidence for CES Preferences*. *The Quarterly Journal of Economics* **135**:1, 503-560. [Crossref]
69. Marshall Reinsdorf, Paul Schreyer. Measuring consumer inflation in a digital economy 339-362. [Crossref]
70. Rolf Färe, Daniel Primont, William L. Weber. 2020. Technical change and the von Neumann coefficient of uniform expansion. *European Journal of Operational Research* **280**:2, 754-763. [Crossref]
71. María Teresa Ballestar, Ángel Díaz-Chao, Jorge Sainz, Joan Torrent-Sellens. 2020. Knowledge, robots and productivity in SMEs: Explaining the second digital wave. *Journal of Business Research* **108**, 119-131. [Crossref]
72. Sam Peltzman. 2020. Productivity, Prices and Productivity in Manufacturing: a Demsetzian Perspective. *SSRN Electronic Journal* **53**. . [Crossref]
73. Jasper Hepp. 2020. Being Small at the Right Moment: Path Dependence after a Shift in the Technological Regime. *SSRN Electronic Journal* **1**. . [Crossref]
74. Ágnes Szunomár. 2019. A digitális nagy ugrás. Lassulás és modernizációs stratégiaváltás Kínában. *Közgazdasági Szemle* **66**:12, 1312-1346. [Crossref]
75. I. S. Lola, M. B. Bakeev. 2019. Effects of Influence of Economic and Technological Development of IT Segment on Digital Transformation of Retail Trade. *Voprosy statistiki* **26**:11, 18-35. [Crossref]
76. Temitayo Shenkoya, Cho Dae-Woo. 2019. Impact of IoT on social innovation in Japan. *Asia Pacific Journal of Innovation and Entrepreneurship* **13**:3, 341-353. [Crossref]

77. Giovanni DOSI, Maria Enrica VIRGILLITO. 2019. Whither the evolution of the contemporary social fabric? New technologies and old socio-economic trends. *International Labour Review* **158**:4, 593-625. [Crossref]

78. Giovanni DOSI, Maria Enrica VIRGILLITO. 2019. L'évolution du tissu social – entre nouvelles technologies et tendances socio-économiques anciennes. *Revue internationale du Travail* **158**:4, 651-688. [Crossref]

79. Giovanni DOSI, Maria Enrica VIRGILLITO. 2019. ¿Hacia dónde evoluciona el tejido social contemporáneo? Nuevas tecnologías y viejas tendencias socioeconómicas. *Revista Internacional del Trabajo* **138**:4, 639-674. [Crossref]

80. Marcin Wroński. 2019. The productivity growth slowdown in advanced economies: causes and policy recommendations. *International Journal of Management and Economics* **55**:4, 391-406. [Crossref]

81. Roxana Mihet, Thomas Philippon. The Economics of Big Data and Artificial Intelligence 29-43. [Crossref]

82. Brian Nolan, Max Roser, Stefan Thewissen. 2019. GDP Per Capita Versus Median Household Income: What Gives Rise to the Divergence Over Time and how does this Vary Across OECD Countries?. *Review of Income and Wealth* **65**:3, 465-494. [Crossref]

83. Daniel E. Sichel. 2019. Productivity Measurement: Racing to Keep Up. *Annual Review of Economics* **11**:1, 591-614. [Crossref]

84. Philippe Aghion, Antonin Bergeaud, Timo Boppart, Peter J. Klenow, Huiyu Li. 2019. Missing Growth from Creative Destruction. *American Economic Review* **109**:8, 2795-2822. [Abstract] [View PDF article] [PDF with links]

85. Daniel D. Katukov, Viacheslav E. Malygin, Nataliya V. Smorodinskaya. 2019. The factor of creative destruction in modern economic growth models and growth policy. *Voprosy Ekonomiki* :7, 95-118. [Crossref]

86. David S. Evans. 2019. Attention Platforms, the Value of Content, and Public Policy. *Review of Industrial Organization* **54**:4, 775-792. [Crossref]

87. Filippo Mezzanotti, Timothy Simcoe. 2019. Patent policy and American innovation after eBay: An empirical examination. *Research Policy* **48**:5, 1271-1281. [Crossref]

88. Lin Zhou, Jianglong Li, Yangqing Dan, Chunping Xie, Houyin Long, Hongxun Liu. 2019. Entering and Exiting: Productivity Evolution of Energy Supply in China. *Sustainability* **11**:4, 983. [Crossref]

89. W. Erwin Diewert, Kevin J. Fox. Productivity Indexes and National Statistics: Theory, Methods and Challenges 707-759. [Crossref]

90. Johannes Bersch, Josefine Diekhof, Bastian Krieger, Georg Licht, Simona Murmann. Productivity Slowdown, Innovation and Industry Dynamics 229-241. [Crossref]

91. Robert Obermaier, Stefan Schweikl. Zur Bedeutung von Solows Paradoxon: Empirische Evidenz und ihre Übertragbarkeit auf Digitalisierungsinvestitionen in einer Industrie 4.0 529-564. [Crossref]

92. Mardi H. Dungey, Denise R. Osborn. 2019. The Gains from Catch-up for China and the US: An Empirical Framework. *SSRN Electronic Journal* . [Crossref]

93. Erik Brynjolfsson, Avinash Collis, W. Erwin Diewert, Felix Eggers, Kevin J. Fox. 2019. GDP-B: Accounting for the Value of New and Free Goods in the Digital Economy. *SSRN Electronic Journal* . [Crossref]

94. Zach Flynn. 2019. Unproductive by Choice: Substitution and the Slowdown in Aggregate Productivity Growth in the United States. *SSRN Electronic Journal* . [Crossref]

95. Nuno Clara, Alexandre Corhay, Howard Kung. 2019. Strategic Product Diversity. *SSRN Electronic Journal* **93**. . [Crossref]

96. Gerald D. Cohen. Macroeconomic Theory and Forecasting 11-36. [Crossref]
97. Clive R. Belfield, Thomas R. Bailey. The Labor Market Value of Higher Education: Now and in the Future 373-414. [Crossref]
98. Benoît Desmarchelier. Service Economies and Complexity 711-728. [Crossref]
99. Weiguang Wang, Guodong (Gordon) Gao, Ritu Agarwal. 2019. Friend or Foe? The Influence of Artificial Intelligence on Human Performance in Medical Chart Coding. *SSRN Electronic Journal* **33**. . [Crossref]
100. Jing Li, Shengyu Li, Hongsong Zhang. 2019. Output Quality, Productivity Growth, and Resource Reallocation. *SSRN Electronic Journal* **83**. . [Crossref]
101. Ana Paula Cusolito, William F. Maloney. Executive Summary: The Elusive Promise of Productivity xvii-xxviii. [Crossref]
102. J. David Brown, Gustavo A. Crespi, Leonardo Iacovone, Luca Marcolin. 2018. Decomposing firm-level productivity growth and assessing its determinants: evidence from the Americas. *The Journal of Technology Transfer* **43**:6, 1571-1606. [Crossref]
103. Chihiro Watanabe, Kashif Naveed, Yuji Tou, Pekka Neittaanmäki. 2018. Measuring GDP in the digital economy: Increasing dependence on uncaptured GDP. *Technological Forecasting and Social Change* **137**, 226-240. [Crossref]
104. Chihiro Watanabe, Yuji Tou, Pekka Neittaanmäki. 2018. A new paradox of the digital economy - Structural sources of the limitation of GDP statistics. *Technology in Society* **55**, 9-23. [Crossref]
105. Giovanni Gallipoli, Christos A. Makridis. 2018. Structural transformation and the rise of information technology. *Journal of Monetary Economics* **97**, 91-110. [Crossref]
106. Sangmin Aum, Sang Yoon (Tim) Lee, Yongseok Shin. 2018. Computerizing industries and routinizing jobs: Explaining trends in aggregate productivity. *Journal of Monetary Economics* **97**, 1-21. [Crossref]
107. Nicholas Crafts. 2018. The productivity slowdown: is it the 'new normal'?. *Oxford Review of Economic Policy* **34**:3, 443-460. [Crossref]
108. Robert J. Gordon. 2018. Declining American economic growth despite ongoing innovation. *Explorations in Economic History* **69**, 1-12. [Crossref]
109. Bruno Ducoudré, Éric Heyer. 2018. Quel nouveau sentier de croissance de la productivité du travail ?. *Revue de l'OFCE* **N° 152**:3, 233-258. [Crossref]
110. . Building Solid Foundations: How to Promote Potential Growth 157-216. [Crossref]
111. Daron mname Acemoglu, Pascual mname Restrepo. 2018. Artificial Intelligence, Automation and Work. *SSRN Electronic Journal* . [Crossref]
112. Wim Naude, Paula Nagler. 2018. Technological Innovation, Entrepreneurship and Productivity in Germany, 1871-2015. *SSRN Electronic Journal* . [Crossref]
113. Richard Schmalensee. 2018. The Collapse of Labor Productivity Growth in U.S. Manufacturing after 2010. *SSRN Electronic Journal* . [Crossref]
114. Erik Brynjolfsson, Felix Eggers, Avinash Gannamaneni. 2018. Using Massive Online Choice Experiments to Measure Changes in Well-Being. *SSRN Electronic Journal* . [Crossref]
115. Filippo Mezzanotti, Timothy S. Simcoe. 2018. Patent Policy and American Innovation after eBay: An Empirical Examination. *SSRN Electronic Journal* . [Crossref]
116. Anna Stansbury, Lawrence H. Summers. 2018. Productivity and Pay: Is the Link Broken?. *SSRN Electronic Journal* **56**. . [Crossref]
117. Richard Schmalensee. 2018. Shifts in U.S. Manufacturing after the Great Recession. *SSRN Electronic Journal* . [Crossref]

118. David S. Evans. 2018. Attention Platforms, the Value of Content, and Public Policy. *SSRN Electronic Journal* . [Crossref]
119. Nicholas Crafts, Terence C. Mills. 2017. Predicting Medium-Term TFP Growth in the United States: Econometrics vs 'Techno-Optimism'. *National Institute Economic Review* **242**, R60-R67. [Crossref]
120. Nicholas Crafts. 2017. Is Slow Economic Growth the 'New Normal' for Europe?. *Atlantic Economic Journal* **45**:3, 283-297. [Crossref]
121. David Byrne, Stephen D. Oliner, Daniel E. Sichel. 2017. Prices of high-tech products, mismeasurement, and the pace of innovation. *Business Economics* **52**:2, 103-113. [Crossref]
122. David S. Evans. 2017. The Economics of Attention Markets. *SSRN Electronic Journal* . [Crossref]
123. Giovanni Gallipoli, Christos Andreas Makridis. 2017. Structural Transformation and the Rise of Information Technology. *SSRN Electronic Journal* . [Crossref]