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Chapter Author(s): John G. Fernald

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Productivity and Potential Output before, during, and after the Great Recession

John G. Fernald, *Federal Reserve Bank of San Francisco*

I. Introduction

When we look back at the 1990s, from the perspective of say 2010, . . . [w]e may conceivably conclude . . . that, at the turn of the millennium, the American economy was experiencing a once-in-a-century acceleration of innovation. . . . Alternatively, that 2010 retrospective might well conclude that a good deal of what we are currently experiencing was just one of the many euphoric speculative bubbles that have dotted human history.

—Federal Reserve Chairman Alan Greenspan (2000)

Disappointing productivity growth . . . must be added to the list of reasons that economic growth has been slower than hoped.

—Federal Reserve Chairman Ben Bernanke (2014)

The past two decades have seen the rise and fall of exceptional US productivity growth. This paper argues that labor and total factor productivity (TFP) growth slowed prior to the Great Recession. It marked a retreat from the exceptional, but temporary, information technology-fueled pace from the mid-1990s to early in the twenty-first century. This retreat implies slower output growth going forward as well as a narrower output gap than recently estimated by the Congressional Budget Office (CBO 2014a).

Industry and state data show that the pre–Great Recession productivity slowdown was in sectors that *produce* information technology (IT) or that *use* IT intensively. Sectors that were obviously unusual or “euphoric” in the first decade of the twenty-first century—including housing and finance—were not the source.

Figure 1 illustrates that the mid-1990s surge in productivity growth

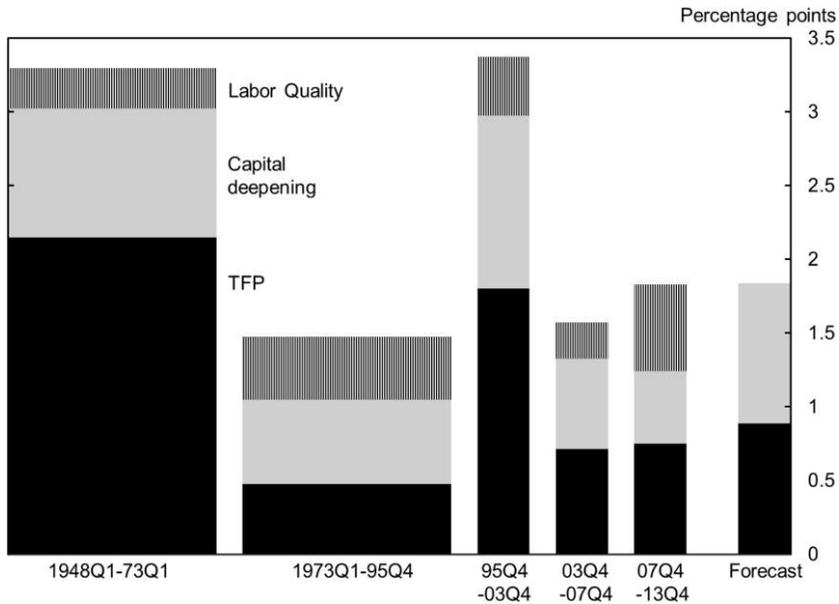


Fig. 1. Contributions to labor productivity growth, business sector

Source: Fernald (2014), BEA, BLS.

ended prior to the Great Recession. The surge in labor productivity growth, shown by the height of the bars, came after several decades of slower growth.¹ But in the decade ending in 2013:Q4, growth has returned close to its 1973–1995 pace. The figure shows that the slower pace of growth in both labor productivity and TFP was similar in the four years prior to the onset of the Great Recession as in the six years since.

That the slowdown predated the Great Recession rules out causal stories from the recession itself. Theory and previous empirical literature (discussed in Section II.D) provides only limited support for the view that the Great Recession should have changed the underlying path of TFP. Figure 1 suggests no evidence that productivity was slower (or much faster) from 2007 to 2013 than in the several years before that. The evidence here complements Kahn and Rich's (2013) finding in a regime-switching model that by early 2005—that is, well before the Great Recession—the probability reached nearly unity that the economy was in a low-growth regime.

A natural hypothesis is that the slowdown was the flip side of the mid-1990s speedup. Considerable evidence, discussed in Section III.A,

links the TFP speedup to the exceptional contribution of IT—computers, communications equipment, software, and the Internet. Information technology has had a broad-based and pervasive effect through its role as a general purpose technology (GPT) that fosters complementary innovations, such as business reorganization (see Bresnahan and Trajtenberg (1995) and Helpman, ed., 1998).

Industry TFP data provide evidence in favor of the IT hypothesis versus alternatives. Notably, the euphoric “bubble” sectors of housing, finance, and natural resources do not explain the slowdown. Rather, the slowdown is in the remaining three-quarters of the economy, and is concentrated in industries that produce IT or that use IT intensively. Information technology users saw a sizable bulge in TFP growth early in the first decade of the twenty-first century, even as IT spending itself slowed. That pattern is consistent with the view that benefiting from IT takes substantial intangible organizational investments that, with a lag, raise measured productivity. By the middle of the first decade of the twenty-first century, the low-hanging fruit of IT had been plucked.

State data on gross domestic product (GDP) per worker rule out indirect channels through which the housing bubble and bust might have mattered. States differ in how much house prices ran up early in the twenty-first century and collapsed after 2006. Those differences could have influenced innovation through net-worth channels. There is little evidence that housing dynamics contributed much to the dynamics of the productivity slowdown. Rather, it is the common cross-state slowdown in IT-intensive industries that predominates.

I then turn to two implications of the mid-2000s productivity slowdown. First, a multisector neoclassical growth model implies steady-state business-sector labor-productivity growth of about 1.9%, as shown at the far right of figure 1. Prior to the Great Recession, typical estimates were notably higher. Using demographic estimates from the CBO (2014a), my benchmark estimate implies longer-term growth in GDP of about 2.1% per year. As figure 1 shows, three out of the past four decades have shown this slower pace of productivity growth. That pace, rather than the exceptional 1995–2003 pace, appears normal.

Second, by 2013, the output gap, defined as the difference between actual and a production-function measure of potential output, is narrower than estimated by the CBO (2014a). I decompose the CBO’s gap into a “utilization gap” that reflects cyclical mismeasurement of TFP as well as an “hours gap.” The CBO estimates that the utilization gap in 2013 was as deep as any time in history other than 1982 and 2009,

and was comparable to its level in 1975. In contrast, empirical estimates from Fernald (2014; following Basu et al. 2013) suggest a small utilization gap.

Figure 2 shows two alternatives to the CBO estimates of potential, with different estimates of the utilization gap. Both use the CBO labor gap to measure deviations of hours worked from steady state. One uses actual TFP, which imposes a utilization gap of zero. When utilization eventually returns to normal—as it plausibly did prior to 2013—this measure is appropriate. The second, labeled “Fernald,” uses my utilization estimate. By 2013, the alternatives imply that about three-quarters of the 2013 shortfall of actual output from the estimated precrisis trend reflects a decline in potential output. These estimates lie well below the

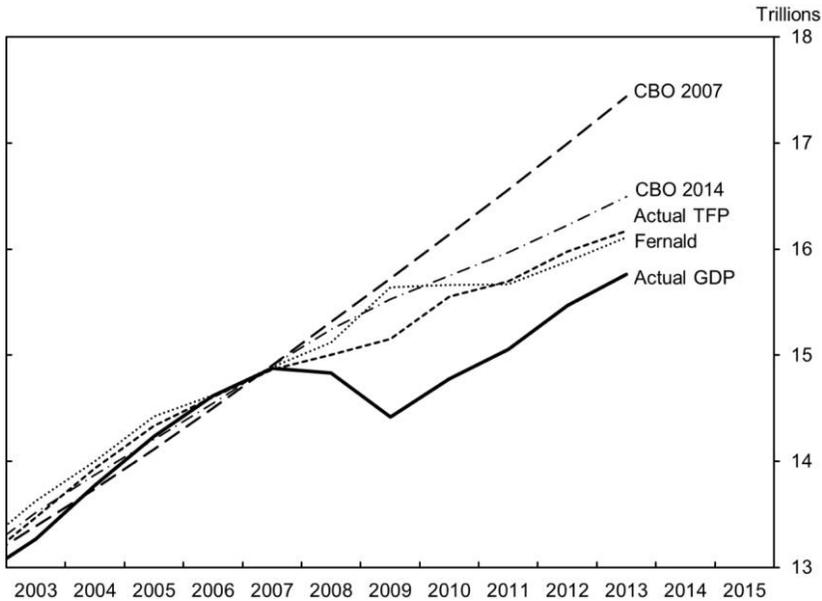


Fig. 2. Potential output and its pre-crisis trend

Notes: Annual data, 2009\$. Figure compares actual real GDP to the CBO’s projections for potential prior to the Great Recession (the 2007 line) and the CBO’s (2014a) projection, as well as two alternative measures of potential that follow the CBO methodology but with different assumptions about utilization. Both alternatives use the CBO’s estimated “hours gap” (deviation of hours from steady state). “Actual TFP” assumes utilization is constant, so that actual TFP measures technology. “Fernald” uses estimated utilization and labor-quality gaps. The “2007” CBO estimates are from January 2008, which were based on data through 2007:Q3. Those estimates have been rescaled to 2009\$ so that the 2007 value equals the level in CBO (2014a).

Source: CBO, BEA, and the author’s calculations.

CBO's (2014a), which itself is well below its prerecession trend. The differences arise from the CBO's assumed path for potential TFP. In contrast to the evidence in this paper, the CBO has no mid-1990s pickup in productivity and much less of a mid-2000s slowdown.

An important caveat is that production-function measures of potential output are inherently cyclical because investment is cyclical. Slow aggregate-demand growth in the recovery has led to slow closing of the output gap. Cyclically weak investment, in turn, has contributed to slow potential growth; indeed, capital input grew at the slowest pace since World War II. Slow capital growth does not directly affect output gaps—in the CBO definition (as well as the usual dynamic stochastic general equilibrium [DSGE] definition), it affects both actual and potential output. In standard models, capacity should rebound (raising potential growth above its steady-state rate) as the economy returns toward its steady-state path.²

Section II discusses “facts” about the slowdown in measured labor and total-factor productivity, and compares the experience during and since the Great Recession to previous recessions and recoveries, finding that productivity experience was comparable. Section III assesses explanations for the productivity slowdown, using industry data and (maybe) regional data. Section IV uses a multisector growth model to project medium- to long-run potential output growth. The section also discusses key uncertainties. Section V then draws on the preceding analysis to discuss current potential output and slack in the context of the general methodology followed by the Congressional Budget Office. Section VI concludes.

II. Productivity Growth before the Great Recession

Trend productivity growth slowed several years *before* the Great Recession.

A. *The mid-2000s Slowdown in Labor-Productivity Growth*

Figure 3 shows the log level of business-sector labor productivity, which rationalizes the subsamples shown in figure 1.³ The mid-1990s speedup in growth is clear. The literature discussed in Section III.A links that speedup to information technology (IT). The slowdown in the mid-2000s is also clear. The dates of the vertical bars are suggested by the Bai-Perron test for multiple structural change in mean growth rates for the period since 1973. I have shown the traditional new-economy

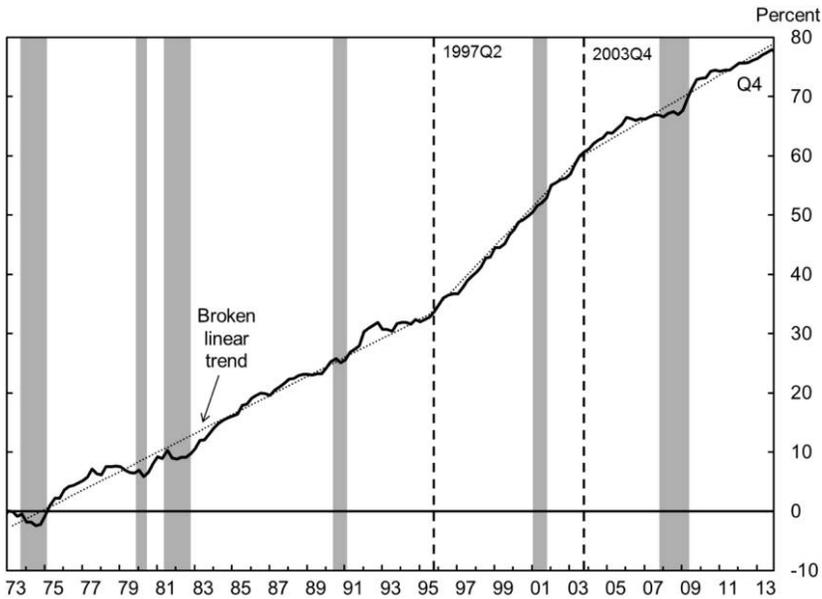


Fig. 3. Business sector labor productivity since 1973

Note: Log level (times 100), measured as cumulative growth since 1973:Q2.

Source: BLS and Fernald (2014).

1995:Q4 start date along with a slowdown date of 2003:Q4. The breaks are statistically significant.⁴

The Bai-Perron results complement the findings of Kahn and Rich (2007, 2013). They estimate a regime-switching model, using data on labor productivity, labor compensation, and consumption. They find that productivity switched from a high-growth to a low-growth regime around 2004. By early 2005, the probability that the economy was in a low-growth regime was close to unity.

B. Growth-Accounting Identities

Growth accounting provides further perspective on the forces underpinning the slowdown. Suppose there is a constant returns aggregate production function for output, Y :

$$Y = A \cdot F(W \cdot K(K_1, K_2, \dots), E \cdot L(H_1, H_2, \dots)). \quad (1)$$

Variable A is technology; K and L are observed capital and labor. Variable W is the workweek of capital and E is effort—that is, unobserved variation in the utilization of capital and labor; K_i is input of a particu-

lar type of capital—computers, say, or office buildings. Similarly, H_i is hours of work by a particular type of worker, differentiated by education, age, and other characteristics. Time subscripts are omitted.

The first-order conditions for cost-minimization imply that output elasticities for a given type of input are proportional to shares in cost. Let α be total payments to capital as a share in total costs and c_i^j , $j \in K, L$, be the shares in the total costs of capital and labor, so that $\sum_i c_i^j = 1$, $j \in K, L$. Then the output elasticity for a given type of capital, say, is αc_i^K . Differentiating logarithmically (where hats are log changes) and imposing the first-order conditions yields:

$$\begin{aligned}\hat{Y} &= \alpha \hat{K} + (1 - \alpha)(\hat{H} + \widehat{LQ}) + \widehat{Util} + \hat{A} \\ &= \alpha \hat{K} + (1 - \alpha)\hat{L} + \widehat{Util} + \hat{A}.\end{aligned}\tag{2}$$

Various input aggregates on the right-hand side are defined as:

$$\begin{aligned}\hat{K} &\equiv c_1^K \hat{K}_1 + c_2^K \hat{K}_2 + \dots, \\ \hat{L} &\equiv c_1^L \hat{H}_1 + c_2^L \hat{H}_2 + \dots \\ \hat{H} &\equiv (H_1/H)\hat{H}_1 + (H_2/H)\hat{H}_2 + \dots \\ \widehat{LQ} &\equiv \hat{L} - \hat{H} \\ \widehat{Util} &\equiv \alpha \hat{W} + (1 - \alpha)\hat{E}.\end{aligned}\tag{3}$$

Growth in capital services, \hat{K} , is share-weighted growth in the different types of capital goods. Similarly, growth in labor services, \hat{L} , is share-weighted growth in hours for different types of workers. Total hours, $H \equiv H_1 + H_2 + \dots$, is the simple sum of hours worked by all types of labor, so its growth rate uses hours as weights, not cost shares. Labor quality growth, \widehat{LQ} , is the contribution of changing worker characteristics to labor services growth beyond raw hours. Finally, \widehat{Util} captures variations in capital's workweek and labor effort.

TFP growth, or the Solow residual, is output growth not explained by (observed) input growth:

$$\begin{aligned}\widehat{TFP} &\equiv \hat{Y} - \alpha \hat{K} - (1 - \alpha)\hat{L} \\ &= \widehat{Util} + \hat{A}.\end{aligned}\tag{4}$$

The second line follows from equation (2). I will always take TFP growth to be this measured Solow residual, defined by the first line in equation (4), and refer to \hat{A} as utilization-adjusted TFP.

A large literature discusses why measured TFP might not reflect technology over the business cycle.⁵ A key reason is unobserved variations in the intensity with which factors are used, \widehat{Util} . Basu, Fernald, and Kimball (2006) and Basu et al. (2013) implement a theoretically based measure of utilization. Their method essentially involves rescaling variations in an observable intensity margin of (detrended) hours per worker. I return to this measure below.

From equations (2) and (4), labor productivity growth, defined as growth in output per hour, is then:

$$\begin{aligned}\hat{Y} - \hat{H} &= \alpha(\hat{K} - \hat{H} - \widehat{LQ}) + \widehat{LQ} + \widehat{Util} + \hat{A} \\ &= \alpha(\hat{K} - \hat{H} - \widehat{LQ}) + \widehat{LQ} + \widehat{TFP}.\end{aligned}\tag{5}$$

Loosely, labor productivity rises if workers have more capital or better skills (quality), or if innovation raises technology. In the short run, cyclical variations in utilization also matter.

C. Aggregate Data and Growth-Accounting Results

Both TFP and capital deepening contributed to the mid-2000s slowdown in labor-productivity growth. Specifically, figure 4 shows components of equation (5) using the quarterly growth-accounting data set described in the appendix. These data provide quarterly business-sector growth accounting variables through 2013. Variables shown are in log levels (i.e., cumulated log changes). The utilization measure applies annual estimates from Basu et al. (2013) to quarterly data. Utilization is based on variations in industry hours per worker. Using restrictions from theory, Basu and colleagues relate unobserved intensity margins of capital's workweek and labor effort to this observed intensity margin.

Panel A shows TFP and utilization-adjusted TFP.⁶ These series grew rapidly from the mid-1990s to the mid-2000s, then essentially hit a flat spot. Panel B shows capital-deepening, $K/(H \cdot LQ)$. In the early twenty-first century, capital-deepening growth slowed (consistent, perhaps, with the slowdown in technology growth). Panel C shows that labor quality accelerated in the Great Recession as low-skilled workers disproportionately lost jobs. Finally, panel D shows utilization itself. This series is clearly highly cyclical. By early 2011, this measure had recovered to a level close to its prerecession peaks. Indeed by the end of the sample, labor productivity (figure 3) or TFP (figure 4, panel A) appear to lie more or less on the slow-trend line from the mid-2000s.

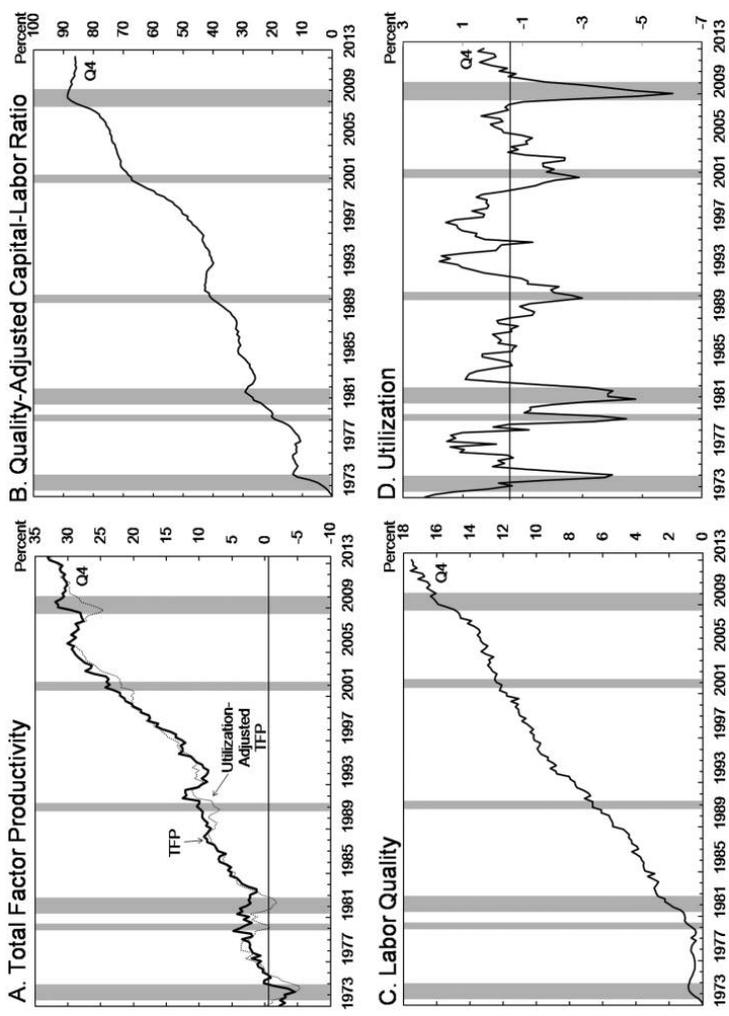


Fig. 4. Evolution of key growth-accounting variables
 Note: Log levels (times 100), measured as cumulative growth since 1973:Q2. Level of utilization is set to zero in 1987:Q4.
 Source: Fernald (2014).

D. *Productivity Growth during the Great Recession*

That the slowdown predated the Great Recession suggests it was not a result of the recession itself. Still, if productivity during the recession were unusual, that might suggest a role for the recession. For example, a few years of bad productivity luck before the recession could have been followed by the greater, and more persistent, bad luck of a severe recession. This section argues this was not the case. Rather, productivity behaved similarly to previous deep recessions: TFP and utilization fell very sharply, but recovered strongly once the recession ended.⁷

Figure 5 shows “spider charts” comparing the Great Recession to the nine previous recessions (1953–2001). In each panel, the horizontal axis shows the number of quarters from the peak. In the Great Recession, for example, quarter 0 corresponds to 2007:Q4. The vertical axis is the percent change since the peak. I remove local trends from all data.⁸

Panels A and B show how unusual output and hours were, with steep declines in both. For the first three quarters (through 2008:Q3), the declines in output and hours worked relative to trend were modest—at the top of the range of historical experience. After Lehman and AIG in quarter 4, output and employment fell precipitously. The trough in detrended output is about as deep as previous deep recessions, but is reached later. (In unfiltered data, the decline is deeper than previous recessions. Detrending has a larger effect in previous deep recessions when trend growth was faster.)

Panel C shows that labor productivity was solidly inside the range of historical experience—indeed, not much different from the average (the white line). Relative to trend, labor productivity fell less than during the 1973 or 1981 recessions.

Of course, labor productivity includes endogenous capital-deepening and labor quality, both of which were strong during the recession (see figure 4, panels B and C). Controlling for those, panel D shows that TFP was right at the bottom of historical experience. The TFP plunged about 5% during the recession and then quickly bounced back in the early phases of the recovery (quarters 6–8, especially).

Factor utilization in panel E “explains” the plunge and rebound in TFP. Utilization fell below the range of historical experience in the recession, then recovered rapidly during the recovery. These estimates suggest that firms substantially used the intensive as well as extensive margin.

Finally, panel F shows utilization-adjusted TFP. That series lies in the

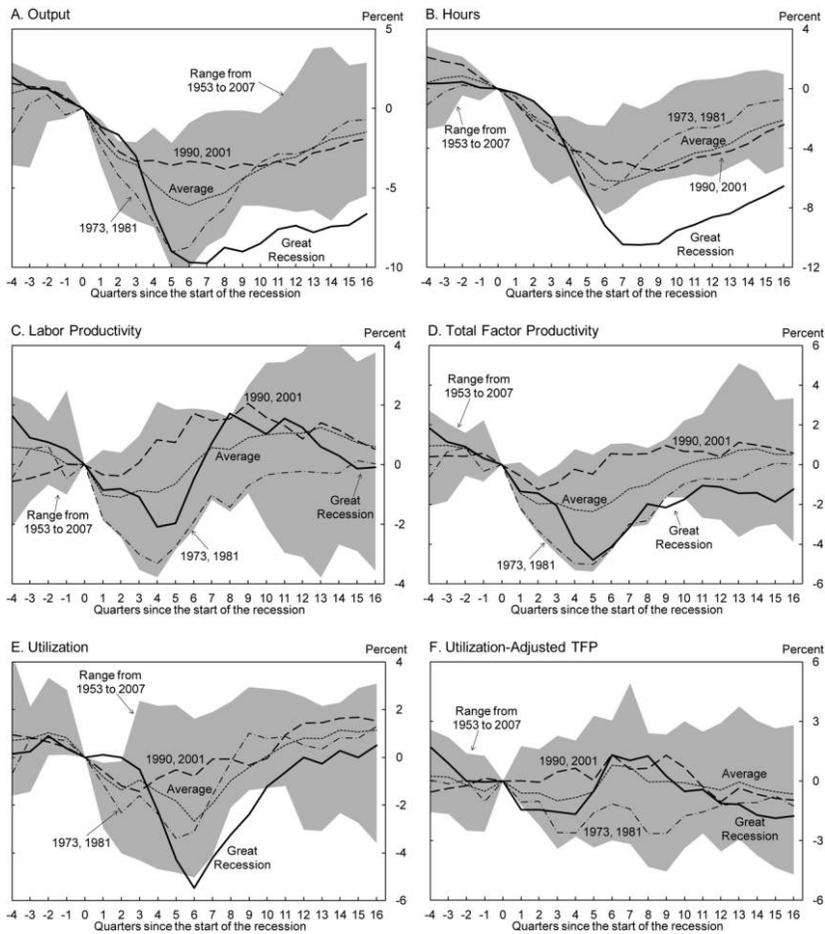


Fig. 5. Comparing recessions

Notes: For each plot, quarter 0 is the NBER business-cycle peak which, for the Great Recession, corresponds to 2007:Q4. The shaded regions show the range of previous recessions since 1953. Local means are removed from all growth rates prior to cumulating, using a bi-weight kernel with bandwidth of 48 quarters.

Source: Fernald (2014).

middle of historical experience, with a spike from quarter 4 (2008:Q4) to quarter 6 (2009:Q2). The spike could reflect temporary effects on utilization-adjusted TFP from the recession. A temporary breakdown in financial intermediation could have led the least productive firms to lose financing (Petrosky-Nadeau 2013), panicked firms could have cut workers exceptionally fast and found temporary efficiency gains that

reversed in the recovery, or it could reflect fear-induced effort by workers. Lazear, Shaw, and Stanton (2013) look at how long it takes a given worker to complete a well-defined task at a single large firm from 2006 to 2010. (They argue the “usual” labor- and capital-hoarding effects are not in their data.) Task-level productivity rose as the Great Recession began. When the recession ended, task-level productivity declined—much like utilization-adjusted TFP.

Overall, though the counterfactual is unknown, the figures do not obviously suggest a major influence of the Great Recession on underlying TFP growth.

Theory is ambiguous about the effects of severe recessions (including financial ones) on the longer-run path of TFP (utilization adjusted or otherwise). In some models, reduced innovation during and after a crisis could lead to a persistently lower level of TFP (e.g., Comin and Gertler 2006). Decker et al. (2013) find that the Great Recession has substantially reduced “dynamism” of the economy, which could reduce the efficiency of resource allocation (see Section III.D). Liu and Wang (2014) model a financial accelerator that leads to procyclical reallocation and productivity. That said, the reallocation effect in some models goes the other way, raising measured TFP in a credit crisis (e.g., Petrosky-Nadeu [2013], or the “cleansing effects” of Caballero and Hammour [1994]). Bloom (2013) points out that high uncertainty can stimulate longer-run innovation.⁹

Overall, there is little empirical evidence for *developed* countries that business cycles (financially related or otherwise) permanently harm the level or growth rate of TFP. The Great Depression was an extraordinarily innovative period (Field 2003; Alexopoulos and Cohen 2009). Fatas (2002) finds that, for the richest countries (but not overall), higher volatility is, if anything, associated with *faster* growth in GDP per capita. Oulton and Sebastiá-Barriel (2013) look at growth-accounting variables following financial crises. They find that, for developed countries, the long-run level of TFP is not significantly changed by a financial crisis; indeed, the point estimate is positive.

III. Why Did TFP Growth Slow?

The data suggest that TFP slowed in the mid-2000s primarily because of the waning of the exceptional growth effects of information technology as a general purpose technology (GPT).

A. *Hypotheses*

This section discusses several hypotheses for the slowdown. I focus on implications for industry and state data, which I use in the subsections that follow to help differentiate the stories.

Waning of the IT-Induced Surge

Studies with aggregate, industry, and plant data link the mid-1990s productivity surge to the direct and indirect effects of IT. Below, I find evidence that the slowdown in the mid-2000s reflected the waning of that exceptional pace. For example, once retailing was reorganized to take advantage of faster information processing, the gains may have become more incremental.

Some IT links are direct. For IT production, the key development was the mid-1990s speedup and subsequent post-2000 slowdown in the pace of technological progress in semiconductors. In the mid-1990s, as Jorgenson (2001) highlights, the semiconductor industry moved to a shorter product cycle, which meant faster gains in performance and quicker price declines. However, several studies find that semiconductor performance gains and price reductions slowed after about 2000.¹⁰

The indirect effects of IT are more complex and nuanced. In retailing, for example, IT led firms to innovate in how they manage sales, inventories, and supply chains; the Internet is an extreme example, in that it made possible completely new ways of doing business. In addition, reallocation toward higher-productivity establishments amplified the effects, as new or existing firms that were particularly adept at using new technologies (and thus more productive) grew, while less capable establishments exited.¹¹ In valve manufacturing, Bartel, Ichniowski, and Shaw (2007) find that IT led to a change in business strategies to focus on product customization rather than large commodity runs. Implementing this change required changes in worker skills as well as in management and human resource practices. More broadly, Brynjolfsson and Hitt (2000) and others highlight the lags associated with complementary managerial and organizational innovations.

These nuances reflect the GPT nature of IT.¹² For a wide swath of the economy, improved ability to manage information and communications has led to changes in how firms do business. It was unclear a priori how long the transformative, explosive opportunities would last.

Basu et al. (2003) and Basu and Fernald (2008) discuss how to map these indirect GPT effects to conventional growth accounting. They model a tight link between accumulating IT capital and intangible organizational capital. Intangible capital leads to interesting dynamics for measured TFP, because it involves both unobserved investment (i.e., output) and unobserved capital (i.e., input).

The Basu et al. (2003) model implies that, as in the data, measured TFP should have temporarily surged in the early twenty-first century. The reason is that growth in IT capital—and, by assumption, intangible capital—skyrocketed in the late 1990s but slumped early in the twenty-first century. That pattern implies that in the 1990s, firms were increasingly diverting resources to producing unmeasured/intangible output. But early in the twenty-first century, those resources returned to producing measured output—boosting measured productivity for a time. Using the Basu et al. (2003) model on aggregate data, Oliner, Sichel, and Stiroh (2007) find that falling investment in unmeasured IT-related intangibles, and the corresponding shift of resources toward producing measured output, accounted for two-thirds of the measured TFP surge in their data from 1996–2000 to 2000–2006 (0.50 out of 0.81% per year).¹³ But with less “seed corn” for the future, they argued that future productivity gains would be slower.

In the empirical work, I examine the broader implication that, regardless of the specific model, the measurement effects are associated with the use of IT. Hence, the slowdown should be concentrated in IT-intensive industries.

Housing and Finance in a Bubble Economy

The IT story emphasizes unusual aspects of the US economy that began in the 1990s and before. But there were unusual features in the first decade of the twenty-first century, including the housing boom and bust, the explosion of often dodgy financial products and services, and large movements in commodity prices.

To assess the importance of direct effects, I throw out those industries. Indirect channels are more subtle. For example, changes in entrepreneurial net worth associated with the housing boom and bust could affect the ability of firms to start or expand, which might influence productivity (possibly with a lag). A priori, it is not clear that the timing works for a 2004–2007 slowdown. Household net worth relative

to disposable income peaked in the 2005–2007 period (averaging almost 650%). Net worth was highest just when productivity growth was slowing. Still, the housing boom could have mattered through some (perhaps unspecified) channel, and state data can provide insight into whether it might be quantitatively important.

Even if the 2004–2007 slowdown is hard to explain with home prices, the collapse after 2006 and/or the Great Recession itself could have contributed further to the slowdown. Fort et al. (2013) report that young and small firms are particularly sensitive to fluctuations in housing prices through a range of credit channels and that start-ups and job churning were hit hard during and since the Great Recession. Regional home price differences are also clearly linked to the intensity of the recession across states (Mian and Sufi 2012). I explore the degree to which state labor productivity responds to state-specific variation in home prices during the recession and (through 2012) recovery.

Finally, a very different channel is that the output of financial services is poorly measured. One concern in the literature (e.g., Wang, Basu, and Fernald 2009) is mismeasurement of value added between producers and users of financial services. I explore that hypothesis by seeing whether the magnitude of the slowdown depends on the intensity of use of financial services.

Other Sources of Mismeasurement, Cyclical or Otherwise

Perhaps productivity growth did not actually slow but measurement got worse? Cyclical mismeasurement from utilization and nonconstant returns does not fit the timing. More complex stories are hard to rule out a priori, but also seem unlikely to explain the magnitude of the slowdown.

Controlling for utilization makes the post-2004 slowdown in TFP growth somewhat larger than measured. Early in the twenty-first century, utilization was flat to down (measured in my quarterly data or with Federal Reserve capacity utilization). In contrast, during the 2004–2007 boom, utilization ticked up.

Increasing returns and markups of price over marginal cost imply that measured TFP should rise when inputs rise (Hall 1990). Input growth (share-weighted capital and labor) was relatively *rapid* (2+% per year) in the fast-productivity-growth late 1990s as well as in the slow-productivity-growth 2004–2007 period. Conversely, input growth

was relatively *slow* (one-quarter to one-half % per year) in the fast-productivity-growth period early in the twenty-first century as well as in the slow-productivity-growth 2007–2013 period.

Indeed, the sign goes the wrong way. Share-weighted input growth sped up by 2 percentage points from the 2000–2004 period to 2004–2007. With constant or modestly increasing returns to scale (e.g., Basu and Fernald 1997), measured TFP growth should, if anything, have sped up a little. Even large diminishing returns (say, 0.8) imply only a modest slowdown—and would imply, counterfactually, that measured TFP growth should have been relatively slow in the late 1990s and relatively fast after 2007.

Basu, Fernald, and Shapiro (2001 [BFS]) assume that investment adjustment costs reduce measured productivity as firms divert resources to installing capital. This story does not explain the TFP slowdown because fixed private nonresidential investment grew at a very similar pace (5% to 6% per year on average) from 1995 to 2004 and from 2004 to 2007. The Basu et al. (2001) calibration implies that adjustment costs subtracted about 0.2 percentage points from measured TFP growth in both subperiods.

Unmeasured quality change is more challenging. Informational technology itself increases product variety, decreases search costs, and provides valuable services for free. For example, producers can readily offer customized, nonstandard products; there are enormous, poorly measured gains to being able to easily obtain any book in the world in a few days (or via immediate download), and GPS and entertaining cat videos on YouTube increase consumer surplus. Brynjolfsson and McAfee (2014) estimate that free Internet goods provide some \$300 billion per year in consumer surplus, or about 2% of GDP. But even if that all appeared over a decade, it is still only 0.2 pp per year.

Moreover, mismeasurement was also severe in the past. There were missing quality improvements for both capital goods (Gordon 1990) and consumer goods and services (e.g., Gordon 2006). In terms of product variety, Broda and Weinstein (2006) measured a fourfold increase in the variety of US imports in the 1970s, 1980s, and 1990s—long before the early twenty-first century slowdown. Similarly, Nakamura (1998) notes that, with IT-related improvements in inventory management, the average supermarket carried two and a half times as many items in 1994 as in 1970. Americans no longer had to settle for “bright yellow mustard, canned peas, and gelatin desserts” (7).

Careful work on measurement requires detailed, often product-

specific analysis. In the industry data, I take a simpler, high-level approach of decomposing the data based on where different industries plausibly fall on the “well-measured” continuum, as in Griliches (1994) and Nordhaus (2002).

Finally, Oliner et al. (2007) discuss other stories of why the strength of the early twenty-first century might have been overstated, consistent with a subsequent slowdown. I do not assess them explicitly but, to the extent they contribute, they reinforce the “return to normal” message of the IT story.

Reduced Dynamism in the Economy

By many measures, the US economy has become less dynamic over time (e.g., Decker et al. 2013). For example, rates of firm entry and job creation and destruction have trended steadily down over the past 30 years with notable further declines in the Great Recession. Such dynamism improves factor allocations and fosters the spread of new ideas. The existing literature does not clearly establish why dynamism has declined. For example, an aging population could be more risk averse, increasing regulation could raise the cost of business entry, or the “idea production function” might have shifted in favor of large, established firms and away from new entrants.

Given the links between home-price dynamics and firm entry noted earlier, the state data may shed light on the recent quantitative importance of this channel. Still, as a longer-term secular trend, reduced dynamism is unlikely to explain the abrupt productivity slowdown in the middle of the first decade of the twenty-first century: dynamism was higher in the slow-productivity-growth 1980s than in the fast-productivity-growth late 1990s and early twenty-first century.¹⁴ That said, the decline in dynamism could complement the IT story to the extent that ongoing gains from IT require new businesses to enter or expand at the expense of incumbents. More generally, reduced dynamism reinforces the message of this paper that growth has slowed and that major forces were in train prior to the Great Recession.

B. Evidence from Industry Data

Industry data support the IT story for the mid-2000s TFP slowdown. The TFP surge after the mid-1990s and its subsequent slowdown was in IT-producing and intensive-IT-using industries. The IT-producing in-

dustries saw productivity explode in the 1995–2000 period. After 2000, productivity returned close to its pre-1995 pace. The IT-intensive industries saw only a modest pickup in the late 1990s, but a marked burst in 2000–2004. After 2004, TFP growth receded close to its pre-1995 pace.

I use Bureau of Labor Statistics (BLS) data for 60 manufacturing and nonmanufacturing industries from 1987 to 2011. I express everything in value-added terms, so that they are conceptually identical to TFP in equation (4).¹⁵ The data do not control for labor quality, LQ , and predate the 2013 National Income and Product Accounts (NIPA) revisions. Nevertheless, when aggregated (using value-added weights) to a private business level, year-to-year changes comove closely with the Fernald TFP series (the correlation is 0.84).

Table 1 shows TFP growth by subperiod for selected industry groupings. Consistent with the earlier results, TFP growth for all business industries sped up in the late 1990s and sped up further (to 2.19% per year) early in the twenty-first century. During the 2004–2007 period, growth slowed markedly to only 0.63%. From 2007 to 2011, business TFP growth recovered a touch, to 0.90%. Some of this apparent pickup reflects the spike in labor quality during the Great Recession. Since the 2007–2011 period might still be affected by cyclical variations in LQ and utilization, below I focus primarily on the pre–Great Recession period. Broad conclusions are robust to using the full sample period.

Line 2 shows TFP growth for the bubble-economy sectors of natural resources, construction and real estate, and finance. The TFP for that group decelerated from 2000–2004 (–0.28% per year) to 2004–2007 (more substantially negative at –1.38%). Weakening TFP in natural resources (line 3) and construction (line 4a) was partially offset by stronger TFP in real estate (line 4b) and finance (line 5).

But importantly, the remaining nonbubble three-quarters of the business economy (line 6) slowed even more than overall private business. Thus, the slowdown did not merely reflect the unusual features of commodities, housing, and finance. This narrow business sector slowed further after 2007.

The lines below show additional summary “cuts” of this narrow business sector. These show that the slowdown was particularly pronounced in IT-producing industries (line 7) and in intensive-IT-using industries (line 9). Figure 6, panel A shows these points graphically. The IT-producing sectors saw a burst in TFP growth in the late 1990s, consistent with the studies of the semiconductor industry noted in Section III.A. (Table 1, line 7a, locates this burst primarily in the production

Table 1
Industry Data on Productivity

	Pre-1995 (1)	1995-2000 (2)	2000-2004 (3)	2004-2007 (4)	2007-2011 (5)	Chng. after 2004 ([4]-[3], that is, 04-07 less 00-04) (6)	VA Weight (Avg., 1988-2011) (7)
(1) Private business	0.83	1.58	2.19	0.63	0.90	-1.55	100.0
(2) Nat. resources (NR), constr., FIRE (NR-C-F)	0.09	0.71	-0.28	-1.38	0.76	-1.11	26.1
(3) Natural resources (NR, i.e., ag. and mining)	0.86	2.46	2.54	-3.88	-0.41	-6.42	3.7
(4) Construction and real estate	-0.11	-1.62	-1.16	-2.57	1.26	-1.41	13.0
(4a) Construction	0.41	-0.78	-2.16	-6.69	1.62	-4.54	6.2
(4b) Real estate and leasing	-0.58	-2.40	-0.18	1.70	0.90	1.89	6.7
(5) Finance and insurance	-0.02	3.27	0.07	0.90	0.64	0.83	9.5
(6) Business (ex. NR-C-F)	1.08	1.87	3.10	1.42	0.95	-1.68	73.9
(7) IT producing	10.49	16.54	11.82	9.03	5.44	-2.79	4.9
(7a) Computer and el. product manuf.	18.53	34.64	21.17	18.99	11.02	-2.18	2.2
(7b) Publishing (incl. software)	1.53	1.88	8.08	1.39	-0.25	-6.69	1.4
(7c) Computer systems design	1.73	0.47	4.61	4.31	3.96	-0.30	1.3
(8) Non-IT prod. (ex. NR-C-F)	0.49	0.77	2.48	0.85	0.60	-1.63	69.0
(9) IT-intensive (ex. NR-C-F AND IT-prod)	0.36	0.50	4.06	0.53	1.18	-3.53	34.9
(10) Non-IT intensive (ex. NR-C-F and IT-prod)	0.61	1.04	0.84	1.20	-0.14	0.37	34.1
(11) Well measured (ex. NR-C-F and IT-prod)	1.19	1.33	3.45	1.59	0.60	-1.86	42.7
(12) Nondurable goods	0.59	-0.79	4.02	0.23	-0.05	-3.80	8.5
(12a) Durables (ex. comp. and semicond.)	-0.94	-0.16	2.70	2.78	-0.39	0.08	9.3
(12b) Equipment, ex. comp., and semicond.	-1.29	-0.22	2.84	4.39	-0.13	1.55	7.6
(12c) Non-equip dur. (metal, mineral, wood)	0.52	0.07	2.05	-4.14	-2.32	-6.19	1.7

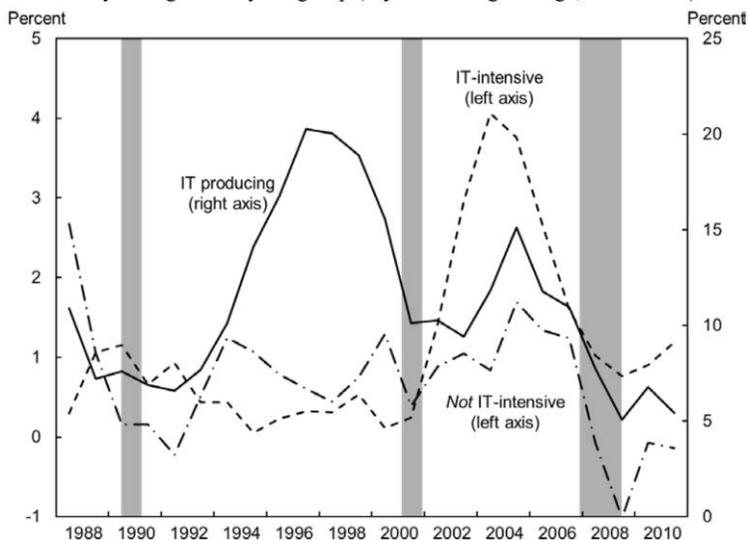
(continued)

Table 1
Continued

	Pre-1995 (1)	1995-2000 (2)	2000-2004 (3)	2004-2007 (4)	2007-2011 (5)	Chng. after 2004 ([4]-[3], that is, 04-07 less 00-04) (6)	VA Weight (Avg., 1988-2011) (7)
(13) Utilities	1.89	-6.75	9.05	-0.57	4.26	-9.61	2.7
(14) Trade	2.41	5.17	2.96	0.45	-0.19	-2.51	14.7
(14a) Wholesale trade	1.99	6.44	5.08	0.43	-1.33	-4.65	6.7
(14b) Retail trade	2.74	4.10	1.23	0.44	0.85	-0.79	8.0
(15) Broadcasting and telecommunications	3.02	-2.41	3.94	10.06	4.30	6.12	2.6
(16) Transportation and warehousing	2.37	2.08	3.23	2.61	1.99	-0.62	4.1
(17) Poorly measured (ex. NR-C-F and IT-prod.)	-0.87	-0.20	1.11	-0.19	0.63	-1.29	26.3
(18) Other informat. (not publ., broadcast.)	-3.77	-11.14	16.27	-1.90	0.33	-18.17	1.2
(19) Services	-0.59	0.30	0.59	0.03	0.75	-0.55	27.2
(19a) Professional, technical, and support	-0.15	0.51	1.59	-0.14	1.07	-1.73	14.9
(19b) Educ., health, and soc. assist	-2.27	-1.68	0.21	0.11	0.79	-0.10	5.9
(19c) Entertainment, accomm., and other	0.04	1.65	-1.44	0.41	-0.12	1.85	6.5
(20) Finance intensive (ex. NR-C-F and IT-prod.)	0.78	2.16	1.31	0.08	0.33	-1.23	40.7
(21) Non-fin. intensive (ex. NR-C-F and IT-prod.)	0.16	-1.15	4.37	2.07	1.06	-2.29	28.3

Notes: Entries are percent change per year, except for value-added weight, which is average percentage share from 1988-2011.

A. Industry TFP growth by subgroup (4-year moving average, annual rate)



B. Slowdown in TFP growth after 2004 and IT intensity

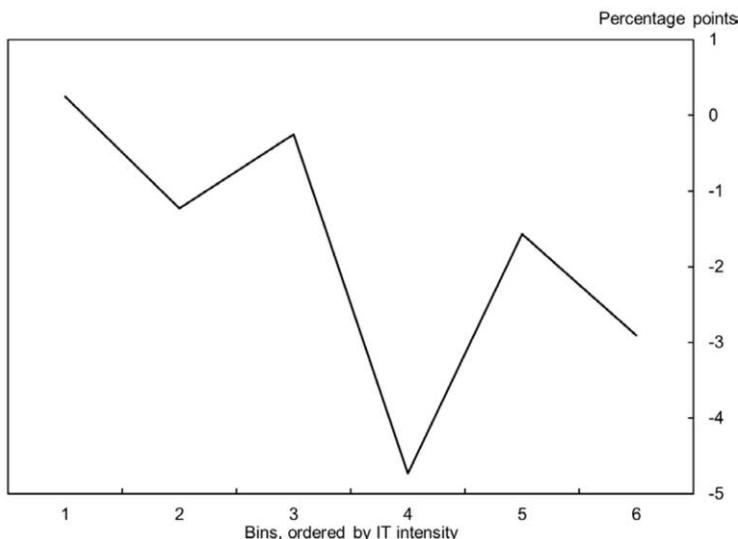


Fig. 6. TFP growth and information technology

Notes: Panel A: Four-year moving average of annual percent changes. Lines shown decompose TFP growth for “narrow business” (i.e., excluding natural resources, construction, and FIRE) into TFP growth for IT-producing, IT-intensive-using, and non-IT-intensive industries. Panel B: Vertical axis shows percentage point slowdown in TFP growth after 2004 (2004–2007 average, relative to 2000–2004 average) for industries aggregated based on IT intensity. Bin 1 to the left is the least IT-intensive group of industries, bin 6 is the most IT intensive.

Source: BLS and the author’s calculations.

of computers and semiconductors.) The pace from 2000 to 2007 was not much different from its pre-1995 pace. Intensive-IT-using industries saw only a modest pickup in the late 1990s, but then productivity exploded early in the twenty-first century. From 2004 to 2007, productivity in that group more or less receded to its pre-1995 pace. In contrast, non-IT-intensive industries saw more consistent performance over time.¹⁶

Figure 6, panel B shows the importance of IT intensity another way. It plots the post-2004 TFP slowdown (through 2007) for bins of industries grouped by IT intensity. Bin “1” on the x-axis is the least IT intensive, and bin 6 is the most. The figure shows that more IT-intensive industries (to the right) had more of a slowdown after 2004. The two least IT-intensive bins on the left showed little slowdown.

A second way to cut the data is well measured versus poorly measured. Well-measured industries are predominately manufacturing and utilities (in addition to natural resources, which I exclude), whereas poorly measured industries are predominately services. As the table shows, both well-measured (line 11) and poorly measured (line 17) industries picked up somewhat in the late 1990s, sped up further early in the twenty-first century, and then slowed markedly (by one and one-quarter to one and three-quarters percentage points) after 2004. Thus, first-cut measurement issues do not seem to be at the heart of the productivity slowdown.

A third cut is finance-intensive versus non-finance-intensive industries. If there was systematic and growing mismeasurement of intermediate financial services—or, perhaps, growing rent extraction by financial firms—then the slowdown should be more pronounced in finance-intensive industries. However, the slowdown turns out to be more pronounced for non-finance-intensive industries. These industries have a larger productivity bump early in the twenty-first century—and, thus, had further to fall. Nevertheless, there is no evidence here that the productivity burst was particularly related to finance.

Thus, the industry data suggest the important role played by the production and use of information technology in explaining the TFP slowdown from 2000–2004 to 2004–2007. These results, and the literature in Section III.A, suggest that IT-intensive industries saw transformative organizational changes associated with IT, which fueled a burst of productivity early in the twenty-first century. Once the low-hanging fruit of reorganization had been plucked, growth returned to normal.

C. Evidence from the US States

Labor productivity slowed broadly in almost all states—especially in IT-intensive industries. More importantly, the state data provide insight into indirect financial and housing channels, since states differ in housing dynamics during the boom and bust. These dynamics explain little of the cross-state variation in the degree to which productivity slowed.

The state data are for GDP per worker. Cross-state variation could reflect innovation, perhaps because, as discussed in Section III.B, credit market access by innovative entrepreneurs is affected by net worth.¹⁷ Credit market access could affect capital deepening as well, and to the extent house-price fluctuations affect aggregate demand, it could affect relative factor utilization across states around the national average. Since the innovation, capital-deepening, and utilization channels are likely to move in the same direction in response to shocks to housing wealth, any effects on labor productivity are an upper bound on the persistent effect on technology or innovation.

Table 2 shows that almost all states saw a broad labor-productivity slowdown. For the entire private economy, 47 out of 51 states (including DC) had slower productivity growth in 2004–2007 relative to 1997–2004. (Extending the slowdown period to 2012, the figure rises to 48.) Natural resources slowed substantially in most states, as did construction and finance, insurance, and real estate (FIRE).

Still, as in the industry data, IT rather than the bubble sectors are the story. As in table 1, IT production (line 7) slowed substantially, and in line 8, within the narrower category that excludes the bubble sectors and IT production, almost all states slow. Within that narrow grouping, IT-intensive industries (line 9) slowed in 50 out of 51 states (Washington, DC was the exception)—and the median slowdown was large. In contrast, only 35 states saw slowdowns in non-IT-intensive industries, and the median slowdown was small. Labor productivity in wholesale trade (line 11), where substantial research has documented the role of IT in fostering reorganizations, slowed in all 51 states after 2004.

What about indirect channels? Table 3, panel A, examines whether the slowdown (2004–2007 relative to 1997–2004) is related to cross-state home price changes. I instrument for home price changes with the Saiz (2010) housing supply elasticity (based on geographic features of metropolitan areas). Mian and Sufi (2012) argue that the elasticity is a good instrument for home price changes in this period: when credit

Table 2
Number of States with Slowdowns in Labor Productivity Growth

	No. Slowing 2004–07 fr. 1997–04 (1)	Median 04–07 Change (2)	No. Slowing 2004–12 fr. 1997–04 (3)	Median 04–12 Change (4)
(1) Private business	47	-1.84	48	-1.44
(2) Nat. res. (NR), constr., FIRE (NR-C-F)	48	-2.72	43	-0.99
(3) Nat. res. (NR, i.e., ag. and mining)	49	-9.45	49	-6.96
(4) Construction	46	-4.63	12	1.33
(5) FIRE	43	-1.64	46	-1.52
(6) Private business (ex. NR-C-F)	47	-1.36	50	-1.65
(7) IT production	45	-4.94	51	-7.09
(8) Private business (ex. NR-C-F and IT prod.)	46	-1.11	47	-1.18
(9) IT intensive	50	-1.84	50	-2.12
(10) Not-IT intensive	35	-0.56	36	-0.30
(11) Wholesale trade	51	-5.19	51	-5.73
(12) Retail trade	49	-2.02	48	-1.33

Notes: Table compares growth in GDP per worker before and after 2004 for various industry groupings. For example, column (1) shows the number of states (out of 51, including Washington, DC) where average productivity growth from 2004–2007 was slower than from 1997–2004. Industry groupings generally follow table 1. Columns (2) and (4) show the median slowdown across states, in percentage points at annual rate.

standards changed early in the twenty-first century, areas with inelastic land supply saw a larger increase in housing prices. Conversely, when credit standards tightened after 2006, areas with inelastic land supply saw larger housing busts. (Units for home price movements are standard deviations relative to the cross-section of states.)¹⁸

There is scant evidence that cross-state productivity slowdowns are related to home price changes during the boom. The house price change is significant for IT-intensive industries (column [3]) and natural resources (column [8]). Still, in both cases, the R^2 is low and the coefficient is positive. Since the average state saw a housing boom, the sign goes the wrong way to explain a widespread slowdown.

For natural resources, a possible channel is that, where home prices ran up more, marginal agricultural land was converted to residential uses—so the quality of land in agricultural production went up. (The share of natural resources in the economy did fall in areas with greater increases in home prices.) Alternatively, the net worth channel could

Table 3
Home Prices and State Labor Productivity Slowdowns

<i>A. $\Delta LP^{2004-07} - \Delta LP^{1997-04}$</i>							
Indep. var.	Dep. var.						
	Private (1)	Excl. NR-F- C+IT Prod. (2)	IT Intensive (3)	Not IT Intensive (4)	Constr. (5)	FIRE (6)	NR (7)
Constant	-2.06 (0.27)	-1.36 (0.28)	-2.66 (0.33)	-0.61 (0.40)	-4.89 (0.69)	-1.66 (0.53)	-14.50 (2.32)
Δ HPI (2001–06)	-0.19 (0.15)	0.10 (0.13)	0.36 (0.13)	-0.024 (0.19)	0.08 (0.30)	-0.12 (0.28)	3.16 (1.06)
R^2	0.02	0.01	0.05	0.01	0.01	0.02	0.01
<i>B. $\Delta LP^{2005-12} - \Delta LP^{1997-05}$</i>							
Constant	-0.71 (0.22)	-1.00 (0.20)	-1.88 (0.34)	-0.28 (0.32)	3.67 (0.54)	-1.18 (0.57)	-1.95 (2.31)
Δ HPI (2006–09)	0.60 (0.13)	0.15 (0.11)	0.11 (0.21)	0.13 (0.20)	1.38 (0.33)	0.79 (0.36)	2.63 (2.02)
R^2	0.14	0.04	0.01	0.18	0.15	0.03	0.01

Notes: Cross-section, population-weighted, IV regressions on 49 US states including Washington, DC; Hawaii and Alaska are omitted because of missing data. Dependent variable is the change in average productivity for the industry aggregate shown; the top panel looks at 2004–2007 from 1997 to 2004, and the bottom panel 2005–2012 from 1997 to 2005. NR is natural resources, C is construction, F or FIRE is finance, insurance, and real estate. Δ HPI (2001–06) is the change in state home price indices from 2001:Q1 through 2006:Q1; Δ HPI (2006–09) is change from 2006:Q1 through 2009:Q2. Δ HPI is normalized by the cross-sectional standard deviation. The Saiz (2010) housing-supply elasticity instruments for the housing-price change.

be particularly important for capital investment in agriculture, where farmers are often land rich but liquidity constrained.

For IT-intensive industries, the significance could reflect net-worth channels, but it could easily reflect that aggregate demand was stronger where house prices ran up more, boosting capital investment and factor utilization. In any case, the R^2 is low and the constant term is a large negative. So, any effects of the housing bubble were swamped by other factors—such as IT.

Table 3, panel B uses a different cut of the data to address the post-2006 housing collapse and Great Recession. National home prices

peaked in 2006 and slid to 2009. Mian and Sufi (2012) argue that the depth of the recession across states is related to the magnitude of this decline, so the state home price data provide an indicator of where the recession itself might have contributed to weak productivity. Under the hypothesis that there were a couple years of prerecession bad luck, followed by the Great Recession, it considers the 2005–2012 period relative to the 1997–2005 period. The right-hand-side variable is the change in home prices from roughly peak to trough (2006 to 2009).

Here, the effects are generally larger, and in line with the Mian-Sufi story for the bubble sectors. For the entire private economy (column [1]), house price changes have a strong association with labor productivity. The effects are located in the bubble sectors—construction and FIRE (columns [5] and [6]) and, to a lesser degree, natural resources (column [7]). Excluding those sectors (column [2]), as well as for IT-intensive and not-IT-intensive sectors, the effect of the housing decline is small and insignificant. Again, for IT-intensive industries, the large and negative constant term is where the action is.

All told, the state data do not suggest that home price movements are an important part of the story. Rather, the state data are consistent with the IT-linked story for the slowdown.

IV. Implications for Medium- and Long-Run Growth

In a multisector neoclassical growth model, the slowdown in TFP growth plausibly implies a pace of labor productivity growth comparable to 1973 to 1995. What follows assumes constant returns, perfect competition, and that utilization growth is zero in steady state. Hence, steady-state growth in technology and measured TFP are equal: $\hat{A}^* = \widehat{TFP}^*$, where stars (*) denote steady-state values.

A. Multisector Projections of Labor-Productivity Growth

In one-sector neoclassical growth models, capital deepening depends on exogenous TFP growth. In the steady state of that model, the capital-output ratio is constant. In US data, however, reproducible capital input grew about 1 pp per year faster than output from 1973 through 2007.

Multisector models, where one (or more) sector produces investment goods and other sectors do not, fit the data better because they generate a rising capital-output ratio. Steady-state capital deepening depends solely on investment TFP: $(\hat{K} - \hat{H}^* - \widehat{LQ}^*) = \widehat{TFP}_I^*/(1 - \alpha)$. In the data,

land is an important form of nonreproduced capital, earning 10% of payments to capital from 2000 to 2007. If c_T is land's share of capital payments, $\alpha^R = \alpha(1 - c_T)$ is the reproducible (nonland) capital share in output, and land use grows at the same rate as labor, then steady-state labor productivity growth is:¹⁹

$$\hat{Y}^* - \hat{H}^* - \widehat{LQ}^* = \widehat{TFP}^* + \alpha^R \cdot \widehat{TFP}_T^* / (1 - \alpha^R). \quad (6)$$

In the one-sector model without land, the right-hand side simplifies to the usual expression: $\widehat{TFP} / (1 - \alpha)$. Land somewhat attenuates the endogenous capital-deepening effect.

In practice, \widehat{TFP}_T^* needs to be the user-cost weighted average of multiple types of capital goods. The price of equipment—especially, but not solely, information technology related—has fallen rapidly relative to the prices of other goods. In contrast, the relative price of structures has risen steadily over time. Hence, I assume there are three final-use sectors as well as (exogenously growing) labor:

$$\begin{aligned} D &= (K_D)^\alpha (AN_E)^{1-\alpha} \\ B &= Q_B (K_B)^\alpha (AN_B)^{1-\alpha} \\ C &= Q_C (K_C)^\alpha (AN_C)^{1-\alpha}. \end{aligned} \quad (7)$$

The **Durable** sector produces equipment and consumer durables. The **Building** sector produces structures. The **Consumption** sector produces nondurables and services. The production functions are identical apart from building-specific and consumption-specific technology shocks, Q_B and Q_C .

Some durable goods, D , are invested and become equipment capital; all new buildings become structures. Both equipment and structures accumulate according to the standard perpetual inventory formula. Land grows exogenously. All three sectors use the same capital aggregate:²⁰

$$K = E^c E S^{1-c} E^{-c_T} T^{c_T} = K_D + K_B + K_C.$$

With perfect competition, relative output prices reflect relative marginal costs. With identical factor prices, relative marginal costs in the model depend solely on relative technologies. In growth rate terms, the relative price of, say, consumption to durable equipment thus gives relative technology:

$$\hat{P}_C - \hat{P}_D = \widehat{MC}_C - \widehat{MC}_D = -\widehat{Q}_C. \quad (8)$$

This approach follows the literature on investment-specific technical change ([ISTC]; e.g., Greenwood, Hercowitz, and Krusell 1997). It relies on strong assumptions that hold imperfectly in practice; see Basu et al. (2013) for an alternative identification. But in the long run, Basu and colleagues find that relative prices do primarily reflect relative technologies.

Figure 7 shows the implied (cumulated) final-use TFPs, where overall TFP is decomposed using equation (8). The final-use TFP measures do not control for utilization, but in the longer run should provide reasonable indicators of technology trends. All three sectors move roughly together until the mid-1960s. Buildings TFP then begins to drift steadily downward. By the early 1970s, consumption TFP largely levels off. In contrast, durables TFP continues to rise steadily until the 1990s.

The difference between the durable and consumption lines is what the literature calls ISTC. In contrast to the implicit interpretation in that literature, the faster apparent pace of ISTC in the 1970s arises from slower growth in consumption TFP, *not* from faster growth in durables (equipment) TFP.

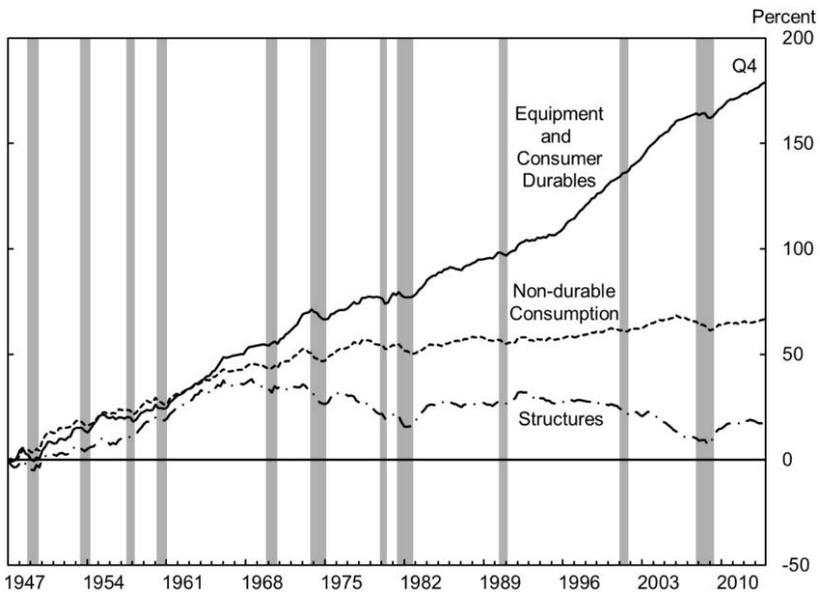


Fig. 7. TFP by final use sector

Note: Log level (times 100), measured as cumulative growth since 1947Q1. Relative TFP is defined by relative prices.

Source: Fernald (2014), BEA, and the author's calculations.

In the mid-1990s, durables TFP does, in fact, accelerate, reflecting IT production. It is difficult to see in the figure, but consumption TFP also grew more quickly. Buildings TFP continues to trend down. In the mid-2000s, prior to the Great Recession, all three series show a reversal in their post-1995 growth pace. Durables TFP grows more slowly, consumption TFP dips a bit, and buildings TFP plunges. In the Great Recession itself, all three series fall somewhat and then bounce back.

How should we use estimates of final-use TFP growth? Pesaran, Pick, and Pranovich (2013) argue that break analysis of the sort done in sections II and II is important for understanding history but *not* for forecasting. The exact magnitude and dates of breaks are uncertain, and postbreak samples are short. In the current problem, for example, each series may break at different times and provide only a short window of (volatile) postbreak data. Pesaran and colleagues show that using estimated break dates is suboptimal in terms of mean-squared forecast errors (MSFE). They argue for forecasting using all available data but adjusting the weights on different observations.

As a benchmark, I use a simple approach that Pesaran et al. call AveW, where one forms forecasts for a range of historical windows and then averages. Pesaran and colleagues find that AveW works well in both Monte Carlo simulations and actual applications. It deals with uncertainty about the precise timing and magnitude of breaks by averaging across them. It is similar to exponential smoothing in that it puts more weight on recent observations, since those observations appear in all of the windows.

I include all possible windows since 1973:Q2 of 24 quarters or longer. Then, for each of the 139 starting dates $s \subset [1973:Q2-2007:Q4]$, I calculate average TFP growth from s through 2014:Q1 for durables, buildings, and consumption and use those growth rates to forecast labor productivity growth, $LP^f(s)$, with equation (6). I then average the forecasts. Hence, $LP^{AveW} = (1/139) \cdot \sum_{s=1973:2}^{2007:4} LP^f(s)$.

The model requires values for (reproducible) capital's share, α^R , and for c_j , $J \subset (E, S, T)$. I focus on average values prior to the Great Recession, averaged from 2001:Q4 through 2007:Q4. The reproducible capital's share, α^R , averaged 31%, and capital share overall averaged 35%. As an alternative, I use the 2014:Q1 reproducible capital share of 34% (the overall share had risen to almost 39%). Other things equal, a higher capital share implies faster growth from equation (6).

The first column of table 4, row 6, shows my benchmark estimate of steady-state labor-productivity growth of a little under 1.9% per year.

Table 4

Projections for Labor Productivity (Output per Quality-Adjusted Hour) (Percent Per Year)

Variable	AveW	Since 1973:Q1	Since 1986:Q4	Since 1995:Q4	Since 2003:Q4
(1) Durables TFP	3.16	2.67	3.23	3.84	2.87
(2) Buildings TFP	-0.45	-0.51	-0.40	-0.65	-0.71
(3) Consumption TFP	0.31	0.32	0.35	0.47	0.11
(4) Overall TFP	0.89	0.77	0.95	1.15	0.63
(5) Investment TFP	2.12	1.75	2.19	2.54	1.84
(6) Labor prod. projection	1.85	1.56	1.93	2.29	1.46
(7) GDP projection	2.10	1.88	2.16	2.43	1.80
(8) <i>Lab. prod. proj. with 2014:Q1 cap. share</i>	1.99	1.68	2.07	2.46	1.58
(9) <i>GDP proj. with 2014:Q1 cap. share</i>	2.20	1.96	2.27	2.56	1.89

Notes: Each column shows inputs into projecting business-sector labor productivity (rows 6 and 8) as well as overall GDP growth (rows 7 and 9). Rows 1 to 5 show inputs into those projections under different assumptions. AveW is the arithmetic average of projections based on all windows that end in 2014:Q1, with starting quarters for the windows that range from 1973:Q2 through 2007:Q4. The remaining columns show selected windows. Labor productivity and GDP projections in rows 6 and 7 assume that capital's share in "reproducible" (nonland) capital as well as the weight on durables and buildings in total "investment" TFP is its average from 2001:Q4 through 2007:Q4. Lines 8 and 9 assume that (reproducible) capital's share remains at its estimated value in 2014:Q1.

That estimate uses the LP^{AveW} measure. Row 8 shows that, with the 2014 value of capital's share, the projection is about 0.2 pp per year faster.

The columns to the right show particular windows. For example, row 6 of the "Since 1973:Q2" column shows $LP(1973:Q2)$, that is, the prediction for labor productivity with average TFP growth 1973:Q2–2013:Q4. Using just the past decade, $LP(2003:Q3)$, implies a forecast of under 1.5%, close to the forecast using data since 1973:1. The benchmark AveW forecast of about 1.9% labor-productivity growth turns out to be similar to $LP(1986:Q4)$.

Finally, productivity influences the long-run equilibrium real interest rate. From the consumption Euler equation for the multisector model, and with a unit intertemporal elasticity of substitution, the steady-state real rate is $r = [TFP_c + \alpha TFP_f / (1 - \alpha)] + n + \rho$. Variable n is population growth and ρ is the rate of time preference. With a reproducible capital share of 0.31, the AveW estimate of the term in brackets is 1.27%. This compares with an average (not shown) during the Great Moderation period (1984:Q1–2007:Q4) of 1.47%, and in the 1995:Q4–2007:Q4 period of 1.99%. Thus, the direct effect of slower growth on the equilibrium

real interest rate may be in the range of .25 to .75%. This is on top of the effects of slowing population growth (n).

B. Key Uncertainties

The model and discussion highlight key issues that will influence future growth. An important question is whether the IT revolution might return after a pause. Syverson (2013) points out that labor productivity during the early twentieth-century-electrification period showed multiple decades-long waves of slowdown and acceleration. Pessimists (e.g., Gordon 2014) think a renewed wave of strong growth is unlikely; optimists (e.g., Brynjolfsson and McAfee 2014) think it is on its way.

Another issue is the model's steady-state assumptions. Fernald and Jones (2014) discuss a model in which relatively steady US historical growth of GDP per hour of around 2% reflects transition dynamics of rising educational attainment and an increasing share of the labor force devoted to research. The steady state of that model suggests much lower growth in labor productivity (about .5% per year) than I project here. Transition dynamics could continue to play out for a long time to come, or even intensify. For example, the rise of "frontier" research in China, India, and elsewhere—as well as machine learning and robots—could lead to faster growth in the next few decades, even if the eventual path is much lower. Fernald and Jones interpret steady-state projections of the sort done here as a local approximation that might be reasonable over the span of a few decades, but not forever.

Not surprisingly, standard errors around long-run projections are large. Müller and Watson (2013) estimate an 80% confidence interval for 10-year projections of nonfarm business output per hour from 1.0 to 3.0% per year; for overall TFP, it ranges from -0.1 to 2.1%.

C. From Labor Productivity to GDP Growth

To translate labor productivity to GDP, I use projections for potential labor input and nonbusiness output from the CBO (2014a) and labor quality estimates from Jorgenson, Ho, and Samuels (2013).

The CBO projects that potential nonfarm business hours by 2024 will slow to 0.64% per year, from 1.4% per year from 1949 through 2007. Labor quality exacerbates this demographic slowdown, since new labor-market cohorts are no more educated than retiring cohorts. I therefore assume zero labor-quality growth. These estimates imply that, in the

benchmark case, business output will grow with productivity (1.85%) and hours (0.64%) = 2.49% per year. For nonbusiness sector output—mainly general government and the service flow from owner-occupied housing—the CBO forecasts 0.85% per year growth at the end of 10 years (in 2024).

Together, the business and nonbusiness projections imply anemic long-run GDP growth of about 2.1% per year. In terms of total GDP per hour, this corresponds to growth of only about 1.6% per year. This projection lies below the average from 1950–2007 of 2.0% per year.

Prior to the Great Recession, a typical long-run projection for GDP growth was 2–2.5% or higher. For example, in early 2007, the CBO projected growth 10 years out of 2.5% per year and GDP per hour of 2.0% per year—close to its long-run trend. Since 2009, Federal Open Market Committee participants have published “longer run” projections for GDP growth. In January 2009, 10 out of 16 participants projected 2–2.5% growth, with the remaining six higher than that.²¹

When the first versions of this paper were written in late 2011 and early 2012, the projection of 2.1% growth, and 1.6% for GDP per hour, was low. In contrast, by early 2014 the numbers reported here are in line with, or above, many other projections. The CBO (2014a) itself projects growth of potential GDP (in 2024) of 2% and GDP per hour of 1.5%. Jorgenson et al. (2013) and Gordon (2014) project GDP per hour growth approximately 10 years out of 1.3%. Byrne, Oliner, and Sichel (2013) project GDP per hour of about 1–1.5%.

V. Implications for Recent Measures of Slack

The pre–Great Recession productivity slowdown implies that, as of 2013, economic “slack” using a production-function definition may be narrower than the CBO (2014a) estimates. The CBO does, in fact, build in slower TFP growth after 2004, but the slowdown is more modest than in the data. If potential is lower than the CBO estimates, then the gap between actual and potential output is smaller.

A. *Alternative Definitions of Potential*

The CBO defines potential in terms of a production function: “the maximum sustainable amount of real (inflation-adjusted) output that the economy can produce” (CBO 2014b, 1). The dynamic stochastic equilibrium (DSGE) literature offers a theoretically coherent alternative:

potential (or natural) output is its value when nominal frictions (sticky prices and wages) and, often, markup shocks are absent.²² Technology shocks directly affect the natural rate of output. But other shocks—say, to the labor-leisure choice or the rate of time preference—may also cause changes in hours worked or factor intensity even in the absence of nominal frictions. The CBO definition excludes these effects.

Nevertheless, the DSGE approach is challenging in the present context. Most models assume that growth in technology has a constant mean—inconsistent with the interpretation in this paper. A fully specified regime-switching (or more general) model is complicated. More generally, estimates tend to be model specific. Different models may interpret the same data quite differently.

Still, Kiley (2013) finds that, in the Federal Reserve estimated dynamic optimization-based (EDO) model, the natural-rate measure of the output gap comoves reasonably closely with a production-function-based measure. Indeed, technology fluctuations affect potential output in DSGE models as well in the production-function (CBO) approach; demand shocks that lead to inefficient fluctuations in hours worked and factor utilization would be captured in both approaches. Finally, the CBO estimates provide a widely cited benchmark.

B. Alternative Estimates of Slack in the CBO Approach

Historically, the CBO attributes almost all movements in the output gap for overall GDP to the (nonfarm) business sector, so I assume the GDP gap is simply a rescaled version of the business-sector gap.²³ In the Cobb-Douglas case, if ω is the business share of the economy:

$$\frac{Y_t}{Y_t^*} = \left(\frac{Y_t^{Bus}}{Y_t^{Bus,*}} \right)^\omega. \quad (9)$$

For the business sector, suppose the production function is Cobb-Douglas:

$$Y_t^{Bus} = K_t^\alpha H_t^{1-\alpha} (LQ_t^{1-\alpha} Util_t A_t). \quad (10)$$

The CBO does not explicitly consider labor quality, so the term in brackets on the right side is measured TFP gross of LQ . The production-function measure of potential output is what the economy could produce given current technology and capacity, assuming that labor and capital are utilized at “normal” (steady-state) levels. Setting $Util^* = 1$, potential output is:

$$Y_t^{Bus,*} = K_t^\alpha H_t^{*1-\alpha} (LQ_t^*)^{1-\alpha} A_t. \quad (11)$$

Taking the ratio, the output gap for the business sector is:²⁴

$$\frac{Y_t^{Bus}}{Y_t^{Bus,*}} = \left(\frac{H_t}{H_t^*} \right)^{1-\alpha} Util_t \left(\frac{LQ_t}{LQ_t^*} \right)^{1-\alpha}. \quad (12)$$

The CBO publishes annual estimates of the business-sector output and hours gaps. Potential hours draws on analysis of demographics, trend labor-force participation, mismatch, and other factors. This equation implicitly defines a CBO “utilization gap” (inclusive of LQ) as:

$$\ln (Util_t^{CBO,LQ}) \equiv \ln (Y_t^{Bus} / Y_t^{Bus,*}) - (1 - \alpha) \ln (H_t / H_t^*). \quad (13)$$

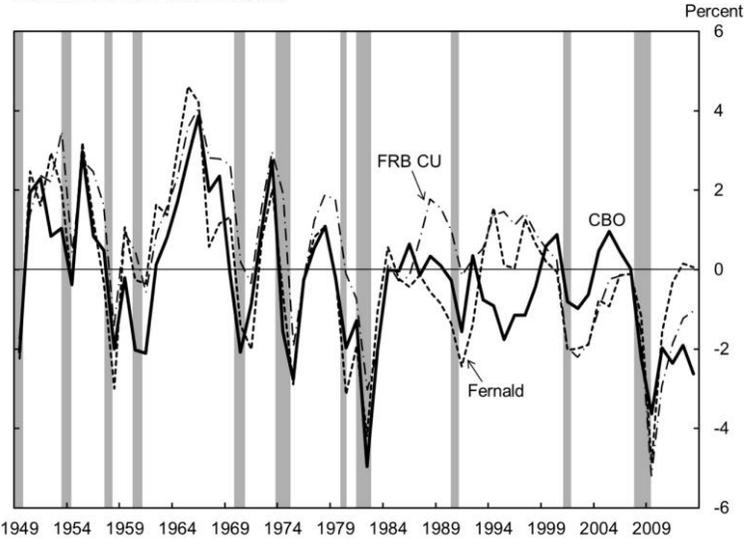
Figure 8, panel A plots this utilization gap, using the 2001–2007 average capital share of 0.34. It also shows the cumulated Fernald utilization series (annual, normalized to match the CBO as of 1987) and the Federal Reserve (FRB) manufacturing capacity-utilization series (relative to its 1981–2007 mean). Over the full sample, the correlation of the CBO and Fernald series is 0.78, which matches the correlation of the CBO and FRB series. The Fernald and FRB series are even more highly correlated (0.82), especially since the early 1990s. The Fernald and FRB measures both suggest a smaller utilization gap in 2012 and 2013 than does the CBO. Indeed, only at the troughs of deep recessions was the CBO gap more negative than in 2013: 2009, 1982, and (barely) 1975.²⁵

The CBO’s (2014a) large utilization gap reflects its assumptions about potential TFP. Figure 8, panel B shows that smooth series along with Fernald TFP and utilization-adjusted TFP.²⁶ The CBO shows faster-trend TFP growth starting in the early to mid-1980s, with no mid-1990s acceleration. There is an upward-level effect early in the twenty-first century, then a smooth path through the end of the sample.

The Great Recession is a particularly striking anomaly, with no evidence of convergence of actual and “potential” TFP. Since the CBO assumes underlying technology is stronger than my estimates imply, they correspondingly need a larger utilization gap to fill in the difference.

Arnold (2009) and CBO (2014b) discuss how the CBO prefers to assume a smooth linear trend for potential TFP (inclusive of LQ) between business-cycle peaks. This peak-to-peak methodology is not particularly model specific, whereas my method depends on a particular model. The disadvantage is that the CBO’s assumed (largely linear) trend is subject to large and ongoing ex post revisions, especially after a new business cycle peak is reached.²⁷ Since 2004, for example, the CBO’s views about TFP growth in the 1990s and early in the twenty-

A. Alternative utilization measures



B. CBO and Fernald estimates of TFP

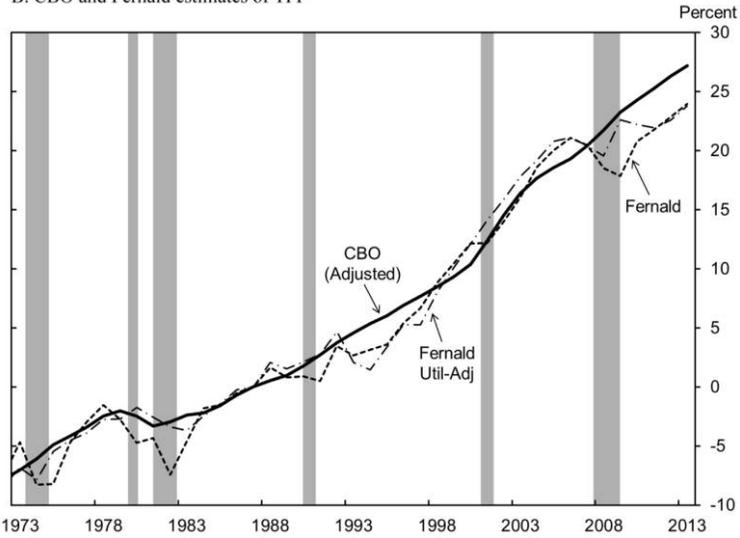


Fig. 8. Comparing factor utilization and TFP

Notes: Panel A: Utilization gaps. The FRB capacity utilization is log deviation from 1981–2007 average, rescaled so standard deviation matches the CBO’s utilization gap. Fernald level of utilization is normalized to match the CBO level in 1987. Panel B: Nonfarm business sector TFP, log deviation from 1987 times 100. The CBO “adjusted” removes trend labor quality and (small) trend differences in capital growth. In panels A and B, Fernald measure has been adjusted from business to nonfarm-business basis.

Source: Fernald (2014), CBO, and author’s calculations.

first century have changed nearly every year. The 2001–2004 bump up in potential TFP growth became much pronounced in the 2009 release, and only in 2014 did the CBO first estimate that TFP growth after 2004 was (modestly) slower than TFP growth in the 1990s. Still, the mid-2000s slowdown in potential TFP growth appears small given the analysis in this paper.

Historically, labor gaps and utilization gaps are strongly positively correlated. Indeed, prior to the Great Recession the correlation of the CBO hours gap with the utilization gap is higher with the Fernald utilization measure (0.70) than with the CBO utilization measure (0.61). The CBO (2014a) estimates that a sizable hours gap remained as of 2013, with $H/H^* = -5.4\%$. Nevertheless, the persistence of the utilization gap, six years after the Great Recession began, is out of line with other evidence that utilization substantially bounced back.

Figure 9 shows the CBO output gap along with two alternatives with different identifying assumptions on utilization. Both continue to use the CBO hours gap. The first uses the Fernald model-based utilization

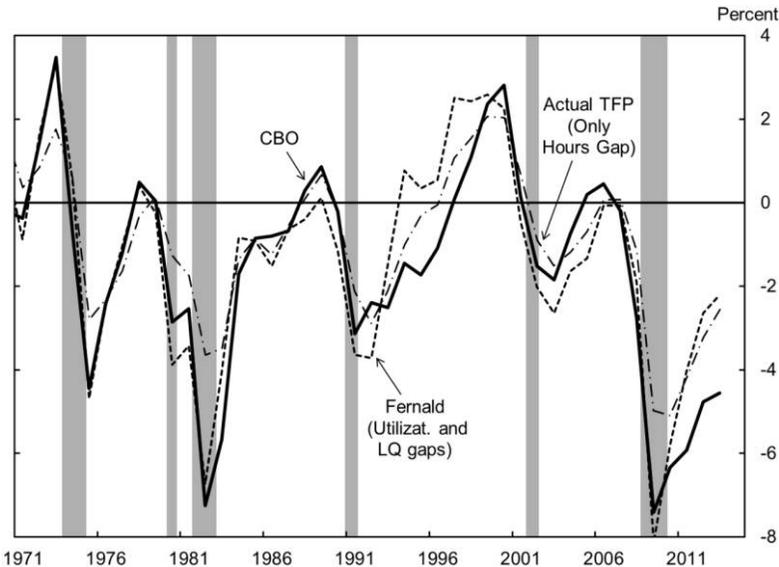


Fig. 9. Output gaps under different assumptions

Notes: “Actual TFP” uses the CBO’s (2014a) hours gap but sets the utilization gap to zero. “Fernald” uses the CBO hours gap, the Fernald utilization gap shown in figure 8, panel A, as well as a (relatively small) estimated labor quality (LQ) gap.

Source: Fernald (2014), CBO, and author’s calculations.

measure, as plotted in figure 8, panel A.²⁸ The second assumes no utilization or LQ gaps by using actual measured TFP. The “output gap” is then simply a rescaled version of the hours gap. Of course, since actual factor utilization is procyclical, this measure of the output gap will not move enough over the cycle and, correspondingly, will imply a measure of potential output that moves too much with actual output. However, once utilization and (labor quality) can safely be assumed to have returned to normal levels, it will correctly measure the gap. Even in this second case, there was a sizable gap at the peak of the Great Recession.²⁹ The reason is that the hours gap is, historically, the main driver of the output gap. In 2013, the hours gap alone contributed 2–2.5% to the output gap.

Because of the hours gap, all three measures of the output gap remain sizable in 2013. But with the Fernald or the actual TFP measures, slack shows up primarily in the people who are *not* working, rather than in the intensity of use of factors that are working. The Bank of England (2014, 6) takes a similar view of the UK economy, where it states: “The Committee judges that there remains spare capacity, concentrated in the labour market.”

The alternatives in figure 9 are illustrative and make strong assumptions. More important than specific numbers is that the analysis suggests being explicit about the sources of output gaps, and it may be more informative to take a stand on utilization gaps than on potential TFP. Even if one assumes an exogenous path for potential TFP, it is worth looking at implied utilization.³⁰

Together, these output-gap assumptions imply the “Actual TFP” and “Fernald” paths of potential shown earlier in figure 2. The annual growth rates are model specific and volatile, but over six years they embody a much lower growth rate of potential because utilization gaps have substantially or completely closed. Either estimate decomposes about three-quarters of the shortfall relative to the 2007 trend into a downgrade of potential, with the remainder an output gap (output below potential). (Of course, the CBO has revised its views about past potential, as well, and now thinks that trend TFP and hours worked were lower in the run up to the recession than they did at the time.)

Could the level of the gap prior to the crisis have been substantially different than shown? The growth-accounting approach in this paper is inherently about growth rates. To benchmark levels, I used the CBO labor gap and set the level of utilization to match the CBO’s utilization gap as of 1987. Given these CBO assumptions, output was close

to potential prior to the Great Recession. If actual output were, in fact, further above potential prior to the crisis, then *today's* output gap would be correspondingly less negative. Still, the 2013 average unemployment rate of 7.4% is well above most natural-rate estimates (the CBO was at 5.9%), consistent with substantial remaining labor-market slack. That constrains how much one can adjust the precrisis period.

Aspects of the US economy were unsustainable in the middle of the first decade of the twenty-first century. The economy produced too many houses and households borrowed too much to finance consumption, but that does not mean that the *level* of output was unsustainable—as opposed to its composition. There is *ex post* misallocation, since construction workers should have produced other things, but they were producing. The excessive consumption in part showed up as imports, not (necessarily) overproducing domestically.

Of course, the potential-output paths in figure 2 are not exogenous, since a cyclical shortfall of investment lowers the capital stock. Lower capital affects potential as well as actual GDP. Once business-cycle dynamics play out, standard models imply that the marginal product of capital will be high relative to steady state, encouraging capital formation. Hence, potential growth will temporarily “overshoot” on its return to steady state (see Hall, chapter 2, this volume).

Even with a smaller gap in 2013, the gap is still large, and it has closed very slowly. In other words, despite the slow growth in potential in the recent period, weak aggregate demand has also been crucial. For example, the housing collapse hit the net worth of households and slowed the housing recovery, government has contracted, and uncertainty has been pervasive (see, e.g., Williams 2013).

My focus has been on TFP, where the Great Recession seems less important than trends related to IT that predated the Great Recession. Nevertheless, there are other channels through which the persistence of a labor gap could persistently lower potential output. These include the possibility that workers lose skills and, potentially, drop out of the labor force permanently. Reifschneider, Wascher, and Wilcox (2013) discuss the implications of this view for monetary policy.

VI. Conclusions

In the quotation that opened this paper, Alan Greenspan in 2000 suggested that the economy was in the midst of a “once-in-a-century acceleration of innovation.” That hope has fallen short. At its peak from

the mid-1990s to early in the twenty-first century, TFP growth was similar to its pace from the 1940s to the early 1970s, but after 2004 the IT-induced burst in TFP growth faded. For three of the past four decades, productivity growth has proceeded relatively slowly, suggesting this slower pace is the benchmark.

Writing near the stock market peak, Greenspan noted, in passing, the possibility of a “euphoric speculative bubble.” With hindsight, the past two decades have seen speculative booms and busts in stock and housing markets, and the worst financial crisis since the Great Depression. It is tempting to point to these factors, including the Great Recession, to explain the swings in productivity growth, but the productivity retreat predated the Great Recession and is not limited to the “bubble sectors,” nor was it more pronounced in states that saw bigger housing price swings (a proxy for indirect effects). Rather, the end of exceptional growth can be traced to industries that produce IT or use IT intensively.

Thus, the easing of productivity growth is the flip side of the productivity bust. For now, the IT revolution is a level effect on measured productivity that showed up for a time as exceptional growth. Going forward, productivity growth similar to its 1973–1995 pace is a reasonable expectation.

The end of exceptional growth implies slower growth in potential output. This fact does not mean that all the economy’s problems in recent years are structural or supply related. After all, output gaps by any measure have closed very slowly despite substantial monetary accommodation. In other words, growth in aggregate demand has also been weak. Slower productivity and population growth also point toward a lower neutral real interest rate, which increases the challenges of providing sufficient monetary stimulus to close gaps.

Uncertainty about any such forecast is inherently high. Jones (2002) argues that twentieth-century US growth depended on rising education and research intensity. That is, maintaining growth required us to pedal ever harder and harder. That is not sustainable in steady state, so his model implies slower long-run growth. But, before we reach that point, there could be another wave of the IT revolution—as Brynjolfsson and McAfee (2014), Baily, Manyika, and Gupta (2013), and Syverson (2013) suggest—or some other unexpected productivity breakthrough. In addition, as Fernald and Jones (2014) suggest, the future growth model might look substantially different from the past—perhaps reflecting the innovative potential of robots and machine learning, or the rise of China, India, and other countries as centers of frontier research. In that

case, the results in this paper could reflect an extended pause, a return to normal before the next wave of transformative growth.

The 2000s slowdown has a parallel with the earlier slowdown of the 1970s. The massive oil price shocks around the same time made them an obvious suspect. Theoretical models had difficulty generating persistent productivity-growth effects from oil and, when oil prices retraced their increases in the mid-1980s, productivity growth did not recover. Similarly, the Great Recession is a suspect for the productivity slowdown in the 2000s, but my analysis exonerates it.

More broadly, it is the *exceptional* growth that appears unusual—prior to 1973, or from 1995 to 2004. Historians of technology (e.g., David and Wright 2003; Field 2003; Gordon 2000) argue that a broad wave of technological breakthroughs led to a surge in productivity growth after World War I that finally played out around the 1970s. For example, Gordon (2000) highlights (a) electricity; (b) the internal combustion engine; (c) “rearranging molecules” (petrochemicals, plastics, and pharmaceuticals); and (d) entertainment, information, and communication (e.g., telephone, radio, movies, TV). Fernald (1999) and Field (2007) point to one-time gains from infrastructure: building the Interstate Highway System was extraordinarily productive; building a second one would not be. The GPT literature suggests that these constellations, like IT, promoted a wide range of complementary innovations that propelled exceptional growth for a time, but not forever.

Appendix

Data

An online appendix provides greater detail and discussion of the data, which are described briefly here.

Quarterly Growth-Accounting Data (Fernald 2014). Data run 1947:Q2–2014:Q1. The vintage used for this paper was from May 7, 2014. Current vintage data are available at http://frbsf.org/economics/economists/jferald/quarterly_tfp.xls. The data set includes quarterly growth-accounting measures for the business sector including output, hours worked, labor quality (or composition), capital input, and total factor productivity. Output is a geometric average from the income and expenditures sides. Factor utilization follows Basu, Fernald, and Kimball (2006) and Basu et al. (2013).

BLS Industry Data. Appendix table 1 provides a list of industries and subgroups.

Table A1
BLS Industries and Definitions of Subgroups Used in the Paper

	NAICX	IT-Prod. (1)	Bus., Excl. Nat. Res., Con., FIRE (2)	IT-In. (in [2]) (3)	Not-IT- Int. (in [202]) (4)	Fin-Int. (in [2]) (5)	Not Fin- Int. (in [22])0 (6)	Well (in [2]) (7)	Poor (in [2]) (8)
1	Manufacturing								
2	Nondurable goods								
3	Food, beverage, and tobacco product manufacturing		X		X		X	X	
4	Textile and textile product mills		X		X		X	X	
5	Apparel, leather, and allied product manufacturing		X		X		X	X	
6	Paper manufacturing		X		X		X	X	
7	Printing and related support activities		X		X		X	X	
8	Petroleum and coal products manufacturing		X	X			X	X	
9	Chemical manufacturing		X	X			X	X	
10	Plastics and rubber products manufacturing		X		X		X	X	
11	Durable goods								
12	Wood product manufacturing		X		X		X	X	
13	Nonmetallic mineral product manufacturing		X		X		X	X	
14	Primary metal manufacturing		X		X		X	X	
15	Fabricated metal product manufacturing		X		X		X	X	
16	Machinery manufacturing		X		X		X	X	
17	Computer and electronic product manufacturing	X	X	X			X	X	
18	Electrical equipment, appliance, and component manufacturing		X		X		X	X	
19	Transportation equipment manufacturing		X		X		X	X	
20	Furniture and related product manufacturing		X		X		X	X	
21	Miscellaneous manufacturing		X		X		X	X	
22	Agriculture, forestry, fishing, and hunting		X	X			X	X	
	11								

(continued)

Table A1

Continued

	NAICX	IT-Prod. (1)	Bus., Excl. Nat. Res., Con., FIRE (2)	IT-In. (in [2]) (3)	Not-IT- Int. (in [202]) (4)	Fin-Int. (in [2]) (5)	Not Fin- Int. (in [22])0 (6)	Well (in [2]) (7)	Poor (in [2]) (8)
23	Farms								
24	Forestry, fishing, hunting, and related activities	111,112							
25	Mining	113-115							
26	Oil and gas extraction	21							
27	Mining, except oil and gas	211							
28	Support activities for mining	212							
29	Utilities	213	X	X			X		
30	Construction	22							
31	Trade	23							
32	Wholesale trade	42,44-45							
33	Retail trade	42	X	X	X	X	X	X	
34	Transportation and warehousing	44, 45	X		X	X	X	X	
35	Air transportation	48-49							
36	Rail transportation	481	X	X	X	X	X	X	
37	Water transportation	482	X	X	X	X	X	X	
38	Truck transportation	483	X	X	X	X	X	X	
39	Transit and ground passenger transportation	484	X	X	X	X	X	X	
40	Pipeline transportation	485	X	X	X	X	X	X	
41	Other transportation and support activities	486	X	X	X	X	X	X	
42	Warehousing and storage	487, 488, 492	X	X	X	X	X	X	
43	Information	493	X	X	X	X	X	X	
44	Publishing (incl. software)	51							
45	Motion picture and sound recording industries	511,516	X	X			X		X
		512	X						

Multifactor productivity (MFP) and IT capital data were downloaded from <http://bls.gov/mfp/mprdownload.htm> (accessed January 16, 2014). IT intensity is based on factor shares, that is, payments for IT as a share of income. “IT intensive” is the set of industries with the highest IT shares that constitute 50% of the value-added weight (averaged 1987–2011) for the non-IT-producing “narrow business” (i.e., excluding natural resources, construction, FIRE, and IT producing) economy. “Well-measured” industries follow Griliches (1994) and Nordhaus (2002). To focus on the “nonbubble” sectors, I exclude (well-measured) agriculture and mining and (poorly measured) construction and FIRE. I also exclude IT-producing industries. For finance intensity, I aggregated industries from annual BLS I-O tables (accessed January 14, 2014) at http://bls.gov/emp/ep_data_input_output_matrix.htm. The finance share was nominal purchases of intermediate financial services as a share of industry gross output. “Finance intensive” is a set of narrow-business industries with the highest shares that constitute 50% of the value-added weight of narrow business excluding IT production.

State productivity and other data. BEA GDP by industry and total full-time and part-time employment by industry were downloaded (February 24, 2014) from <https://bea.gov/regional>. Chain addition and subtraction were used to construct subgroup aggregates to correspond with the BLS industry groupings. State home prices are from Core Logic and housing elasticity measures are from Saiz (2010). Metropolitan-area elasticities were aggregated to a state level using population weights. (I thank John Krainer and Fred Furlong for providing me with these data.) For exploratory regressions, Liz Laderman provided me with BDS data on small job births per capita by state.

CBO data. CBO (2014a) projections for GDP and for (nonfarm) business GDP were accessed via Haver Analytics in February 2014. The nonfarm-business labor gap compares unpublished BLS data on hours worked in nonfarm business relative to the CBO’s published potential nonfarm business hours. The unpublished BLS productivity-and-cost hours data match the published index values perfectly.³¹

Endnotes

Contact the author at Research Department, Federal Reserve Bank of San Francisco, 101 Market St., San Francisco, CA 94105, or at John.Fernald@sf.frb.org. This is a substantially revised and updated version of a paper that first circulated in 2012. I thank Erik Brynjolfsson, Susanto Basu, Mary Daly, Charles Fleischman, Fred Furlong, Robert Gordon, Bob Hall, Bart Hobijn, Chad Jones, Óscar Jordà, Liz Laderman, Zheng Liu, Steve Oliner, Nick Oulton, Jonathan Parker, Bob Shackleton, Dan Sichel, John Williams, and Dan Wilson for helpful comments and conversations. I also thank seminar participants at several

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1. The appendix discusses data sources for the figure and the rest of the paper. Section II.B defines and discusses the growth-accounting decomposition.

2. Reifschneider et al. (2013) and Hall (chapter 2, this volume) discuss this channel.

3. As discussed in the data appendix, "output" combines expenditure- and income-side data, so labor productivity differs slightly from the BLS productivity and cost release (which uses expenditure-side data). See Nalewaik (2010) for a discussion of the merits of income versus expenditure.

4. As in Fernald (2007), I test whether mean growth (the drift term for a random walk) has breaks. Estimated break dates differ slightly for (real) income- and expenditure-side estimates of labor productivity, but significance levels are similar. For the expenditure side, the point estimate for the speedup is 1997:Q2; for the income side, it is 1995:Q3. I stuck with the traditional 1995:Q4 date. For the slowdown, with expenditure the estimated date is 2003:Q4, shown in the figure; with income, it is 2006:Q1. For utilization-adjusted TFP, described in the next section, it is 2005:Q1. Despite uncertainty on exact dates, it clearly predates the Great Recession. In terms of statistical significance, looking at, say, expenditure-side labor productivity from 1973:Q2 through 2013:Q4, the Bai-Perron WDMax test of the null of no breaks against an alternative of an unknown number of breaks rejects the null at the 2.5% level. The UDMax version of the same test rejects the null at the 5% level. The highest significance level is for the null of no breaks against the alternative of two breaks, which is significant at the 5% level. In the full sample from 1947:Q1 on, there appears to be an additional break at 1973:Q2, as expected.

5. See Basu and Fernald (2002) for discussion and references. They also discuss how to interpret measured TFP when constant returns and perfect competition do not apply and an aggregate production function does not exist.

6. The UDMax and WDMax tests for the null of no breaks against the null of an unknown number of breaks in utilization-adjusted TFP is significant at about the 5% level.

7. Galí, Smets, and Wouters (2012) focus on the recovery and, as I do, argue that, following the Great Recession, productivity performance was in line with historical experience. That is, they argue that during the recovery, the problem was slow output growth, not unusual productivity growth. Daly et al. (2013a) discuss the cyclical behavior of labor productivity and TFP (and the degree to which it has changed) using the same data as here. In 2007 and 2008, a few commentators noted that productivity might be slowing (e.g., Fernald, Thipphavong, and Trehan 2007; Jorgenson, Ho, and Stiroh 2008). With hindsight, the prerecession origins are now clear. Before and during the Great Recession, real-time data obscured the slowdown in trend and overstated productivity's strength early in the recession. Almost every revision since 2005 has lowered the path of labor productivity, with most revision to output (the numerator). Until the 2010 revision, productivity appeared to have risen sharply and steadily throughout the recession. Daly et al. (2014) discuss how data revisions helped resolve apparent deviations from Okun's Law.

8. Detrending does not affect conclusions. Following a Jim Stock recommendation, I removed local trends with a bi-weight kernel with bandwidth 48 quarters. The local means for both output and labor productivity growth decline from about 2.25% in 2007:Q4 to under 2% by 2013:Q4.

9. Basu and Fernald (2009) discuss additional channels. Reifschneider et al. (2013) discuss a broader range of possible supply-side effects from recessions, including on labor markets.

10. See Jorgenson et al. (2008), Byrne et al. (2013), and Pillai (2013) for references.

11. See Doms (2004) and Foster, Haltiwanger, and Krizan (2006). Fernald and Ramnath (2003) provide a brief case study of how Walmart used IT to raise productivity.

12. See, for example, Greenwood and Yorokoglu (1997), Brynjolfsson and Hitt (2000), Basu et al. (2003), and Brynjolfsson and McAfee (2014).

13. The online appendix discusses the Basu et al. (2003) model in more detail. In my quarterly TFP data set, IT capital (information processing and software) grew 16%/year from 1995:Q3 to 2000:Q4, but only 8%/year from 2000:Q4 to 2004:Q4. (The IT capital share of total income actually edged up slightly, but remained between 6 and 7% throughout.)

Corrado, Hulten, and Sichel (2009) discuss broader measures of intangible investment and ways to measure them. Van Reenen et al. (2010) report substantial evidence for the IT-linked intangibles story in microdata.

14. An exception is high-tech industries, where Haltiwanger, Hathaway, and Miranda (2014) report high dynamism in the late 1990s tech boom but, as the industry has matured, job and firm turnover has eased.

15. Value-added is like a partial Solow residual, controlling for share-weighted intermediate inputs. Apart from small approximation error, value-added-weighted growth in industry value-added TFP is equivalent to Domar-weighted growth in gross-output TFP. Conceptually, this bottom-up approach differs from top-down TFP measurement because of input-reallocation terms. Jorgenson et al. (2013) find these terms are, on average, small.

16. In discussing this paper, John Haltiwanger questioned the reliability of the industry capital-flow table that underlies the BLS estimates of industry IT intensity. It is based largely on occupational employment, and so may be more directly related to IT *workers* than IT capital. Importantly, the link to IT remains, as emphasized here.

17. In regressions not shown, I confirm that across states, changes in start-up activity are, indeed, associated with (instrumented) changes in home equity. In some specifications, start-up activity is associated modestly with state labor-productivity growth, though the explanatory power was always low. The state data are probably too coarse to provide substantial evidence on this channel.

18. I do not remove the mean before standardizing by the cross-sectional standard deviation, so that the constant term is *net* of the contribution of the mean change in house prices over the period.

19. See the online appendix. Because land and labor grow at the same rate, equation (6) omits an “excess” land-growth term: $\alpha^t \cdot (\hat{T}^* - \hat{H}^* - LQ^*) / (1 - \alpha^t)$, where \hat{T}^* is land (Terra), and $\alpha^t = \alpha c_t$ is the share of land in total cost. That term adds two basis points over the entire sample period and zero basis points from 1995 through 2007.

20. The appendix discusses the general properties of this model and discusses its fit. In the empirical implementation, I add inventories as a durable output, which effectively increases the equipment weight, c_E . The model abstracts from potentially important issues. First, production functions and the capital aggregate are equal across sectors, but actual sectoral factor shares are not (see Basu et al. 2013). Second, all functions are taken to be Cobb-Douglas. These first two assumptions simplify steady-state calculations, which are best interpreted as a local approximation when shares do not change too much. Third, the model assumes a closed economy. If, say, the ability to import computer components reduces the relative price of computers, the model interprets the lower price as faster relative TFP. The lower relative price, in the closed-economy model or in a comparable open-economy model, encourages capital deepening. Hence, for the incentives to purchase computers, the closed-economy assumption seems fine. Fourth, recent literature, some discussed in Section III.A, focuses on intangible capital. Conceptually, this is an additional capital good that the economy produces and uses, where we do not observe the investment or the stock of intangibles. At different times, the investment versus service flow effect may dominate measurement. Corrado and Hulten (2014) find that, over the 1980–2011 period, accounting for intangibles makes only a few basis points of difference to “adjusted” GDP per hour, though the split between capital deepening and TFP is affected. Finally, Hobijn and McKay (2007) question whether relative investment prices reflect relative technologies. Despite these caveats, the online appendix shows that the model fits historical experience well.

21. Numbers are reported in the minutes at <http://federalreserve.gov/monetarypolicy/fomcalendars.htm>. Projection data are presented in bins. I have rounded the “2.4 to 2.5%” bin to 2.5%. Estimates are for total GDP; it is not possible to decompose FOMC projections into productivity versus demographics.

22. See Basu and Fernald (2009) or Kiley (2013) for an extended discussion and references.

23. The correlation of the gap from equation (9) with the actual CBO GDP gap is 0.998. The CBO (2014b) discusses some of their underlying assumptions. As shorthand below, I refer to “nonfarm business” as “business.”

24. Kiley (2013) uses this decomposition (apart from labor quality) to derive a “CBO gap” in the EDO DSGE model. Note also that any cyclical deviations from “potential TFP” regardless of source, is labeled as utilization.

25. The FRB capacity utilization has a downward trend prior to the Great Recession, which is not accounted for here. The labor-quality gap—which is included with the CBO gap but not with the others—makes the CBO measure even more out of line. The reason is that the LQ gap tends to *rise* in recessions (when utilization is low), since lower-educated workers disproportionately lose jobs.

26. The CBO measure has been adjusted for trend labor quality and for differences between the CBO and Fernald measures of capital’s growth contribution, which makes the measures more conceptually similar. These adjustments add little volatility to the CBO estimates. The Fernald series in the figure has been converted to a nonfarm business basis using the gap between the BLS estimates of business and nonfarm business MFP.

27. The CBO (2014b, 5) says: “Particularly significant changes in CBO’s estimates of potential output can occur after the economy reaches a new business cycle peak, an event that usually leads CBO to change the period over which it estimates . . . trends.” Arnold notes that the CBO may wait for years to implement all revisions to the historical path.

28. It is also necessary to take a stand on the labor-quality gap in equation (12). I use a bi-weight kernel with bandwidth of 10 years to estimate “trend” labor-quality growth. That estimate implies relatively fast-trend labor-quality growth in the Great Recession (around 0.4% per year). Actual labor quality rose even faster, as low-skilled workers disproportionately lost jobs, opening up a labor-quality gap during and following the Great Recession that peaks at about a 1 percentage point (positive) contribution to the overall output gap.

29. For comparison, the Federal Reserve’s FRB/US model has a gap of 2.8% in 2013, fairly close to the Fernald measure. (Those estimates, based on the Fleischman and Roberts [2011] state-space model, are at <http://federalreserve.gov/econresdata/frbus/us-models-package.htm>; accessed April 4, 2014).

30. Note that the two alternatives in figure 9 are robust to measurement error in growth in capital or in underlying technology—neither of which appears in the “output gap” ratio (12). In contrast, assuming an exogenous technology process is sensitive to mismeasurement of capital or technology. For example, suppose capital was scrapped at unusual rates during the Great Recession, because the economy had too many backhoes. Growth in true capacity would be lower than measured and potential would be overestimated. Since actual TFP will be low, the observer would incorrectly infer (from equation [13]) that utilization was low. Of course, firms might instead have deferred scrapping of old but still serviceable capital.

31. I thank Bob Arnold at the CBO and John Glaser at the BLS for help in understanding the data.

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