Productivity and Potential Output Before, During, and After the Great Recession

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Abstract

U.S. labor and total-factor productivity growth slowed several years prior to the Great Recession. The timing rules out stories related to disruptions from the Great Recession, and industry and state data rule out "bubble economy" stories related to housing or finance. In industry and state data, the slowdown is especially pronounced for industries that use information technology (IT) intensively as well as for IT producers. These results are consistent with a return to more normal productivity growth after nearly a decade of extraordinary gains associated with IT. A calibrated growth model suggests trend productivity growth is similar to its 1973-1995 trend. Slower underlying productivity growth also has implications for current assessments of economic slack. As of 2013, two alternatives to the benchmark CBO measure imply lower potential output and smaller output gaps. About ¾ of the shortfall of actual output from (overly optimistic) pre-recession estimates of trend reflects a reduction in the level of potential.

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1. 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.
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> 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….The reasons for weak productivity growth are not entirely clear…It may be a result of the severity of the financial crisis...[or] reflect longer-term trends…
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> Federal Reserve Chairman Ben Bernanke (2014).

In 2000, productivity growth was robust and strong. By 2014, it was not. This paper argues that the slowdown in labor and total-factor-productivity (TFP) growth predated the Great Recession. It marked a retreat from the exceptional, but temporary, information-technology (IT)-fueled pace from the mid-1990s to the early 2000s. This retreat implies slower output growth in the medium run as well as a narrower output gap than currently estimated by the Congressional Budget Office (CBO, 2014a) for the recent past.

The early- to mid-2000s retreat from exceptional productivity growth is apparent in aggregate, industry, and state data. Industry and state data show that the slowdown is particularly pronounced in sectors that produce information technology (IT) or that use IT intensively. In contrast, sectors that were obviously unusual ("euphoric," even, in Chairman Greenspan's phrasing) in the mid-2000s—namely, construction, finance, and natural resources—were not the source of the slowdown.

Figure 1 illustrates a key takeaway from this paper, namely, that labor productivity and TFP slowed prior to the Great Recession, ending the spike that began in the mid-1990s. The 1990s surge in labor productivity growth, shown by the height of the bars, came after several decades of slower growth. However, in the decade that ended in 2013:Q4, growth has been close to its 1973-95 pace. The decade is broken into the four years prior to the onset of the Great Recession and the six years since. Growth in labor productivity and TFP have been similar over these sub-periods, and only modestly faster than the 1973-95 period.[1] Hence, three out of the past four decades have shown this slower pace of growth—suggesting this is the normal pace, not the exceptional 1995-2003 pace.

That the slowdown predated the Great Recession largely rules out causal stories from the recession itself. Previous theoretical and empirical literature (discussed in Section 2.4) provides only limited support for the view that the Great Recession itself should have subsequently changed the underlying path of TFP. And Figure 1 suggests no evidence that productivity was slower (or much faster) from 2007-2013 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—i.e., 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 is simply the flip side of the speedup in the mid-1990s. Considerable evidence, discussed in Section 3.1, ties that speedup to the exceptional contribution of information technology— computers, communications equipment, software, and the Internet. IT appeared to have a broad-based and pervasive effect on measured total factor productivity (TFP) through its role as a general purpose technology (GPT) that fostered complementary innovations, such as business reorganization. The GPT story is essentially one of a drawn-out level effect on measured productivity. Ex ante, the question was simply how large the ultimate effect would be.

Industry TFP data provide evidence on the IT hypothesis versus alternatives. One is that the slowdown is explained by housing, finance, and natural resources. These sectors behaved anomalously in the mid-2000s, and their productivity did slow. But the remaining ¾ of the economy slowed even more. So those "bubble sectors" do not explain the slowdown. In the broader economy, the slowdown is particularly pronounced in IT-producing sectors and sectors that intensively use IT, supporting the IT story.

State data on GDP per worker provide evidence on indirect channels through which the housing bubble and bust might matter. States differ in the magnitude of house-price movements (both up and down), which could influence innovation through net-worth channels. But there turns out to be limited evidence that such factors contribute in an important way to the dynamics of the productivity slowdown. Rather, it is the common cross-state slowdown in IT-intensive industries that predominates.

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[1] Then Appendix discusses data sources for the figure and the rest of the paper. Section 2.2 defines and discusses the growth-accounting decomposition.

I then turn to two implications of the mid-2000s productivity slowdown. The first involves longer-run growth. With reasonable estimates of underlying technology trends, a multi-sector neoclassical growth model implies steady-state business-sector labor-productivity growth of about 1.9 percent, as shown at the far right of Figure 1. Prior to the Great Recession, typical estimates were notably higher (see Jorgenson, et al., 2008). Incorporating demographic estimates from the Congressional Budget Office (2014a), my benchmark estimate for productivity performance implies longer-term growth in GDP about 2.1 percent.

A second implication is that, by 2013, the output gap, defined as the difference between actual and a production-function measure of potential output, is narrower than estimated by CBO (2014a).[2] I decompose CBO's gap into a "utilization gap" that reflects cyclical mismeasurement of TFP as well as an "hours gap." 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, Fernald, Fisher, and Kimball, BFFK, 2013) suggest that the utilization gap was small.

Figure 2 shows two alternative estimates of the path of potential output, based on alternative estimates of the utilization gap but using the CBO labor gap. One uses actual TFP, which imposes that the utilization gap is always zero. When utilization eventually returns to normal—as it plausibly did prior to 2013—this measure is appropriate. The second, labeled 'Fernald,' uses my estimated utilization measure. By 2013, the two alternatives are similar, and lie well below the CBO (2014a) which, in turn, is notably lower than the pre-recession CBO trend.

Relative to my measure, the CBO incorporates a much smoother underlying path of TFP. In contrast to the evidence in this paper, they have no mid-1990s pickup in productivity and much less of a mid-2000s slowdown. In addition to these low frequency shifts, empirical estimates imply a much more variable rate of (random walk) technological progress from year-to-year. My estimates of long-run trends going forward are not much different than the CBO's, but my analysis of the recent period differs noticeably, in that I have a much less persistent utilization gap. In my own estimates, about ¾ of the 2013 shortfall of actual output from the pre-crisis trend reflects a decline in potential output.

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[2] Section 5.1 discusses alternative definitions of potential output and output gaps.

Of course, production-function measures of potential output inherently have an important cyclical element because capacity growth has a cyclical element. Slow growth in the recovery (with slow closing of output gaps) has contributed to cyclically weak investment. Capital input in recent years grew at the slowest pace since World War II. This slow growth in capital does not directly affect output gaps—since, in the CBO definition (as well as the usual DSGE definition), it affects both actual and potential output. But it does imply slower recent growth in the full-employment level of output. Capacity should rebound (raising potential growth above its steady-state rate) as the economy returns towards its steady-state path.[3]

Section 2 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 3 assesses explanations for the productivity slowdown, using industry data and (maybe) regional data. Section 4 uses a multi-sector growth model to project medium- to long-run potential output growth. Section 5 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.

2. Productivity Growth before the Great Recession

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

2.1. The mid-2000s Slowdown in Labor Productivity Growth

Figure 3 shows the log-level of labor productivity for the business sector.[4] The speedup in growth during the mid-1990s is clear. Considerable literature discussed in Section 3.1.1 links that speedup to information technology (IT). The slowdown in the early to mid-2000s is also clear.

Figure 3 rationalizes the subsamples shown above in Figure 1. The mid-1990s acceleration in labor productivity ended in the early- to mid-2000s. The dates of the vertical bars are suggested by Bai-Perron test for multiple structural change in mean growth rates for the period since 1973. For the new regimes, I have

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[3] Reifschneider, Wascher, and Wilcox (2013) and Hall (2014) discuss this channel.

[4] 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).

shown the "traditional" new-economy 1995:Q4 start date along with a slowdown date of 2003:Q4. The breaks are statistically significant.[5]

The Bai-Perron results that show a slowdown in the early to mid-2000s are reinforced by the findings of Kahn and Rich (2011, 2013). They estimate a regime-switching model, using data on labor productivity, labor compensation, and consumption. They find that the 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.

2.2. 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:

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

A is technology. K and L are observed capital and labor input. W is the workweek of capital and E is effort—i.e., unobserved variation in the utilization of capital and labor. K_i is input of a particular type of capital—computers, say, or office buildings. Similarly, H_i is hours of work by a particular type of worker, differentiated by skills, education, age, and so forth. Time subscripts are omitted for notational simplicity.

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

[5] 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 the significance levels are not much different. For the usual expenditure-side measure, the point estimate for the speedup is 1997:Q2; for the income side, it is 1995:Q3. I stuck with the traditional 1995:Q4 dating in the literature. Turning to the slowdown, with expenditure the estimated date is 2003:Q4, as shown in the figure; with income, it is 2006:Q1. For utilization-adjusted TFP, described in the next section, it is 2005:Q1. Because most people focus on expenditure-side labor productivity, I have taken 2003:Q4 as the slowdown date. Despite uncertainty on exact dates, it clearly predates the Great Recession. In terms of statistical significance, looking at 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 2-1/2 percent level. The UDmax version of the same test rejects the null at the 5 percent level. The highest significance level is for the null of no breaks against the alternative of 2 breaks, which is significant at the 5 percent level. In the full sample from 1947:Q1 on, there appears to be an additional break at 1973:Q2, as expected.

elasticity for a given type of capital, say, is αc_i^K . Differentiating logarithmically (where hats are log-changes), imposing the first-order conditions, and omitting time subscripts 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: :

$$\begin{aligned}&\hat{K} \equiv c_1^K \widehat{K_1} + c_2^K \widehat{K_2} + ..., \\ &\hat{L} \equiv c_1^L \hat{H}_1 + c_2^L \hat{H}_2 + ... \\ &\hat{H} \equiv \hat{H}_1 + \hat{H}_2 + ... \\ &\widehat{LQ} \equiv \hat{L} - \hat{H} \\ &\widehat{Util} \equiv \alpha\hat{W} + (1-\alpha)\hat{E}\end{aligned} \tag{3}$$

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 classified by observable characteristics such as age and education, which assumes relative wages reflect relative marginal products. Total hours growth, $\hat{H}$, is the simple sum of hours worked by all types of labor. Labor quality growth, $\widehat{LQ}$, tells how much changing worker characteristics contribute to labor services growth beyond raw hours. Finally, $\widehat{Util}$ represents variations in capital's workweek and labor effort.

TFP growth, or the Solow residual, is output growth not explained by growth in observed inputs:

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

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

A large literature discusses why short-term fluctuations in measured TFP might reflect factors other than technology.[6] Over the business cycle, a key reason, is unobserved variations in the intensity with which factors are used, $\widehat{Util}$. Basu, Fernald, and Kimball (BFK, 2006) and Basu, Fernald, Fisher, and Kimball

[6] 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.

(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 (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 speaking, labor productivity rises if workers have more capital; if their quality improves; or if innovation raises technology. In the short run, cyclical variations in utilization also matter.

2.3. Aggregate Data and Growth-Accounting Results

Slower growth in both TFP and capital deepening led to the mid-2000s labor productivity slowdown.

Figure 4 shows components of equation (5) using the quarterly growth-accounting dataset 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 BFFK (2013) to quarterly data. BFFK and BFK consider a more general framework than in Section I.B to allow for non-constant returns, imperfect competition, and cyclical reallocation effects. Because of the limitations of quarterly data, however, the measure used here controls only for utilization.

The figure shows that both TFP and capital deepening contributed to the mid-2000s slowdown in labor productivity growth. Panel A shows TFP and utilization-adjusted TFP. The eye clearly identifies the pre-Great-Recession slowdown, and a Bai-Perron test confirms its significance for utilization-adjusted TFP.[7] Panel B shows capital-deepening, $K/(H \cdot LQ)$. In the early 2000s, capital deepening growth slowed. Panel C shows labor quality, which 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 pre-recesssion peaks. (A caveat, of course, is that there's a potential end-point problem because the underlying data on industry hours per worker need to be detrended.)

By mid-2012, labor productivity (Figure 3) or TFP (Figure 4A) appear to lie more or less on the slow trend line from the mid-2000s.

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[7] 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 percent level.

2.4. Productivity Growth during the Great Recession

That the slowdown predated the Great Recession suggests it was not a result of the recession itself. In 2007 and 2008, a few commentators noted that productivity might be slowing (e.g., Fernald, Thipphavong, and Trehan, 2007, and Jorgenson, Ho, and Stiroh, 2008). But productivity is volatile, even over three or four years. With hindsight, the pre-recession origins are now clearer.

Of course, if productivity during the Great Recession were particularly unusual, that might suggest a need to reconsider whether the recession contributed substantially to the slowdown. 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. In fact, much of the informal commentary during the Great Recession, argued something quite different—that labor productivity, at least, seemed unusually strong (e.g., Daly and Hobijn, 2010). This section takes the middle ground that during and immediately after the Great Recession, productivity behaved similarly to previous deep recessions: TFP and utilization fell very sharply, but recovered strongly once the recession ended.[8]

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 a local trend from all data.[9]

Panel A shows 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 (late in 2008:Q3), output and employment fell precipitously. The trough in detrended output is about as deep as previous deep recessions (i.e., at the bottom of the shaded range) but is reached later. (In unfiltered data, the decline is deeper than previous

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[8] Gali, 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 dataset as here.

[9] Conclusions are not affected by the detrending. Following a Jim Stock recommendation, I removed local trends using a biweight kernel with bandwidth 48 quarters. An HP filter does more violence to the data, but is similar though choppier. The local means for both output and labor productivity growth decline from about 2-1/4 percent in 2007:Q4 to under 2 percent by 2013:Q4. The local mean for TFP growth declines from 1.0 percent to 0.9 percent.

recessions. But trend output growth was about 3-1/2 percent during the 1973-75 recession, compared with 2 to 2-1/4 percent in 2007-2009). Hours fell well outside historical experience.

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. That relative strength is consistent with informal commentary.

But of course, labor productivity includes endogenous capital-deepening and labor quality, both of which were very strong during the recession (see Figure 4B and C). Controlling for those, Panel D shows that TFP was right at the bottom of historical experience. TFP plunged about 5 percent 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. Based on observed hours per worker, it shows that the intensity of factor use fell sharply during the recession. This measure of utilization falls below the range of historical experience. Utilization then recovered rapidly during the recovery. These estimates suggest that firms made very substantial use of the intensive as well as extensive margin.

Finally, Panel F shows utilization-adjusted TFP, which is TFP less utilization. That series bounces around in the middle of historical experience, with a spike from quarter 4 (2008:Q4) to quarter 6 (2009:Q2). Petrosky-Nadeau (2013) argues that it could reflect a temporary breakdown in financial intermediation, if the least productive firms lost financing. It could also be "panic and normalization." Panicked firms during the Great Recession could have cut workers exceptionally fast and found new, if temporary, efficiency gains; if those gains were unsustainable, it could have reversed as the economy began growing. Lazear, Shaw, and Stanton (2013) focus on fear-induced effort on the part of workers. Specifically, they 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 that their task-level data are separate from "usual" labor-and capital-hoarding effects. Task-level productivity began to rise as soon as the Great Recession began and rose faster in areas where unemployment rose more quickly. When the Great Recession ended, task-level productivity declined (even though unemployment was still high), much like utilization-adjusted TFP.

The counterfactual is unknown, and some recession effects might show up as random-walk level shocks, even if the growth path were largely unaffected. Still, the figures do not obviously suggest a major influence of the Great Recession on underlying TFP growth, consistent with the earlier Figure 1.

Theory is ambiguous about the effects of severe recessions (including financial ones) on the longer run path of TFP (utilization-adjusted or otherwise), but the cross-country evidence is not strong. 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. Liu and Wang (2013) model how a financial accelerator could lead to procyclical reallocation and procyclical productivity. That said, the reallocation effect in some models goes the other way, raising measured aggregate TFP in response to a credit crisis (e.g., Petrosky-Nadeu, 2013, or the "cleansing effects" of Caballero and Hammour, 1994). And Bloom (2013) points out that high uncertainty can stimulate longer-run innovation.[10]

Overall, the empirical evidence for *developed* countries that business cycles (whether financially related or otherwise) permanently harm the level or growth rate of TFP is weak. The Great Depression appears to have been 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 (2014) focus on financial crises, and break out growth-accounting variables. 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.

As a final observation on the Great Recession, real-time data obscured the slowdown in trend, and overstated productivity's strength early in the recession. Figure 6 shows labor productivity by vintage. The dates correspond to the annual (or, in 2009 and 2013, comprehensive) NIPA revisions; these revisions incorporate additional source data for previous years. Almost every revision since 2005 has lowered the path of labor productivity, with most revision to output (the numerator). These revisions made the slowdown more apparent. Real-time data also overstated the strength of labor productivity growth early in the recession. Until the 2010 revision, productivity appeared to have risen sharply and steadily throughout the recession. The sizeable downward revisions suggest some of the challenges of doing analysis in real time.[11]

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[10] Basu and Fernald (2009) discuss additional channels. Reifschneider, Wascher, and Wilcox (2013) discuss a broader range of possible supply-side effects from recessions, including on labor markets.

[11] Daly et al (2014) discuss how data revisions helped resolve apparent deviations from Okun's Law.

3. Why Did TFP Growth Productivity 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).

3.1. 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.

3.1.1. Waning of the IT-induced surge

Below, I find evidence that the slowdown in the mid-2000s is the flip side of the IT-induced surge in the mid-1990s. Under this hypothesis, the general-purpose-technology (GPT) benefits of IT raised the measured level of TFP, which showed up for almost a decade as faster growth. Ex ante, it was hard to know how long the transition would last, but the low-hanging fruit may have been plucked by the mid-2000s. For example, once you do a fundamental reorganization of retail, the gains become more incremental.[12]

Studies with aggregate, industry, and plant data link the mid-1990s surge in U.S. productivity to the direct and indirect effects of IT. As Jorgenson, Ho, and Stiroh (JHS, 2008) and others emphasized, technological progress in producing a capital good like IT has two direct effects on <u>labor</u> productivity. First, if the IT goods are domestically produced, it boosts TFP growth. Second, a falling user cost induces greater capital-deepening by IT users. But empirically, measured TFP growth increased broadly—in IT-using, as well as IT-producing, sectors (see, e.g., Basu, Fernald, Oulton, and Srinivasan, BFOS, 2003 and JHS).

GPT stories explain the broad effects. There could be some pure spillovers of knowledge across firms. But firms also invest in intangible organizational capital to benefit from faster information processing.[13] The story is essentially about measurement: Intangible investment and capital aren't observed. BFOS map GPT stories to conventional growth accounting (see appendix XX), with observed IT capital proxying for unobserved intangible capital. The model proxy, $s_{K^{ICT}} \Delta k_t^{ICT}$, involves both the weight ($s_{K^{ICT}}$,

[12] Foster, Haltiwanger, and Krizan (2006) discuss the reorganization of retailing and its link with productivity.

[13] See, e.g., Greenwood and Yorokoglu, 1997, Brynjolfsson and Hitt, 2000, and BFOS. Van Reenen et al (2010) report substantial evidence for the IT-linked-intangibles story in micro data. Corrado, Hulten, and Sichel (2006) suggest ways to measure intangible investment more directly.

i.e., the share of payments to IT capital in total production cost) and the IT growth rate, Δk_t^{ICT}. The link to IT growth draws on evidence that expansions of IT capital are associated with intangible investments to reorganize production. The share weight accounts for the scale or magnitude of intangible capital. For example, if firms use little IT capital, then, for any given growth rate of IT capital, unobserved IT-related reorganizations are less likely to be quantitatively important.[14]

The GPT story suggests interesting dynamics for measured productivity growth. Loosely, the story implies that IT-using firms—who invested heavily in IT in the late 1990s—should have seen a temporary, but lagged, surge in measured productivity growth. The reason is that, when firms are investing in intangible organizational capital, measured productivity actually *declines* relative to true technology, as firms divert resources to producing unobserved intangible investment. With a lag, firms benefit from the accumulated intangible capital and measured productivity rises relative to true technology. Oliner, Sichel, and Stiroh (OSS, 2007) note that the BFOS proxy peaks around 2000 and then falls off. That should imply a surge in measured TFP in IT-using industries in the early 2000s, since firms were no longer diverting as many resources to intangible investment. Indeed, when OSS compare aggregate TFP (excluding IT production) in 1995-2000 with 2000-06, they find that swings in IT-related intangibles accounts for almost 2/3 of the surge (0.50 out of 0.81 percent per year). Their estimates imply reduced intangibles investment in the early 2000s and lower measured productivity gains thereafter (consistent with the evidence).

In the industry data, the IT hypothesis suggests that the slowdown should be larger in IT-intensive industries. That is, regardless of specifics of timing, the measurement effects are associated with the use of IT. Appendix B provides further discussion of possible tests of this hypothesis.

3.1.2. Housing and finance in a bubble economy

The IT story emphasizes unusual aspects of the U.S. economy that began in the 1990s and before. But there were unusual features in the 2000s—the housing boom and bust, the explosion of often-dodgy financial products and services, and large movements in commodity prices. Industry and state data allow me

[14] Oliner, Sichel, and Stiroh (2007) estimate that the nominal share of IT-linked intangible investments in (true) output averaged about 5 percent 1973-2000; the intangible capital's share of income was a little higher. They estimate that intangible investment and capital services rose about 7 percent per year over this period.

to assess their direct and indirect roles. In terms of direct channels, I can simply throw out those industries. But indirect channels are more subtle.

For example, indirect effects could work through home equity and net worth channels. 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, though, it's not clear that the timing works for a 2004-2007 slowdown. Household net worth relative to disposable income surged in the 1990s (peaking at 614 percent in 1999); after retreating in the early 2000s it then surged again to a new high in the 2005-2007 period (averaging almost 650 percent). So 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.

In addition, the state data provide another way to look at whether the Great Recession itself contributed to the slowdown. Fort, Haltiwanger, Jarmin, and Miranda (2013) report that young and small firms are particularly sensitive to fluctuations in housing prices—which took a big hit during the Great Recession—through a range of potential credit channels. Not surprisingly, they find that startups and job churning have been hit very hard during and since the Great Recession.[15] Even if the 2004-2007 slowdown is hard to explain with this story, reduced dynamism related to the Great Recession could have contributed further. Regional home price differences are clearly linked to the intensity of the recession across states (Mian and Sufi, 2012). So I explore the degree to which state (labor) productivity is reacting 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 are poorly measured. One concern raised in the literature (e.g., Wang, Basu, and Fernald, 2009) is that there could be 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.

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[15] Decker, Haltiwanger, Jarmin, and Miranda (2013) make a more general point, that the U.S. economy has become less dynamic over time in terms of firm and job creation and destruction. Such dynamism appears to improve allocations and foster the spread of new ideas, and appears linked to aggregated productivity. This reduced dynamism appears to be a longer-term secular trend, and per se seems unlikely to explain the abrupt slowdown in the mid-2000s.

3.1.3. Other sources of mismeasurement, cyclical or otherwise

A particularly simple hypothesis is that productivity growth didn't actually slow, it's just that measurement was worse. Simple stories of cyclical mismeasurement (utilization and non-constant returns) do not work, but more complex measurement stories are hard to rule out a priori.

Variations in factor utilization go the wrong way to explain the slowdown in productivity from 2000-04 to 2004-07. In the early 2000s, utilization was flat to down (measured in my quarterly dataset, or with the Federal Reserve's capacity utilization series). In contrast, during the 2004-07 boom, utilization rose. Hence, the "true" slowdown after controlling for utilization was even larger than measured.

What about non-constant returns to scale and markups? These factors would imply that TFP is not technology, because output elasticities are not equal to factor shares (Hall, 1990). The timing again does not work. Input growth (share-weighted capital and labor) was relatively rapid (2+ percent per year) in the fast-productivity-growth late 1990s as well as in the slow-productivity-growth 2004-07 period. Conversely, input growth was relatively slow (¼ to ½ percent per year) in the fast-productivity-growth early 2000s as well as in the slow-productivity-growth 2007-2013 period.

Indeed, the sign goes the wrong way to explain the mid-2000s slowdown. Share-weighted input growth sped up by 2 percentage points from the 2000-04 period to 2004-07. In industry and aggregate data, returns to scale are estimated to be close to or modestly greater than one (e.g., Basu and Fernald, 1997), implying measured TFP growth should, if anything, have sped up a little. Even large diminishing returns (say, 0.8) would 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 (BFS, 2001) and Oliner, Sichel, and Stiroh (2007) assume that installing investment goods is costly in terms of measured productivity, because firms divert resources to installing the capital. This story does not explain the slowdown in TFP growth because fixed private non-residential investment grew at a very similar pace (5 to 6 percent per year on average) from 1995-2004 and from 2004-2007. Using the calibration from BFS, adjustment costs associated with this investment growth subtracted about 0.2 percentage points from measured TFP growth in both subperiods.

Of course, mismeasurement could instead reflect that price indices have gotten markedly worse at capturing quality change. IT itself contributes, by increasing product variety, decreasing search costs, and providing valuable services for free. For example, producers can readily offer customized, non-standard products; there are enormous, poorly measured gains to being able to obtain any book in the world in a few days (if not available for instantaneous download) without extensive, time-consuming search; and GPS and entertaining cat videos on YouTube increase consumer surplus. Brynjolfsson (20xx) estimates that free Internet goods provide some $300 billion/year in consumer surplus, or about 2 percent of GDP.

A priori, it is difficult to say whether mismeasurement has become more important in the past decade, since measurement challenges are longstanding. Even if all the $300 billion in unmeasured surplus arose in the past decade, that's only 0.2 pp/year on growth, compared with a slowdown in labor productivity growth of around 1-1/2 percentage point. And earlier estimates suggest considerable missing quality improvements last century, whether in capital goods or consumer goods (see Gordon, 1982, 2006). In terms of product variety, Broda and Weinstein (2006) measured a four-fold increase in the variety of U.S. imports in the 1970s, 1980s, and 1990s—long before the 2000s slowdown.

Careful work on quantifying mismeasurement requires detailed, often product-specific analysis, as described in Gordon (2006) and Broda and Weinstein (2006). This work is important, and the need is ongoing. 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. Griliches (1994) argued that that much of the productivity slowdown in the mid-1970s took place in relatively poorly measured industries, such as services, and I follow his classification (see appendix).

Finally, Oliner, Sichel, and Stiroh (2007) discuss other stories why the early 2000s strength 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.

3.2. 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 particularly pronounced in IT-producing and intensive IT-using industries. IT-producing industries saw productivity explode in the 1995-2000 period. After 2000, productivity returned close to its pre-1995 pace. 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 BLS data for 60 manufacturing and non-manufacturing industries from 1987-2011. I express everything in value-added terms, so that they are conceptually identical to TFP in equation (4).[16] The data do not control for labor quality, *LQ*, and predate the 2013 NIPA revisions. Nevertheless, when aggregated to a private-business level, year-to-year changes comove closely with the Fernald TFP series (the correlation is 0.84). (All growth rates are aggregated using value-added weights.)

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 percent per year) in the early 2000s. During 2004-2007, growth slowed markedly to only 0.63 percent. From 2007-2011, business TFP growth recovered a touch, to 0.90 percent. Some of this apparent pickup reflects the spike in labor quality during the Great Recession. Since the 2007-2011 period may still be affected by cyclical variations in *LQ* and utilization, below I focus primarily on the pre-Great-Recession period.[17]

Line 2 shows TFP growth for the bubble-economy sectors of natural resources, construction and real estate, and finance. TFP in those industries did decelerate sharply from 2000-04 (-0.28 percent per year) to 2004-07 (more substantially negative at -1.38 percent). TFP in natural resources (line 3) and construction (line 4a) were sharply negative, partially offset by strong TFP in real estate (line 4b) and finance (line 5)

Importantly, however, even when you exclude those bubble sectors (line 6), the remaining ¾ of the business economy slowed even more than overall private business. Thus, the slowdown was not merely a direct reflection of the unusual features of commodities, housing, and finance. In this broader economy, there was a further slowdown after 2007.

The lines below show additional summary "cuts" of the narrow business sector. Most importantly, these data show that the slowdown was particularly pronounced in IT-producing industries and in intensive IT-using industries. Figure 7 shows these points graphically. IT-producing sectors saw a burst in TFP

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[16] Value-added TFP rescales gross-output TFP by dividing by one minus the intermediate-input share. This is equivalent to computing industry value-added as a Tornquist index and then calculating TFP as in equation (4). 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 a top-down approach to TFP measurement because of input-reallocation terms. Using a consistent dataset, Jorgenson, Ho, and Samuels (2013) find these reallocation terms are, on average, small.

[17] For example, annual average utilization growth in 2011 is affected by quarterly changes in utilization from the second quarter of 2010 on—and utilization had certainly not returned to normal by then.

growth in the late 1990s. (Table 1 (line 7a) shows that this burst was primarily located in the production of computers and semiconductors.) The pace from 2000-2007 was not much different from its pre-1995 pace.

Line 8 shows that non-IT-producing industries—the vast share of the (narrow, i.e., excluding natural resources, construction, and FIRE) business sector—saw a pickup from the late-1990s to the early 2000s. That group of industries slowed sharply in the 2004-07 period, again to a rate modestly below its pre-1995 pace. Lines 9 and 10, and Figure 8, show that within this group, all of the interesting action is in the IT-intensive set of industries. TFP in that group saw only a modest pickup in the late 1990s but then productivity exploded in the early 2000s. From 2004-07, productivity more or less receded to its pre-1995 pace. In contrast, non-IT-intensive industries saw more consistent performance over time.

Thus, the industry data highlight the importance of intensive IT-using industries as well as IT producers in explaining the slowdown in productivity. As another perspective on IT intensity, Figure 7 shows the post-2004 slowdown (through 2007) on the vertical axis for industries grouped based on IT intensity. Bin "1" on the x-axis is the least IT-intensive, bin 6 is the most. The figure shows a general pattern 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, highlighted by Griliches (1994) and Nordhaus (2002), is well measured versus poorly measured. Well-measured industries are predominately manufacturing and utilities (in addition to natural resources, which I exclude from this measure), 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 in the early 2000s, and then slowed markedly (by 1-1/4 to 1-3/4 percentage points) after 2004. Thus, first-cut measurement issues do not seem to be at the heart of the productivity slowdown.[18]

As a third cut, I look at finance-intensive versus non-finance-intensive industries. If the story were systematic and growing mismeasurement of intermediate financial services—or, perhaps, growing rent extraction by financial firms—one might expect the slowdown to be more pronounced in finance-intensive

[18] Of course, quality adjustment could have gotten systematically worse in IT-intensive industries, especially previously well-measured ones. One might have thought this would go along with at least some pickup in share-weighted IT growth. But both the IT share, and IT growth, have declined over time.

industries. However, the slowdown turns out to be more pronounced for non-finance-intensive industries. These industries have a larger productivity bump in the early 2000s—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 2000-04 to 2004-07. Appendix XX considers further evidence from the industry details, but reaches a similar conclusion.

3.3. Evidence from the U.S. States

State data on GDP per worker provide further insight into factors underpinning the productivity slowdown. 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. In a few cases, house price movements are associated with cross-state differences in labor productivity. However, house-price dynamics explain little of the cross-state variation in the degree to which productivity slowed.

The state data are for labor productivity. Hence, the cross-state differences could reflect innovation, but could also reflect cross-state differences in capital deepening or factor utilization. As discussed in Section 3.1, credit-market access by entrepreneurs is likely to be affected by net worth; small, young businesses, especially, are dependent on home equity (see Fort, Haltiwanger, Jarmin, and Miranda, 2013).[19] Of course, credit market access could affect capital deepening, as well. And to the extent aggregate demand is affected by house-price fluctuations (see Mian and Sufi, 2011), that 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 a housing shock, 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 across various subgroupings of industries. For the entire private economy, 47 out of 51 states (including D.C.) had slower

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[19] In regressions not shown, I confirm that across states, changes in startup activity are correlated with changes in home equity. In some specifications, startup activity appears to be 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, or to identify causation.

productivity growth in 2004-07 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 FIRE.

Still, as we saw with the industry data, IT rather than the bubble sectors are the broad story. Consistent with Table 1, IT production (line 7) slowed substantially; and, in line 8, within the category that excludes the bubble sectors and IT production, most states slow. Within that narrow grouping, IT-intensive industries (line 9) slowed in 50 out of 51 states (Washington, D.C. 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. Lines 11 and 12 show wholesale and retail trade—two specific industries where substantial research has documented the role of IT in fostering reorganizations. Labor productivity in wholesale trade slowed in all 51 states after 2004.

What about indirect channels? The top panel of Table 3 examines whether the productivity changes for different industry groupings from 2004-2007 relative to 1997-2004 are related to cross-state home-price changes. In all cases, 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 standards changed in the early 2000s, 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. In the table, home-price movements are expressed in standard deviation units relative to the cross-section of states. [20]

Table 3 shows limited evidence that cross-state productivity slowdowns are related to home-price changes during the boom. Such a relationship, if it existed, could reflect the role of entrepreneurial net worth, or differences in capital deepening or utilization; it could also be spurious (e.g., the high-elasticity Midwest has more agriculture). But in any case, home-price movements are not an important part of the story. The only industry groupings where the house-price change is significant are IT-intensive industries (column 3) and the aggregate of natural resources, construction, and FIRE (column 4), and natural resources (column 8). In both cases, the sign of the estimates is positive, so that stronger home prices are associated with stronger productivity—and thus go the wrong way to explain the productivity slowdown.

[20] 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.

For natural resources, a possible channel is that, in areas where home-prices ran up more, marginal agricultural land was converted to residential uses—so the quality of land in agricultural production went up. (Indeed, not shown, the share of natural resources in the economy fell in areas with greater increases in home prices.) Alternatively, the net worth channel could 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 that mitigated the productivity slowdown. But it could easily reflect aggregate demand effects, as in Mian and Sufi (2012). Aggregate demand was stronger where house-prices ran up more; this could have led to more capital investment or higher rates of utilization. But in any case, the R^2 is low and the constant term is a large negative. So even if the housing bubble contributed to productivity dynamics, its effect was swamped by other factors—such as IT.

Of course, home prices peaked in 2006 and then slid down to 2009. Mian and Sufi (2012) argue strongly that the depth of the recession effects across states is related to the magnitude of this decline. So the state data can provide some sense of where the recession itself may have contributed to weak productivity. The bottom panel uses a different cut of the data. Under the hypothesis that there were a couple years of bad luck, followed by the Great Recession, it considers the 2005-2012 period relative 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 entire private economy (column 1), house-price changes have a strong association with labor productivity. This appears to be mainly a bubble-economy story—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 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 broader story, though they may matter for some industries. Rather, the state data are consistent with the IT-linked story for the slowdown.

4. Implications for Medium and Long-Run Growth

I now turn to implications of the slowdown in TFP growth. This section projects longer-run growth using the steady-state of a neoclassical growth model. The estimates imply a plausible return to a pre-1995 growth pace. From equation (5), steady-state output growth is the sum of growth in labor productivity and labor input:

$$\hat{Y}^* = \left[\alpha \left(\hat{K} - \hat{H}^* - \widehat{LQ}^* \right) + \hat{A}^* \right] + \left[\hat{H}^* + \widehat{LQ}^* \right] \tag{6}$$

Stars (*) denote potential or steady-state values. $\left(\hat{K} - \hat{H}^* - \widehat{LQ}^* \right)$ is steady-state capital deepening.

What follows generally assumes constant returns and perfect competition and that utilization growth is zero in steady-state. Hence, steady-state growth in technology and measured TFP are equal: $\hat{A}^* = \widehat{TFP}^*$.

4.1. Multi-Sector Projections of Labor Productivity Growth

In the one-sector neoclassical growth model (e.g., the Solow model), capital deepening depends on exogenous TFP growth. In the steady state of that model, the capital-output ratio is constant. In U.S. data, however, business-sector capital input grew about ¾ pp per year faster than output from 1973 through 2007.

Multi-sector models, where one (or more) sector produces investment goods and other sectors do not can generate a rising capital-output ratio. Capital deepening then depends solely on TFP in the investment sector (see the appendix). If all capital goods are reproducible, potential labor productivity in equation (6) is:

$$\hat{Y}^* - \hat{H}^* - \widehat{LQ}^* = \widehat{TFP} + \alpha \cdot \widehat{TFP_I} / (1-\alpha) . \tag{7}$$

In practice, land , T (for **T**erra), is also an important input. Adding exogenous (non-reproducible) land to the model attenuates the capital-deepening effect, since the weight on reproducible $\widehat{TFP_I}$ depends on the share of *reproducible* capital in output. If α^R is the reproducible capital share in output, and if land use grows at the same rate as labor, the equation becomes:[21]

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[21] See the appendix. By assuming land and labor grow at the same rate, equation (8) omits an "excess" land-growth term: $\alpha^T \cdot (\hat{T}^* - \hat{H}^* - \widehat{LQ}^*) / (1-\alpha^T)$, where $\alpha^T = \alpha c_T$ is the share of land in total cost. That term adds about 2 basis points over the entire sample period and 0 basis points from 1995 through 2007, so I henceforth ignore it.

$$\hat{Y}^* - \hat{H}^* - \widehat{LQ}^* = \widehat{TFP} + \alpha^R \cdot \widehat{TFP_I} / (1-\alpha^R) \tag{8}$$

To implement this equation, I draw on the following theoretical and empirical observations:

- Theory tells us that investment TFP determines capital-deepening
- 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.
- Land is a sizeable non-reproduced capital input that can be pulled into the business sector from other uses. I take it as exogenous.

Hence, I assume there are three final-use sectors that produce using capital and (exogenously growing) labor:

$$\begin{aligned} D &= \quad (K_D)^\alpha (AN_E)^{1-\alpha} \\ B &= Q_B (K_B)^\alpha (AN_B)^{1-\alpha} \\ C &= Q_C (K_C)^\alpha (AN_C)^{1-\alpha} \end{aligned} \tag{9}$$

The **D**urable sector produces equipment and consumer durables. The **B**uilding sector produces structures. The **C**onsumption sector produces non-durables 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; some are used as inventories (a form of capital input). 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, which uses equipment *E*, structures *S*, and land *T* [22]

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

[22] The appendix discusses the general properties of this model. In the empirical implementation, I add inventories as a durable output, which effectively increases the equipment weight in capital, 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 BFFK, 2014); 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, considerable recent literature, including the papers discussed in Section 3.1.1, focuses on intangible capital. Conceptually, this is an additional capital good that the economy produces and uses. However, we do not observe the investment (production) or the stock of intangibles that yields a flow of services (the uses). At different times, the investment versus service flow may dominate measurement. Corrado and Hulten (2013) find that, over the 1980-2011 period, accounting for intangibles as an investment good makes only a few basis points of difference to "adjusted" GDP per hour, though the split between capital deepening and TFP is affected.

Despite these caveats, the model fits historical experience well.

I use relative output prices to identify relative technology growth. The output price in each sector is a markup, μ, over marginal cost, *MC*. So the relative price of, say, consumption to durable equipment is:

$$\widehat{P_C} - \widehat{P_D} = \left(\widehat{\mu_C} + \widehat{MC_C}\right) - \left(\widehat{\mu_D} + \widehat{MC_D}\right) \tag{10}$$

With identical production functions and factor prices, marginal cost depends solely on relative technologies. With perfect competition, the markups both equal one and, hence:

$$\widehat{P_C} - \widehat{P_D} = -\widehat{Q_C} \tag{11}$$

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, Fernald, Fisher, and Kimball, BFFK 2013, for an alternative identification. But in the long-run, BFFK find that relative prices do primarily reflect relative technologies.

Figure 9 shows the resulting final-use TFPs, where overall TFP is decomposed using equation (11) and then cumulated into log-levels. The final-use TFP measures do not control for utilization, but in the longer-run should provide reasonable indicators of technology trends. According to this decomposition, all three sectors move roughly together until the mid-1960s. The level of TFP for buildings 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 the ISTC 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.

In the mid-1990s, durables TFP does, in fact, accelerate, reflecting IT production. Given the scale of the figure, it's difficult to see, 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.

Table 4 compares steady-state implications of the model to labor productivity data. Despite its simplifications, the model matches overall and subsample growth closely. The model with land has a lower effective capital share, which better captures the magnitude of the pickup after 1995. Relative to a one-sector model, the multisector version more closely matches subsample variation. The one-sector model especially underpredicts capital deepening after 1973. Equivalently, because it assumes the capital-output ratio is constant in steady state, it misses the trend increase in the capital-output ratio in the data.

To use this model for steady-state projections, we need to plug in estimates of final-use TFP growth. Pesaran, Pick, and Pranovich (PPP, 2013) argue that, although break-analysis of the sort done in Sections 2 and 3 is important for understanding history, it is *not* necessarily helpful for forecasting. In general, there is uncertainty about the exact magnitude and dates of breaks, and post-break samples may well be short. In the current problem, for example, each series may break at different times and provide only a short window of (volatile) post-break data. PPP show that focusing on estimated break dates is suboptimal in terms of mean-squared forecast errors (MSFE). They argue for making forecasts looking at all the available data but then adjusting the weights on different observations to account for the fact that the world is changing over time.

My benchmark projection uses a simple approach they call AveW, where one forms forecasts for a range of historical windows and then averages. They 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.[23]

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 2013:Q4 for durables, buildings, and consumption and use those growth rates to forecast labor productivity growth, $LP^f(s)$, with equation (8). 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 $c_J, J \subset (E,S,V,T)$. 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 percent, and capital share overall averaged 35 percent. As an alternative, I use the 2012 reproducible capital share of 35 percent (the overall share had risen to 38 percent). Other things equal, a higher capital share implies faster growth from equation (8).

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[23] The implicit weights in the AveW measure may not be optimal. PPP derive what they call "robust optimal weights," which are less intuitive. However, they find the AveW approach usually performs well. Given the many sources of uncertainty in long-term projections, the AveW measure gives a reasonable benchmark.

The first column of Table 5 shows my benchmark inputs, and projections, for steady-state labor-productivity growth, using the LP^{AveW} measure. My benchmark, in row (6), is 1.9 percent per year. Row (8) shows that, with the 2012 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)*, i.e., the prediction for labor productivity using data since 1973:Q2. That particular forecast puts equal weights on the slow 1970s and 1980s as the fast growing 1995-03 period. Focusing on the past decade, *LP(2003:Q3)*, implies a forecast of only 1.62 percent, very close to the forecast using data since 1973:1. Finally, the benchmark AveW forecast turns out to be similar to *LP(1986:Q4)*.

Not surprisingly, the standard error around any long-run projection is large. Mueller and Watson (2013) estimate that the 80 percent confidence interval for 10-year projections of non-farm business output per hour range from 1.0 to 3.0 percent per year; for overall TFP, it ranges from -0.1 to 2.1 percent.

More interestingly, the model and discussion highlight some of the 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-20th-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 MacAfee, 2014) think it's on its way.

Another issue is that model's steady-state assumption might not be correct. Fernald and Jones (2014) discuss a model in which relatively steady historical growth of GDP per hour of close to 2 percent 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 TFP and labor productivity growth (about ½ percent per year) than I project here. But 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, albeit one that might be reasonable over the span of a few decades but not forever.)

4.2. From labor productivity to GDP growth

For some purposes, GDP rather than the labor-productivity projection is more natural. I use projections for potential labor input and non-business output from the CBO (2014a) for that estimate.

The CBO expects relatively slow labor-force growth in the long-term: Potential non-farm business hours in 2024 will grow at 0.64 percent per year, compared with growth of 1.4 percent per year from 1949 through 2007. Jorgenson et al (2013) estimate that by the end of this decade, labor quality will plateau, since new labor-market cohorts have no more educational attainment than retiring cohorts. I therefore assume zero labor-quality growth. These estimates imply that longer-run business output in the benchmark case will grow at the sum of growth in productivity (1.91 percent) and hours (0.64 percent) = 2.55 percent per year.

For non-business sector output—mainly general government and the service flow from owner-occupied housing—CBO forecasts 0.85 percent per year growth at the end of 10 years (in 2024). Together, the business and non-business projections imply relatively anemic long-run GDP growth of about 2.1 percent per year. In terms of total GDP per hour, this corresponds to growth of only about 1.6 percent per year. This projection lies below the average from 1950-2007 of 2.0 percent per year.

Prior to the Great Recession, a typical long-run projection was 2-1/2 percent or higher. For example, in early 2007, the CBO projected growth 10 years out of 2.5 percent per year, and GDP per hour of 2.0 percent per year—close to its long-run trend. Since 2009, Federal Open Market Committee participants publish “longer run” projections for GDP growth four times a year. In January 2009, more than 60 percent of participants (10 out of 16) reported a longer-run projection of 2-1/2 percent, with the remaining participants higher than that.[24]

When the first versions of this paper were written, in late 2011 and early 2012, the projections in this paper were at the very low end of what I could find.[25] Typical projections from the CBO or the FOMC had changed only modestly since the beginning of the recession. In contrast, by early 2014, the numbers reported here are in line with, or above, most other projections. The CBO (2014a) itself projects growth of

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[24] Numbers are reported in the minutes at http://www.federalreserve.gov/monetarypolicy/fomccalendars.htm. There are at most 19 FOMC participants, and often fewer, depending on whether there are unfilled governor positions. Projection data are presented in bins. I have rounded the “2.4 to 2.5 percent” bin to 2-1/2 percent. Estimates are for total GDP, and so it is not possible to decompose FOMC projections into productivity or demographics.

[25] The earliest public working paper version of this paper was in September 2012, and projected long-run growth of 2.1 percent per year.

potential GDP (in 2024) of 2 percent and GDP per hour of 1.5 percent. Jorgenson et al (2013) and Gordon (2014) project GDP per hour growth approximately 10 years out of 1.3 percent. Byrne, Oliner, and Sichel (2013) project GDP per hour of about 1-1/2 percent.

5. 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 CBO (2014a) estimates. The CBO does, in fact, build in slower TFP growth after 2004. But the slowdown is more modest than the data suggest is needed. If potential is lower than the CBO estimates, then the gap between actual and potential output is smaller.

5.1. Alternative Definitions of Potential

The CBO's defines potential as "the maximum sustainable amount of real (inflation-adjusted) output that the economy can produce" (CBO, 2014b, page 1). The dynamic stochastic equilibrium (DSGE) literature offers an appealing, theoretically coherent, alternative to this production-function definition: Potential (or natural) output is its value when nominal frictions (sticky prices and wages) and, often, markup shocks are absent.[26] 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. These changes are ruled out by the CBO method.

Nevertheless, the DSGE approach is challenging in the present context. First, its estimates are model-specific. Different models may interpret the same data quite differently. Second, most models assume that growth in technology has a constant mean, which is inconsistent with the interpretation in this paper. A fully-specified regime-switching (or more general) model is complicated. The need to specify how the underlying trends evolve is an example of the model-specificity of the natural-rate estimates.

Still, Kiley (2013) finds that, in the context of the Federal Reserve Board's 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; and demand shocks that lead to inefficient fluctuations in labor and factor utilization would

[26] See, Basu and Fernald (2009) or Kiley (2013) for an extended discussion and references.

be captured in both approaches. Finally, the CBO estimates provide a widely cited benchmark supported by careful of comprehensive analysis of many features of the economy.

5.2. Alternative Estimates of Slack in the CBO Approach

Conceptually, the GDP gap can be expressed in terms of gaps in the business (or non-farm business) sectors, and in the non-business sectors. Historically, the CBO attributes almost all movements in the overall output gap to the (non-farm) business sector, so I assume the overall gap is simply a rescaled version of the business-sector gap.[27] In the Cobb-Douglas case, if ω is the business share of the economy:

$$\frac{Y_t}{Y_t^*} = \left(\frac{Y_t^{Bus}}{Y_t^{Bus,*}}\right)^{\omega} \tag{12}$$

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

$$Y_t^{Bus} = K_t^{\ \alpha} H_t^{1-\alpha}\left(LQ_t^{1-\alpha} Util_t\, A_t\right) \tag{13}$$

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 defined as 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:

$$Y_t^{Bus,*} = K_t^{\ \alpha} H_t^{*\,1-\alpha}\,(LQ_t^{*\,1-\alpha} A_t\,)\,. \tag{14}$$

Taking the ratio, the output gap for the business sector is:[28]

$$\frac{Y_t^{Bus}}{Y_t^{Bus,*}} = \left(\frac{H_t}{H_t^*}\right)^{1-\alpha} Util_t \left(\frac{LQ_t}{LQ_t^*}\right)^{1-\alpha} \tag{15}$$

The CBO publishes annual estimates of the business-sector output and hours gaps. The hours gap 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:

$$\ln\left(Util_t^{CBO,LQ}\right) \equiv \ln\left(Y_t^{Bus} / Y_t^{Bus,*}\right) - (1-\alpha)\ln\left(H_t / H_t^*\right) \tag{16}$$

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[27] The gap from equation (12) has a correlation with the actual CBO GDP gap of 0.998.

[28] This decomposition follows Kiley (2010), who uses it (minus the labor-quality piece) to derive a "CBO gap" in the context of a DSGE model. CBO (2014b) discusses some of their underlying assumptions. Note that any cyclical deviations from "potential TFP," regardless of source, will be labeled as utilization.

Figure 10A 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. But 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, the only times in history that the CBO gap has been more negative than in 2013 were at the troughs of deep recessions: 2009, 1982, and (barely) 1975.[29]

CBO's (2014a) large utilization gap reflects its assumptions about potential TFP. Figure 10B shows that smooth series along with Fernald TFP and utilization-adjusted TFP.[30] The CBO shows faster trend TFP growth starting in the early- to mid-1980s, with no mid-90s acceleration. There is an upward level effect in the early 2000s, then a smooth path through the end of the sample.

But 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 have a larger utilization gap to fill in the difference.

Arnold (2009) and CBO (2014b) discuss how the CBO typically imposes a smooth linear trend for potential TFP (inclusive of *LQ*) between business-cycle peaks. The advantage of the peak-to-peak methodology is that it is not particularly model-specific. The disadvantage is that the CBO's assumed (largely linear) trend is potentially subject to large and ongoing ex-post revisions, especially after a new business cycle peak is reached.[31] Since 2004, for example, the CBO's views about TFP growth in the 1990s

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[29] 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. The effect is probably not too large. Estimating trend labor quality as discussed below, the standard deviation of the LQ gap is only ½ percent per year, compared with a business-sector output gap standard deviation of nearly 4 percent per year.

[30] 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 non-farm business basis using the gap between the BLS estimates of business and non-farm business MFP.

[31] CBO (2014b, p.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.

and 2000s have changed nearly every year. The 2001-2004 bump up in potential TFP growth became much pronounced in the 2009 release; only in 2014 did the CBO first estimate that TFP growth after 2004 was (modestly) slower than TFP growth in the 1990s. CBO staff are careful and knowledgeable, and need to consider and balance a range of issues. Still, the slowdown in potential TFP growth appears small given the analysis in this paper.

Historically, labor gaps and utilization gaps are strongly positively correlated. When there is a labor gap—and CBO (2014a) estimates that as of 2013, $H / H^* = -5.4$ percent—there is typically a utilization gap in the same direction. (Interestingly, prior to the Great Recession the correlation of the CBO hours gap with the utilization gap is a bit higher with the Fernald utilization measure (0.70) than with the CBO utilization measure (0.61).) However, 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.

Two alternative identifying assumptions therefore suggest themselves. The first is to use a model-based measure of utilization, such as the Fernald (updated Basu-Fernald-Kimball) measure plotted in Figure 10A. That provides the benchmark "Fernald" estimate of the output gap in Figure 1. It is also necessary to take a stand on the labor-quality gap in equation (15). I use a biweight 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 percent per year). Actual labor-quality rose even faster, as low-skilled workers lost 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.

A second approach simply assumes no utilization or LQ gaps, and uses actual measured TFP. For this approach, the "output gap" is simply a rescaled version of the hours gap. Of course, since actual factor utilization is cyclical, this measure of the output gap will not move enough—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.

Figure 11 compares the resulting output gaps to the CBO estimate. Even using actual TFP, and assuming utilization does not vary, there was a sizeable gap at the peak of the Great Recession. The reason is that the hours gap is, historically the main driver of the output gap. By 2013, however, the hours gap contributed only about 2-1/2 percent to the output gap. The Fernald (utilization-adjusted TFP) measure moves much more closely with the CBO measure but, by 2013, had narrowed much more. With this measure, slack shows up primarily in the people who aren't working, rather than in the intensity of use of factors that are working. The Bank of England (2014) takes a similar view of the U.K. economy, where (p.6) it states: "The Committee judges that there remains spare capacity, concentrated in the labour market...."

The two alternatives in Figure 11 are illustrative and make strong assumptions. But they are robust to measurement error in growth in capital or in underlying technology. The reason is that TFP is measured as a residual. Hence, ceteris paribus, anything that affects actual output affects measured TFP as well. And actual output depends on true capital and technology. This is why capital and technology do not appear in the "output gap" ratio (15).[32]

Together, these output gap assumptions imply the "Fernald" path of potential shown in Figure 2. The annual growth rates are model-specific and so could be too volatile. But the broad point is that, over 6 years, they embody a much lower growth rate of potential because utilization gaps have substantially or completely closed. The "Fernald" estimate here decomposes about 3/4 of the shortfall relative to the 2007 trend into a downgrade of potential, and about half into an output gap (output below potential).

Of course, these potential-output paths are not exogenous, since a cyclical shortfall of investment lowers the capital stock. The role of capital is obscured by the focus on gaps (where capital doesn't appear explicitly). But 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. Hall (2014) discusses capital dynamics extensively.

My focus has been on TFP, where the effects of the Great Recession seem 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 persistently lower potential output. These include the possibility that workers lose skills and, potentially, drop out of the labor force permanently. Reifschneider et al (2013) discuss the implications of this view for monetary policy.

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[32] 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, e.g., because the economy had too many back hoes. Then 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 (16)) that utilization was low. Of course, firms might instead have deferred scrappage of old but still serviceable capital.

Finally, consider the period prior to the crisis, say in 2006. The growth-accounting approach in this paper is inherently about growth rates, rather than levels. To benchmark levels, I used the CBO labor gap and I set the level of utilization to match the CBO's utilization-gap as of 1987 (and set the LQ gap to zero as well). Given these CBO assumptions, output did not appear to be much different than potential leading up 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 percent is well above most natural-rate estimates (the CBO was at 5.9 percent), consistent with substantial remaining labor-market slack. That constrains how much of a pre-crisis adjustment one could make.

Certainly, aspects of the economy were unsustainable in the mid-2000s. The economy produced too many houses, and U.S. households borrowed excessively to finance consumption. But these do not necessarily imply 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. And the excessive consumption in part showed up as imports, not (necessarily) overproducing domestically.

Finally, the fundamental difference in perspective relative to the CBO is that the CBO assumes a smooth process for technology, whereas empirical estimates are much more volatile. This volatility is inherent in modern macro models, whether flex-price RBC models in which technology shocks drive business cycles; or in sticky price/wage New Keynesian models such as EDO (see Kiley 2013). The Fernald utilization-adjusted TFP series are only slightly less volatile (in annual data) than raw Solow residuals, and are about equally volatile to the shocks estimated in DSGE models.[33] Alternative indicators, such as technology book publications, are also highly volatile (e.g., Alexopoulos and Cohen, 2009). Understanding why year-to-year technology is so volatile remains a challenge.

6. Conclusions

The past two decades has seen the rise and fall of exceptional U.S. productivity growth. 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, so far, fallen short. At its peak from the mid-1990s to early 2000s, TFP growth was similar to its pace from the 1940s to early 1970s (and probably since

[33] I thank Hess Chung for sending me the EDO shocks.

the 1920s). But from 2004 to 2013, the IT-induced burst in TFP growth faded. For three of the past four decades, productivity growth has proceeded more slowly, suggesting that this slower pace is a better benchmark for normal growth.

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 use information technology intensively or that produce IT.

Thus, the easing of productivity growth is the flip side of the productivity burst. For now, the IT revolution appears as a level effect on measured productivity that showed up for a time as exceptional growth. Productivity growth similar to its 1973-95 pace is a reasonable expectation.

Uncertainty about any such forecast is inherently high. Jones (2002) argues that 20th century U.S. growth was built on rising education and research intensity, which will not persist in steady state. But, of course, before we reach that point, there could well be another wave of the IT revolution—as Brynjolfsson and McAffee (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.

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. But 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 <u>exceptional</u> growth that appears unusual—prior to 1973, or from 1995-2004. Historians of technology (e.g., David and Wright, 2003; Field, 2003; and 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 1970s. For example, Gordon (2000) highlights (i) electricity, (ii) the internal combustion engine, (iii) "rearranging molecules" (petrochemicals, plastics, and pharmaceuticals), and (iv) entertainment, information, and communication (e.g., telephone, radio, movies, TV). Fernald (1999) and Field (2007) point especially to the role of infrastructure. The GPT literature suggests that these constellations, like information technology, promoted a range of complementary innovations that propelled exceptional growth for a time, but not, perhaps, forever.

Bibliography

Aaronson, Daniel and Daniel G. Sullivan (2001). "Growth in worker quality." Federal Reserve Bank of Chicago *Economic Perspectives,* , Vol. 25, 4th Quarter.

Alexopoulos, Michelle and Jon Cohen (2009). "Measuring our ignorance, one book at a time: New indicators of technological change, 1909–1949." *Journal of Monetary Economics*, Volume 56, Issue 4, May, Pages 450-470.

Arnold, Robert (2009). "The Challenges of Estimating Potential Output in Real Time." Federal Reserve Bank of St. Louis Review, July/August 2009, 91(4), pp. 271-90.

Bank of England (2014). "Inflation Report." February.

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

Basu, Susanto and John G. Fernald (2002). "Aggregate Productivity and Aggregate Technology." *European Economic Review*.

Basu, Susanto and John G. Fernald. "Information and communications technology as a general-purpose technology: evidence from U.S industry data." *Economic Review*, Federal Reserve Bank of San Francisco, pages 1-15.

Basu, Susanto and John Fernald (2009). "What Do We Know and Not Know About Potential Output?" *St. Louis Fed Review.*

Basu, Susanto, John Fernald, Jonas Fisher, and Miles Kimball (2010). "Sector-Specific Technical Change." Manuscript, Federal Reserve Bank of San Francisco.

Basu, Susanto, John Fernald, and Miles Kimball (2006). "Are Technology Improvements Contractionary?" *American Economic Review*.

Basu, Susanto, John Fernald, Nicholas Oulton, and Sally Srinivasan (2003). "The Case of the Missing Productivity Growth: Or, Does Information Technology Explain Why Productivity Accelerated in the United States but Not the United Kingdom?" NBER Macroeconomics Annual, 2003.

Bresnahan, T. F., and M. Trajtenberg. (1995). General-purpose technologies:"Engines of growth"? *Journal of Econometrics* 65(Special Issue, January): 83-108.

Broda, Christian and David E. Weinstein (2006). "Globalization and the Gains from Variety," *The Quarterly Journal of Economics*, vol. 121(2), pages 541-585, May.

Brynjolfsson, Erik, and L. M. Hitt. (2000). "Beyond computation: Information technology, organizational transformation and business performance." *Journal of Economic Perspectives* 14(4):23-48.

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

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

Caballero, Ricardo J and Mohamad L. Hammour (1994). "The Cleansing Effect of Recessions." *American Economic Review*, vol. 84(5), pages 1350-68, December

Congressional Budget Office (2014a). "The Budget and Economic Outlook: 2014 to 2024." The Congress of the United States, Congressional Budget Office. February 2014. http://www.cbo.gov/publication/45010.

Congressional Budget Office (2014b). "Revisions to CBO's Projection of Potential Output Since 2007." The Congress of the United States, Congressional Budget Office. February 2014. http://www.cbo.gov/publication/45012

Comin, Diego and Mark Gertler (2006). "Medium-Term Business Cycles." *American Economic Review,* vol. 96(3), pages 523-551, June.

Corrado, Carol, and Charles Hulten (2013). "Innovation Accounting." In: *Measuring Economic Sustainability and Progress*. National Bureau of Economic Research.

Corrado, Carol, Charles Hulten, and Daniel Sichel (2006). "Intangible Capital and Economic Growth." *Review of Income and Wealth*, Series 55, No. 3, September 2009

Daly, Mary C. and Bart Hobijn (2010). "Okun's Law and the Unemployment Surprise of 2009." FRBSF Economic Letter, 2010-07.

Daly, Mary C., John G. Fernald, Fernanda Nechio, and Oscar Jordà (2014). "Interpreting Deviations from Okun's Law." FRBSF *Economic Letter*, Forthcoming.

David, Paul and Gavin Wright (2003). "General Purpose Technologies and Productivity Surges: Historical Reflections on the Future of the ICT Revolution." In Paul A. David and Mark Thomas (eds.), *The Economic Future in Historical Perspective*. Oxford University Press.

Dean, Edwin R. and Michael J. Harper (2001). "The BLS Productivity Measurement Program." In New Developments in Productivity Analysis, Charles R. Hulten, Edwin R. Dean and Michael J. Harper, editors. University of Chicago Press.

Decker, Ryan John Haltiwanger, Ron S Jarmin, and Javier Miranda (2013). "The Secular Decline in Business Dynamism in the U.S." Manuscript, University of Maryland.

Eisfeldt, Andrea and Adriano Rampini (2006). "Capital reallocation and liquidity." *Journal of Monetary Economics* 53: 369–399.

Fatas, Antonio (2002). "The Effects of Business Cycles on Growth." In *Economic Growth: Sources, Trends and Cycles*, Eds. Norman Loayza and Raimundo Soto. Central Bank of Chile.

Fernald, John G. (1999). "Roads to Prosperity? Assessing the Link between Public Capital and Productivity." American Economic Review, 89(3): 619-638.

Fernald, John G. (2007). "Trend Breaks and Contractionary Technology Improvements." *Journal of Monetary Economics*.

Fernald, John G. (2012). "A Quarterly Utilization-Adjusted Series on Total Factor Productivity." Manuscript, http://www.frbsf.org/economics/economists/jfernald.html. Data supplement at http://www.frbsf.org/economics/economists/jfernald/quarterly_tfp.xls.

Fernald, John, David Thipphavong, and Bharat Trehan (2007) "Will Fast Productivity Growth Persist?" FRBSF Economic Letter 2007-09.

Field, Alexander J. (2003). "The Most Technologically Progressive Decade of the Century." *American Economic Review*, 93(4): 1399-1413.

Field, Alexander J. (2007). "The Origins of U.S. Total Factor Productivity Growth in the Golden Age." Cliometrica, 1:63-90.

Fleck, Susan (2011). "Measuring State-level Productivity in the Private Industry Sector." Manuscript, Bureau of Labor Statistics, December 2011.

Foster, Lucia, John C. Haltiwanger, and Cornell J. Krizan (2006). "Market Selection, Reallocation, and Restructuring in the U.S. Retail Trade Sector in the 1990s," *The Review of Economics and Statistics*, vol. 88(4), pages 748-758, November.

Galí, Jordi, Frank Smets, and Rafael Wouters (2012). "Slow Recoveries: A Structural Interpretation." Manuscript, CREI.

Gordon, Robert J. (1990). The Measurement of Durable Goods Prices, Chicago: University of Chicago Press.

Gordon, Robert J. (2006). "The Boskin Commission Report: A Retrospective One Decade Later," *International Productivity Monitor*, vol. 12, pages 7-22, Spring.

Gordon, Robert J. (2010). "Revisiting U.S. Productivity Growth over the Past Century with a View of the Future." NBER Working Paper 15834, March.

Gordon, Robert J. (2014). "The Demise of U.S. Economic Growth: Restatement, Rebuttal, and Reflections." NBER WP 19895, February.

Greenspan, Alan (2000). "Technology and the economy." Speech to the Economic Club of New York, New York, New York, January 13.

Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell (1997). "Long-Run Implications of Investment-Specific Technological Change," *American Economic Review*, vol. 87(3), pages 342-62.

Greenwood, Jeremy and Mehmet Yorukoglu (1997). "1974," *Carnegie-Rochester Conference Series on Public Policy*, Elsevier, vol. 46(1), pages 49-95, June.

Hall, Robert E. (2014). "Quantifying the Lasting Harm to the U.S. Economy from the Financial Crisis." Manuscript prepared for *NBER Macroeconomics Annual*, 2014.

Hobijn, Bart and Alistair McKay (2007). "Spurious Investment Prices." Unpublished manuscript, Federal Reserve Bank of San Francisco.

Helpman, Elhanan, ed. (1998). General Purpose Technologies and Economic Growth. Cambridge, MA: MIT Press.

Jorgenson, Dale W., Frank M. Gollop, and Barbara M. Fraumeni (1987). *Productivity and U.S. Economic Growth*. Cambridge , Harvard University Press.

Jorgenson, Dale W., Mun S. Ho, and Jon D. Samuels (2013). "Economic Growth in the Information Age: A Prototype Industry-Level Production Account for the United States, 1947-2010." Manuscript, Harvard University.

Jorgenson, Dale W., Mun S. Ho, and Kevin J. Stiroh (2008). "A Retrospective Look at the U.S. Productivity Growth Resurgence." *Journal of Economic Perspectives*, 22(1): 3-24.

Kahn, James A., and Robert W. Rich (2007). "Tracking the New Economy: Using Growth Theory to Detect Changes in Trend Productivity." *Journal of Monetary Economics*, Volume 54, Issue 6, September 2007, Pages 1670–1701.

Kahn, James and Robert Rich (2013). "Productivity Model Update." http://www.newyorkfed.org/research/national_economy/richkahn_prodmod.pdf. (Dec.)

Kiley, Michael T., 2013. "Output gaps," *Journal of Macroeconomics*, Elsevier, vol. 37(C), pages 1-18.

Lazear, Edward P., Kathryn L. Shaw, and Christopher Stanton (2013). "Making Do with Less: Working Harder During Recessions." NBER Working Paper 19328.

Liu, Zheng, and Pengfei Wang. 2014. "Credit Constraints and Self-Fulfilling Business Cycles." American Economic Journal: Macroeconomics, 6(1): 32-69.

Mian, Atif R. and Amir Sufi (2012). "What explains high unemployment? The aggregate demand channel." NBER Working Papers 17830.

Nalewaik, Jeremy J. (2010). "The Income- and Expenditure-Side Measures of Output Growth," Brookings Papers on Economic Activity, vol. 1, pp. 71-106.

Oliner, Stephen D. and Daniel E. Sichel, 2000. "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?" *Journal of Economic Perspectives*, vol. 14(4), pages 3-22, Fall.

Oliner, Stephen D., Daniel E. Sichel, and Kevin Stiroh (2007). "Explaining a Productive Decade." *Brookings Papers on Economic Activity*.

Oulton, Nicholas and María Sebastiá-Barriel (2013). "Effects of Financial Crises on Productivity, Capital and Employment. Paper Prepared for the IARIW-UNSW Conference on "Productivity: Measurement, Drivers and Trends." Sydney, Australia, November 26-27, 2013.

Pesaran, Hashem, Andreas Pick and Mikhail Pranovich (2013). "Optimal forecasts in the presence of structural breaks." *Journal of Econometrics*, 177(2) 134-152.

Petrosky-Nadeu, Nicolas (2013). "TFP during a Credit Crunch." *Journal of Economic Theory*, 148(3) May 2013.

Reifschneider, Dave, William Wascher, and David Wilcox (2013). "Aggregate Supply in the United States: Recent Developments and Implications for the Conduct of Monetary Policy." FEDS Working Paper 2013-77.

Saiz, Albert (2010). "The Geographic Determinants of Housing Supply." *Quarterly Journal of Economics*, 125 (3): 1253-1296.

Syverson, Chad (2013). "Will History Repeat Itself? Comments on 'Is the Information Technology Revolution Over?'" *International Productivity Monitor*, vol. 25, pages 37-40, Spring.

Van Reenen, John, Nicholas Bloom, Mirko Draca, Tobias Kretschmer, Raffaella Sadun, Henry Overman, and Mark Schankerman (2010). "The Economic Impact of ICT." Research report, SMART N. 2007/0020.

Wang, J. Christina, Susanto Basu, and John Fernald (2009). "A General-Equilibrium Asset-Pricing Approach to the Measurement of Nominal and Real Bank Output." In Price Index Concepts and Measurement, Erwin Diewert, John Greenlees and Charles Hulten, editors.

Whelan, Karl (2003). "A Two-Sector Approach to Modeling U.S. NIPA Data." *Journal of Money, Credit and Banking*, vol. 35(4), pages 627-56, August.

Appendix A: Data

Fernald (2012) Quarterly Growth-Accounting Data

These data are available at http://www.frbsf.org/economics/economists/jfernald/quarterly_tfp.xls. They include quarterly growth-accounting measures for the business-sector, including output, hours worked, labor quality (or composition), capital input, and total factor productivity from 1947:Q2 on. In addition, they include a measure of factor utilization that follows Basu, Fernald, and Kimball. They are typically updated several months after the end of the quarter. Once aggregated to an annual frequency, they are fairly close to the annual BLS multifactor productivity estimates, despite some differences in coverage and implementation.[34] The data are described in greater detail in Fernald (2012).

Key data sources for estimating (unadjusted) quarterly TFP for the U.S. business sector are:

(i) Business output: A geometric average of output as measured from the income and expenditures sides, as recommended by Nalewaik (2011), The expenditure (gross domestic product) side is reported in NIPA tables 1.3.5 and 1.3.6 (gross value added by sector). Nominal business income (the counterpart of gross domestic income) is GDI less nominal non-business output from table 1.3.5. Real business income uses the expenditure-side deflators.

(ii) Hours: From the quarterly BLS productivity and cost release.

(iii) Capital input: Weighted growth in 15 types of disaggregated quarterly capital (5 types of non-residential equipment, 5 types of structures, 3 types of intellectual property, plus inventories and land.) Estimated user costs are used to generate weights in capital input. For equipment, structures, intellectual property, and inventories, the underlying source is the BEA. For land, I interpolate and extrapolate from BLS estimates of land input into the business sector.

(iv) Factor shares: Based on NIPA data on corporate business total business factor costs and payments to labor and capital. Following Jorgenson, Gollop, and Fraumeni (1987) and the BLS, cost equals revenue net of taxes on production and imports (TOPI), plus subsidies, plus the portion of TOPI that is properly allocated to capital (property and motor vehicle taxes). I implicitly allocate proprietors' income between labor and capital so that labor's share of non-corporate, non-government businesses matches the share for non-financial corporations.

(v) Labor composition: From 1979:1 on, I use estimates that follow Aaronson and Sullivan (2001), as updated by Bart Hobijn and Joyce Kwok. Prior to 1979, I interpolate and extrapolate annual data from BLS multifactor productivity data.

(vi) Investment versus consumption technology: To decompose aggregate TFP along final demand lines, I create three Tornquist price indices from NIPA data. The first is the price of "equipment," defined as equipment, software, and consumer durables. The second is the price of structures, defined as residential and non-residential structures. The third is the price of non-durable "consumption," defined as everything else—i.e., the price of business output less equipment and structures. I assume the relative price of equipment investment

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[34] To name six minor differences: (i) BLS covers *private* business, Fernald covers total business. (ii) BLS uses expenditure-side measures of output, whereas Fernald combines income and expenditure-side measures of output. (iii) BLS assumes hyperbolic (rather than geometric) depreciation for capital. (iv) BLS uses more investment categories, available only at an annual frequency. (v) Fernald does not include rental residential capital. (vi) The labor-quality methods are slightly different. Some of these differences reflect what can be done quarterly versus annually. For a review of the methodology and history of the BLS measures, see Dean and Harper (2001).

corresponds, quarter-by-quarter, to TFP in consumption relative to equipment investment. (This measure of relative TFP is not, of course, necessarily equal to technology change period by period.)

To estimate a quarterly series on aggregate utilization, the key data source is the following:

(vii) Hours-per-worker (H^i / N^i) by industry from the monthly employment report of the BLS. These are used to estimate a series on industry utilization $\Delta \ln U_i = \beta_i \Delta \ln(H^i / N^i)$, where β_i is a coefficient estimated by Basu, Fernald, Fisher, and Kimball (BFFK, 2013). I then calculate an aggregate utilization adjustment as $\Delta \ln U = \sum_i w_i \Delta \ln U_i$, where w_i is the industry weight from BFK (taken as the average value over the full sample).

The resulting utilization-adjusted series differs conceptually from the BFFK purified technology series along several dimensions. BFFK use detailed industry data to construct estimates of industry technology change that control for variable factor utilization and deviations from constant returns and perfect competition. They then aggregate these residuals to estimate aggregate technology change. Thus, they do not assume the existence of a constant-returns aggregate production function. The industry data needed to undertake the BFFK estimates are available only annually, not quarterly. As a result, the quarterly series estimated here does not control for deviations from constant returns and perfect competition.[35]

BLS Industry Data

Multifactor productivity (MFP) data by industry cover 60 manufacturing and non-manufacturing industries. MFP is synonymous with TFP. The industry data do not control for labor quality. These data are available at http://www.bls.gov/mfp/mprdload.htm (downloaded January 16, 2014). For more discussion of the data, see http://www.bls.gov/opub/mlr/2010/06/art2full.pdf. For the methodology used in estimating KLEMS multifactor productivity measures, see Michael J. Harper, Bhavani Khandrika, Randal Kinoshita, and Steven Rosenthal in "Nonmanufacturing industry contributions to multifactor productivity, 1987-2006," Monthly Labor Review, June 2010, pp. 16-31 (see http://www.bls.gov/opub/mlr/2010/06/art2full.pdf) and William Gullickson "Measurement of Productivity Growth in U.S. Manufacturing," Monthly Labor Review, July 1995, pp. 13-27 (see http://www.bls.gov/mfp/mprgul95.pdf).

IT intensity: To differentiate IT-intensive from non-IT intensive industries, I ranked industries based on the estimated payments for IT as a share of income (that is, the portion of capital's share of income that is attributable to IT, averaged over the full sample period—though using 1987-90 average makes little if any difference). Starting with the most IT-intensive industry, I selected industries until I reached 50 percent of the value-added weight (averaged 1987-2011) for the non-IT-producing "narrow business" economy. See Table A-1.

Finance intensity: The BLS produces annual I-O tables at the level of 195 industries/commodities, available at http://www.bls.gov/emp/ep_data_input_output_matrix.htm (accessed January 14, 2014). I aggregated industries 169 private business input-output industries to 60 BLS MFP industries

[35] The output data also differ, both in vintage and data source, from the annual data used by BFK.

according to NAICS codes. I then measure the finance share for each industry as nominal purchases of intermediate finance and insurance services (there are five such commodities in the underlying I-O tables) relative to total output of the industry. Finance usage was nominal purchases of various financial services as a share of industry gross output. "Finance intensive" is set of industries with the highest shares that constitute 50 percent of the value-added weight of narrow business excluding IT production.

IT Producing: As noted in Appendix Table 1, I define IT-producing industries to be (i) computer and electronic product manufacturing; (ii) publishing (including software); and (iii) computer systems integration and design. These three account for the vast majority of final expenditure on computers, communications, and software. Note that I exclude "information and data processing services" (e.g., cloud storage), since that provides intermediate services rather than final investment in hardware. That is, it is a substitute for direct ownership of IT hardware.

Well-measured industries: Griliches (1994) imagines "a 'degrees of measurability' scale, with wheat production at one end and lawyer services at the other. One can draw a rough dividing line on this scale between what I shall call 'reasonably measurable' sectors and the rest…." Griliches and Nordhaus draw the dividing line slightly differently. For Table 1, I largely follow Nordhaus, except that (as noted already) I exclude (well-measured) agriculture and mining and (poorly measured) construction and FIRE. I also exclude IT-producing industries. Well-measured thus comprises manufacturing (ex. computers and semiconductors), utilities, transportation, trade, and selected services (broadcasting and telecommunications, and accommodations). Switching trade and the selected services from well-measured to poorly-measured would make the slowdown in well-measured a bit less pronounced. Nevertheless, both well-measured and poorly-measured show a deceleration of more than a percentage point after 2004, so the main takeaway is unaffected by this choice.

State productivity

- BEA GDP by industry and persons engaged in production by industry were downloaded (February xx, 2014) from ____.
- These data are prior to the 2013 benchmark revision, so numbers differ slightly from reported elsewhere.
- Chain addition and subtraction were used to construct subgroup aggregates along the lines of the industry breakdown in Appendix Table 1.

Other state data

- Home prices are from Core Logic, and housing elasticity measures are from Saiz (2011). The Saiz 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).
- From Business Dynamics Statistics database, I measure the creation of firms with 1-5, 5-9, and 10-19 people over the year. I then divide by population to generate small job births per capita by state. (I thank Liz Laderman for providing me with these data).

How I use the CBO data

- CBO publishes projections for GDP and for (non-farm) business GDP. To estimate output of nonprofits and government (i.e., the "non-non-farm" sector) I assume farms grow with other businesses, and ignore the difference between non-farm and total business. Using the NIPA nominal business weights in GDP (0.76, averaged 1995-2007), I can back out an estimated non-business output.
- CBO publishes projections for labor-force growth and for non-farm business hours. In 2024, the potential labor force in CBO (2014a) grows at 0.5 percent, whereas NFB hours grows 0.64 percent. According to CBO staff, the difference primarily reflects continuing decline in government hours (i.e., a shift towards the business sector). So for the total economy, I use the growth in the potential labor force.
- The non-farm-business labor gap is from comparing unpublished BLS data on hours worked in non-farm business relative to CBO's published potential non-farm business hours. The unpublished BLS productivity-and-cost hours data match the published index values perfectly.[36]
- To convert the CBO NFB TFP projections into figures more comparable to Fernald (2014) or the BLS, I need an estimate of trend labor quality (which is included in the CBO figures but not in the others)..

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

Appendix Figure A-1

		NAICS	IT-prod. (1)	Bus, excl. Nat Res, Con, FIRE (2)	IT-int. (in (2)) (3)	Not-IT-int. (in (2)) (4)	Fin-int. (in (2)) (5)	Not fin. Int (in (2)) (6)	Well (in (2)) (7)	Poor (in (2)) (8)
1	Manufacturing	MN								
2	Nondurable goods	ND								
3	Food, beverage and tobacco product manufacturing	311,312		x		x		x	x	
4	Textile and textile product mills	313,314		x		x		x	x	
5	Apparel, leather, and allied product manufacturing	315,316		x		x		x	x	
6	Paper manufacturing	322		x		x		x	x	
7	Printing and related support activities	323		x		x		x	x	
8	Petroleum and coal products manufacturing	324		x	x			x	x	
9	Chemical manufacturing	325		x	x			x	x	
10	Plastics and rubber products manufacturing	326		x		x		x	x	
11	Durable goods	DM								
12	Wood product manufacturing	321		x		x		x	x	
13	Nonmetallic mineral product manufacturing	327		x		x		x	x	
14	Primary metal manufacturing	331		x		x		x	x	
15	Fabricated metal product manufacturing	332		x		x		x	x	
16	Machinery manufacturing	333		x	x			x	x	
17	Computer and electronic product manufacturing	334	x	x						
18	Electrical equipment, appliance, and component manufacturin	335		x		x		x	x	
19	Transportation equipment manufacturing	336		x		x		x	x	
20	Furniture and related product manufacturing	337		x		x		x	x	
21	Miscellaneous manufacturing	339		x	x			x	x	
22	Agriculture, forestry, fishing, and hunting	11								
23	Farms	111,112								
24	Forestry, fishing, hunting, and related activities	113-115								
25	Mining	21								
26	Oil and gas extraction	211								
27	Mining, except oil and gas	212								
28	Support activities for mining	213								
29	Utilities	22		x	x			x	x	
30	Construction	23								
31	Trade	42,44-45								
32	Wholesale trade	42		x	x		x		x	
33	Retail trade	44,45		x		x	x		x	
34	Transportation and warehousing	48-49								
35	Air transportation	481		x	x			x	x	
36	Rail transportation	482		x		x	x		x	
37	Water transportation	483		x	x		x		x	
38	Truck transportation	484		x		x	x		x	
39	Transit and ground passenger transportation	485		x		x	x		x	
40	Pipeline transportation	486		x	x		x		x	
41	Other transportation and support activities	487,488,492		x		x		x	x	
42	Warehousing and storage	493		x		x		x	x	
43	Information	51								
44	Publishing (incl. software)	511,516	x	x						
45	Motion picture and sound recording industries	512		x	x			x		x
46	Broadcasting and telecommunications	515,517		x	x			x	x	
47	Information and Data Processing Services	518,519		x	x			x		x
48	Finance, Insurance, and Real Estate	52-53								
49	Credit intermed. and related activities	521,522								
50	Securities, commods, and other fin. invest. activities	523								
51	Insurance carriers and related activities	524								
52	Funds, trusts, and other financial vehicles	525								
53	Real estate	531								
54	Rental and leasing services and lessors of intangible assets	532,533								
55	Services	54-81								
56	Legal services	5411		x		x	x			x
57	Computer systems design	5415	x	x						
58	Miscellaneous professional, scientific, and technical services	5412-5414,5416-5419		x	x		x			x
59	Management of companies and enterprises	55		x	x		x			x
60	Administrative and support services	561		x	x		x			x
61	Waste management and remediation services	562		x		x	x			x
62	Education services	61		x		x		x		x
63	Ambulatory health care services	621		x	x		x			x
64	Hospitals and nursing and residential care facilities	622,623		x		x	x			x
65	Social assistance	624		x		x	x			x
66	Performing arts, spectator sports, museums, and related indu	711,712		x		x	x			x
67	Amusement, gambling, and recreation industries	713		x		x	x			x
68	Accommodation	721		x		x	x		x	
69	Food services and drinking places	722		x		x		x		x
70	Other services	81		x		x	x			x

Appendix B. Overview of BFOS (2003) estimating equation[37]

Formally, BFOS assume an IT user produces market output Y and (unobserved) intangible investment A, (where the market output can be transformed one-to-one into intangible investment) with a production function:

$$Q_{it} \equiv Y_{it} + A_{it} = F\left(Z_{it}G(K_{it}^{ICT}, C_{it}), K_{it}^{NT}, L_{it}\right), \quad i = 1...N$$

A accumulates to intangible/organizational capital C that, together with IT capital, K^{IT}, produces services. The separability assumption on G captures the link between reorganization and IT.

Differentiating, one can show that measured growth in TFP (in terms of observed market output and observed inputs) is:

$$\Delta TFP = \left[\frac{F_C C}{Y}\right]\Delta c - \left[\frac{A}{Y}\right]\Delta a + \frac{F_Z Z}{Y}\Delta z$$

Measured TFP misses the investment in intangibles as well as the service flow from those intangibles. Other things equal, measured TFP *falls* when growth in unobserved investment, Δa, is faster. It *rises* when growth in complementary/organizational capital, Δc, is faster.

BFOS use the separability assumption for G to express the output elasticity $F_C C / Y$, and the growth rates Δc and Δa, in terms of IT observables and a small number of parameters. Note that, with perfect competition, the first-order conditions imply $F_C C / Y = P_{K,C} C / PY$. Suppose G is a CES function and $\Delta p_{K,j}, j \subset \{ICT, C\}$ be the user cost of the two types of capital. With the separability assumption, the first-order conditions for C and K imply that IT-intensive firms—those with a high share of IT in observed market output—are complementary intensive:

$$\frac{P_{K,C}C}{PY} = \left(\frac{1-\alpha}{\alpha}\right)^{\sigma}\left(\frac{P_{K,C}}{P_{K,IT}}\right)^{1-\sigma}\left(\frac{P_{K,IT}K^{IT}}{PY}\right) = \beta\left(\frac{P_{K,C}}{P_{K,IT}}\right)^{1-\sigma} s_{K^{ICT}}$$

Separability also implies a link between Δc and Δk^{ICT}:

$$\Delta c_t = \Delta k_t^{ICT} + \sigma(\Delta p_{K,ICT} - \Delta p_{K,C})_t$$

The remaining challenge is to measure unobserved investment. From the perpetual inventory formula $C_{it} = A_{it} + (1-\delta_C)C_{it-1}$, we can express Δa_t in terms of Δc_t and Δc_{t-1}:

$$\Delta a_t = \frac{C}{A}\left[\Delta c_t - \frac{(1-\delta_C)}{(1+g)}\Delta c_{t-1}\right]$$

These allow us to express

$$\to \Delta TFP = [F_C - 1]\beta\tilde{k}_t + \left[\frac{(1-\delta_C)}{(1+g)}\right]\beta\tilde{k}_{t-1} + s_G\Delta z, \qquad \text{(A1)}$$
$$\text{where } \tilde{k}_t = s_{K^{ICT}}\left[\Delta k_t^{ICT} + \sigma(\Delta p_{K,ICT} - \Delta p_{K,C})_t\right]\left(P_{K,C}/P_{K,IT}\right)^{1-\sigma}$$

---

[37] See BFOS and Basu and Fernald (2008) for further details and derivations.

In this expression, the current and lagged growth rate of (suitably transformed) IT capital reflects its assumed link with growth of C and A. The share-weighting reflects the fact that, to have an important effect on measurement, this intangible capital must be sufficiently important. If IT capital has a high share then, other things equal, the model interprets it as implying that intangible capital also has a high share.

Contemporaneously, the coefficient on $\tilde{k}_t$ is negative (since $F_C \approx r + \delta_C < 1$). That reflects that, other things equal, if current IT-capital is growing, the model assumes that that *A* is also growing fast, which reduces measured TFP. The coefficient on lagged $\tilde{k}_{t-1}$ is positive, since (for given Δc_t), higher $\tilde{k}_{t-1}$ implies fewer diverted resources Δa today.

BFOS used equation (A1) as a cross-sectional estimating equation. For that purpose, they ignored the relative price terms in operationalizing $\tilde{k}_t$. That is, they took $\tilde{k}_t = s_{K^{ICT}} \Delta k_t^{ICT}$. This is probably not a major problem for the cross-sectional implications, where the relative-price effects are largely common across sectors, so the important cross-industry differences show up in the IT share and IT growth. The relative-price terms are largely soaked up in the coefficients.

In contrast, Oliner, Sichel, and Stiroh (2007) focus on the time-series dimension of this model. For those purposes, the relative-price trends are likely to be much more important. They relate the model to the broader literature on measuring intangible investment to calibrate $\sigma = 1.25$ and to measure the trends in relative user costs (in all periods, the user cost of IT falls sharply, so the relative user costs rise at 7-10 percent per year).

The model above suggests some cross-sectional implications, which I explore in the text:

1. In the model, the proxy for IT use should be the IT income share multiplied by IT growth, not merely the IT income share. That said, the latter is more common in the literature, and the two ways of identifying IT-intensive industries turn out to identify almost the same industries and yield the same results.
2. In the context of the mid-2000s slowdown, the model implies that the major slowdown should have been in IT-intensive industries (however measured), since that's where the interesting intangible "action" is.
3. The model says that measured TFP growth depends negatively on current share-weighted IT growth but positively on its lagged value. Note that since the current and lagged values are likely to be correlated, if we omit the lagged term, omitted-variable considerations imply that the sign of the relationship is ambiguous.
4. Taking literally as an estimating equation, (A1) implies that current $\tilde{k}_t$ should be negative (as the diverted resources/investment effect dominates) whereas lagged $\tilde{k}_{t-1}$ should be positive. The lags involved are unclear in the stylized model, which omits dynamic considerations such as adjustment costs and time-to-build for reorganization.
5. Suppose the early 2000s strength in measured TFP in part reflected that firms were cutting back on intangible investments. That is, those industries stopped diverting resources to unobserved investment and measured TFP spiked. If that's the story, then the subsequent slowdown in the mid-2000s (2004-2007 relative to 2000-2004) should have been largest for the industries that saw the largest deceleration in share-weighted IT in the early 2000s. A

To be added: Discussion of results from BFOS regression.

Appendix C: Projecting Labor Productivity in Neoclassical Growth Models

This appendix discusses how to estimate steady-state labor productivity growth from estimates of underlying technology growth. It uses a neoclassical model to derive the implications for capital deepening. Section A summarizes the familiar one-sector Solow model. Section B develops a two-sector Solow model, which highlights the key takeaways and intuition for the multi-sector model. Section C derives the (straightforward, but somewhat tedious) extension to the case with consumer durables, land, and inventories.

A few equations will be useful as preliminaries. Let hats over a variable represent log changes. As an identity, output growth, $\hat{Y}$, is labor-productivity growth plus growth in hours worked, $\hat{H}$:

$$\hat{Y} = (\hat{Y} - \hat{H}) + \hat{H} \ .$$

We focus here on full-employment labor productivity, so we abstract from utilization.

Growth in total factor productivity, or the Solow residual, is defined as

$$\widehat{TFP} = \hat{Y} - \alpha\hat{K} - (1-\alpha)\hat{L} \tag{18}$$

where α is capital's share of income and (1-α) is labor's share. Defining $\hat{L} \equiv \hat{H} + \widehat{LQ}$, where $\widehat{LQ}$ is labor "quality" (composition) growth[38], output per hour growth is:

$$(\hat{Y} - \hat{H}) = \widehat{TFP} + \alpha(\hat{K} - \hat{L}) + \widehat{LQ}. \tag{19}$$

Growth in output per hour worked reflects TFP growth; the contribution of capital deepening, defined as $\alpha(\hat{K} - \hat{L})$; and increases in labor quality. Economic models suggest mappings between fundamentals and the terms in this identity.

It is sometimes useful to rearrange (19) to yield:

$$(\hat{Y} - \hat{H}) = \widehat{TFP} / (1-\alpha) + \alpha(\hat{K} - \hat{Y}) + \widehat{LQ} \tag{20}$$

We now show how a one-sector and two-sector model map to these equations. Then we allow for a third sector, and for inventories, and land.

A. The one-sector Solow model

The Solow model provides a particularly simple model that maps exogenous growth in technological progress and the labor force to endogenous capital deepening.

Consider an aggregate production function $Y = K^{\alpha}(AN)^{1-\alpha}$, where labor-augmenting technology *A* grows at rate *g*, and labor input *N* (which captures both raw hours *H* and labor quality *LQ*—henceforth, I do not generally differentiate between the two) grows at rate *n*. Expressing all variables in terms of "effective labor" *AN* yields:

$$y = k^{\alpha}, \text{ where } y = Y / AN \text{ and } k = K / AN. \tag{21}$$

Capital accumulation takes place according to the perpetual-inventory formula, $\dot{K} = I - \delta K$. Let *s* is the saving rate, so that *sy* is investment per effective worker. In steady-state:

$$sy = (n + \delta + g)k \tag{22}$$

Because of diminishing returns to capital, the economy converges to a steady state where *y* and *k* are constant. At that point, investment per effective worker is just enough to offset the effects of depreciation, population growth, and technological change on capital per effective worker. In steady state, the unscaled

[38] In the BLS multifactor productivity dataset, from 1948 through 2012, hours grew 1.10 percent per year, and labor quality/composition grew 0.32 percent per year. Hence, more than a quarter of labor input growth in the MFP data reflects labor quality. As discussed in the text, labor quality, in turn, reflects the mix of hours across workers with different levels of education, experience, and so forth.

levels of Y and K grow at the same rate $g+n$; capital-deepening, K/N, grows at rate g. Labor productivity Y/N, i.e., output per unit of labor input, also grows at rate g.

From the production function, measured TFP growth is related to labor-augmenting technology growth by:

$$\widehat{TFP} = \hat{Y} - \alpha\hat{K} - (1-\alpha)\hat{L} = (1-\alpha)g .$$

The model maps directly to equations (19) and (20) above. In steady state, $\hat{K} = \hat{Y}$, and, as in equation(20), output per unit of labor grows at $g = \widehat{TFP}/(1-\alpha)$. Alternatively, in terms of equation(19), the endogenous contribution of capital deepening to labor-productivity growth is $\alpha(\hat{K} - \hat{L}) = \alpha g = \alpha \cdot \widehat{TFP} / (1-\alpha)$. Thus, we can write growth in output per hour in a form that corresponds closely with the two-sector version below:

$$\hat{Y} - n = \widehat{TFP} + \alpha \cdot \widehat{TFP} / (1-\alpha) \qquad (23)$$

Growth in output per unit of labor depends on standard TFP growth and induced capital deepening.

B. The two-sector Solow model

In contrast to the predictions of the one-sector model, the capital-output ratio in the data rises steadily after the early 1970s. The literature on investment specific technical change suggests a straightforward fix for this model failure: Capital-deepening doesn't depend on *overall* TFP, but on TFP in the investment sector. A key motivation for this literature is the declining price of business investment goods, especially equipment and software, relative to the price of other goods (such as consumption). The most natural interpretation of the declining relative price is faster technical change in producing investment goods (especially high-tech equipment).[39]

Consider a simple two-sector Solow-type model, where s is the share of nominal output that is invested each period.[40] One sector produces investment goods that are used to create capital; the other produces consumption goods. The two sectors use the same Cobb-Douglas production function, but with potentially different technology levels:

$$I = K_I^{\alpha}(A_I L_I)^{1-\alpha}$$

$$C = QK_C^{\alpha}(A_I L_C)^{1-\alpha}$$

In the consumption equation, we have implicitly defined labor-augmenting technological change as $A_C = Q^{1/(1-\alpha)} A_I$ in order to decompose consumption technology into the product of investment technology A_I and a "consumption specific" piece, $Q^{1/(1-\alpha)}$. Let investment technology A_I grow at rate g_I and the consumption-specific piece Q grow at rate q. Perfect competition and cost-minimization imply that price equals marginal cost. If the sectors face the same factor prices (and the same rate of indirect business taxes), then relative marginal costs depend solely on relative technology:

$$\frac{P_I}{P_C} = \frac{MC^C}{MC^I} = Q$$

The sectors also choose to produce with the same capital-labor ratios, implying that $K_I / A_I L_I = K_C / A_I L_C = K / A_I L$. We can then write the production functions as:

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[39] On the growth accounting side, see, for example, Jorgenson (2001) or Oliner and Sichel (2000); see also Greenwood, Hercowitz, and Krusell (1997).

[40] This model is a fixed-saving rate version of the two-sector neoclassical growth model in Whelan (2003) and is isomorphic to the one in Greenwood, Hercowitz, and Krusell (1997). Greenwood *et al*. choose a different normalization of the two technology shocks in their model.

$$I = A_I L_I \left(K/A_I L\right)^{\alpha}$$
$$C = QA_I L_C \left(K/A_I L\right)^{\alpha} \tag{24}$$

We can now write the economy's budget constraint in a simple manner:

$$Y^{\text{Inv. Units}} \equiv [I + C/Q] = A_I(L_I + L_C)\left(K/A_I L\right)^{\alpha}, \text{ or}$$
$$y^{\text{Inv. Units}} = k^{\alpha}, \text{ where } y^{\text{Inv. Units}} = Y^{\text{Inv. Units}} / A_I L \text{ and } k = K / A_I L. \tag{25}$$

Output here is expressed in investment units, and "effective labor" is in terms of technology in the *investment* sector. The economy mechanically invests a share s of nominal investment, which implies that investment per effective unit of labor is $i = s \cdot y^{\text{Inv. Units}}$.[41]

Capital accumulation turns out to take the same form as in the one-sector model, except that it is only growth in investment technology, g_I, that matters. In particular, in steady state:[42]

$$sy^{\text{Inv. Units}} = (n + \delta + g_I)k \tag{26}$$

The production function (25) and capital-accumulation equation (26) correspond exactly to their one-sector counterparts. Hence, the dynamics of capital in this model reflect technology in the investment sector alone. In steady state, capital per unit of labor, K/L, grows at rate g_I, so the contribution of capital deepening to labor-productivity growth from equation (19) is

$$\alpha(\hat{K} - \hat{L}) = \alpha g_I = \alpha \cdot \widehat{TFP_I} / (1-\alpha) \tag{27}$$

Consumption technology in this model is "neutral," in that it does not affect investment or capital accumulation; the same result generally carries over to the Ramsey version of this model, with or without variable labor supply. (Basu, Fernald, Fisher, and Kimball, 2011, discuss the idea of consumption-technology neutrality in greater detail.)

In the data, output is not expressed in investment units but as chained units. Chain GDP growth is defined as share-weighted growth in final expenditure categories:

$$\hat{Y} = s\hat{I} + (1-s)\hat{C}$$

From equation (25), in steady state, when $k = K / A_I L$ is constant, $\hat{I}$ grows at rate $(n+g_I)$ and $\hat{C}$ grows at rate ($n + g_I + \hat{q}$). Hence, $\hat{Y} = n + g_I + (1-s)\hat{q}$ and the capital-output ratio grows at $\hat{K} - \hat{Y} = (n + g_I) - (n + g_I + (1-s)\hat{q}) = -(1-s)\hat{q}$ Since consumption TFP growth is generally lower than investment TFP growth, $\hat{q}$ is negative in the data, and the model predicts that the measured capital-output ratio is increasing. Note that overall TFP growth in chain-units is:

$$\begin{aligned} \widehat{TFP} &= \hat{Y} - \alpha\hat{K} - (1-\alpha)\hat{L} \\ &= n + g_I + (1-s)\hat{q} - \alpha(n + g_I) - (1-\alpha)n \\ &= (1-\alpha)g_I + (1-s)\hat{q} \end{aligned} \tag{28}$$

Hence, using (19) and ??, growth in output per unit of labor can be written:

$$\hat{Y} - n = g_I + (1-s)\hat{q} = \widehat{TFP} + \alpha\frac{\widehat{TFP_I}}{(1-\alpha)} \tag{28}$$

---

[41] $s \cdot y^{\text{Inv. Units}} = \left[P_I I/(P_I I + P_C C)\right]\left[\left(I + P_C C / P_I\right) / A_I L\right] = I/A_I L$

[42] The time-derivative $\dot{k} = d/dt(K/AL) = (K/AL)(\dot{K}/K - n - g_I)$. Substituting the capital accumulation equation, $\dot{K} / K = I / K - \delta$, yields $\dot{k} = i - (n + g_I + \delta)k$. In steady-state, $\dot{k} = 0$. Substituting for i yields (26).

This equation takes the same form as (23), except that capital deepening is solely in terms of investment-sector TFP growth.

To take this model to the data, we need to decompose aggregate TFP growth (calculated from chained output) into its consumption and investment components. Given the conditions so far, the following two equations hold:

$$\widehat{TFP} = s \cdot \widehat{TFP_I} + (1-s)\widehat{TFP_C}$$
$$\widehat{P_C} - \widehat{P_I} = \widehat{TFP_C} - \widehat{TFP_I}$$

Prices, investment shares, and aggregate TFP are known. Hence, these are two equations in two unknowns— $\widehat{TFP_I}$ and $\widehat{TFP_C}$.[43]

C. Three sector model

In practice, there are multiple types of capital. The most important distinction is between fast-growing equipment and more slowly growing structures. The argument would naturally extend to more types of capital, as well. Suppose that there's a **D**urable sector that produces equipment, a **B**uilding sector that produces structure, and a **C**onsumption sector: [44]

$$\begin{aligned} D &= (K_D)^{\alpha}(AL_E)^{1-\alpha} \\ B &= Q_B(K_B)^{\alpha}(AL_B)^{1-\alpha} \\ C &= Q_C(K_C)^{\alpha}(AL_C)^{1-\alpha} \end{aligned} \tag{29}$$

Some durable goods are consumed as durables. Other durable goods are invested and become equipment capital according to the usual perpetual inventory equation. Similarly, new buildings become gross investment in structures. All three sectors use the same capital aggregate, which uses equipment *E* and structures *S*.

$$K = E^{c_E} S^{1-c_E} = K_D + K_B + K_C \tag{30}$$

To solve for steady state growth rates, I follow Whelan (2003). In steady state, growth of equipment and structures must be the same in all uses, and labor growth (at rate *n*) is the same in all uses. Let g_X be steady-state growth in variable *X*. In steady-state, the perpetual-inventory formula implies that growth of investment in durables or buildings is equal to growth in the capital stocks of equipment and structures, respectively.[45] That is, $g_E = g_D$ and $g_S = g_B$. In growth rates, then:

$$\begin{aligned} g_D &= \alpha(c_E g_D + (1-c_E)g_B) + (1-\alpha)(\hat{a}+n) \\ g_B &= \alpha(c_E g_D + (1-c_E)g_B) + (1-\alpha)(\hat{a}+n) + \hat{q}_S = g_D + \hat{q}_B \\ g_C &= \alpha(c_E g_D + (1-c_E)g_B) + (1-\alpha)(\hat{a}+n) + \hat{q}_C = g_D + \hat{q}_C \end{aligned} \tag{31}$$

---

[43] The calculations in the text use the official price deflators from the national accounts. Gordon (1990) argues that many equipment deflators are not sufficiently adjusted for quality improvements over time. Much of the macroeconomic literature since then has used the Gordon deflators. Of course, as Whelan (2003) points out, much of the discussion of biases in the CPI involve service prices, which also miss a lot of quality improvements, making the overall effect uncertain. Hobijn and McKay (2007) also question these hedonic adjustments.

[44] The mnemomics—**D**urables rather than **E**quipment, for example—is to clearly differentiate the flow output of producing sectors from the accumulated stock of equipment and structures.

[45] In steady-state, $I/K = g + \delta$. Since the right-hand-side is constant, *I* must grow at the same rate as *K*.

This is a straightforward system of simultaneous equations that yields:

$$\begin{aligned} g_D &= (\hat{a}+n)+\frac{\alpha(1-c_E)}{1-\alpha}\hat{q}_B \\ g_B &= g_D+\hat{q}_B \\ g_C &= g_D+\hat{q}_C \end{aligned} \tag{32}$$

Chain GDP growth is share-weighted growth in final expenditure categories. If s_D is the final-expenditure-share of durables and s_B is the final-expenditure-share of buildings, then:

$$\begin{aligned} g &= s_D g_D + s_B g_B + (1-s_D-s_B)g_C \\ &= g_D + s_B\hat{q}_B + (1-s_D-s_B)\hat{q}_C \\ &= (\hat{a}+n)+\left[\frac{\alpha(1-c_E)}{1-\alpha}+s_B\right]\hat{q}_B+(1-s_D-s_B)\hat{q}_C \end{aligned} \tag{33}$$

Growth in output per unit of labor is then:

$$g-n=\hat{a}+\left[\frac{\alpha(1-c_E)}{1-\alpha}+s_B\right]\hat{q}_B+(1-s_D-s_B)\hat{q}_C \tag{34}$$

Standard TFP growth for each sector is not in labor-augmenting form, so it equals:

$$\begin{aligned} \widehat{TFP_D} &= (1-\alpha)\hat{a} \\ \widehat{TFP_B} &= (1-\alpha)\hat{a}+\hat{q}_B=\widehat{TFP_D}+\hat{q}_B \\ \widehat{TFP_C} &= (1-\alpha)\hat{a}+\hat{q}_C=\widehat{TFP_D}+\hat{q}_C \end{aligned} \tag{35}$$

Overall TFP growth in this economy is output growth less share-weighted input growth:

$$\widehat{TFP}=g-\alpha(c_E g_D+(1-c_E)g_B)-(1-\alpha)n \tag{36}$$

Using the second line of (33) and then substituting from (32), we find:

$$\begin{aligned} \widehat{TFP} &= [g_D+s_B\hat{q}_B+(1-s_D-s_B)\hat{q}_C]-\alpha(g_D+(1-c_E)\hat{q}_B)-(1-\alpha)n \\ &= (1-\alpha)g_D-\alpha(1-c_E)\hat{q}_B+s_S\hat{q}_B+(1-s_D-s_B)\hat{q}_C-(1-\alpha)n \\ &= (1-\alpha)(\hat{a}+n)+\alpha(1-c_E)\hat{q}_B-\alpha(1-c_E)\hat{q}_B+s_B\hat{q}_B+(1-s_D-s_B)\hat{q}_C-(1-\alpha)n \\ &= \widehat{TFP_D}+s_B\hat{q}_B+(1-s_D-s_B)\hat{q}_C \end{aligned} \tag{37}$$

Note that aggregate TFP growth is also equal to share-weighted sectoral TFP growth using (35)..

Define investment TFP growth, $\widehat{TFP_I}$, in terms of <u>user cost (factor share)</u> weights (rather than expenditure weights):

$$\begin{aligned} \widehat{TFP_I} &= c_E\widehat{TFP_D}+(1-c_E)\widehat{TFP_B} \\ &= \widehat{TFP_D}+(1-c_E)\hat{q}_B \end{aligned} \tag{38}$$

We can now write growth in output per unit of labor from (34) in terms of overall and investment-sector TFP growth:

$$
\begin{aligned}
g-n &= \hat{a}+\left[\frac{(1-\alpha)s_B+\alpha(1-c_E)}{1-\alpha}\right]\hat{q}_B+(1-s_D-s_B)\hat{q}_C \\
&= \left[(1-\alpha)\hat{a}+s_B\hat{q}_B+(1-s_D-s_B)\hat{q}_C\right]+\alpha\hat{a}+\left[\frac{(1-\alpha)s_B+\alpha(1-c_E)}{1-\alpha}-s_B\right]\hat{q}_B \\
&= \widehat{TFP}+\left(\alpha\hat{a}+\left[\frac{\alpha(1-c_E)}{1-\alpha}\right]\hat{q}_B\right) \\
&= \widehat{TFP}+\frac{\alpha}{1-\alpha}\widehat{TFP_I}
\end{aligned}
\tag{39}
$$

Although the derivation is somewhat involved, this is exactly the same equation as for the two-sector model.

Finally, note that the existence of consumer durables (produced by the durable sector) does not affect this calculation. The weight on durables in final expenditure, s_D, already includes all final uses of durable output (whether for investment or for durable consumption). However, the user cost weight of equipment includes only the portion used for equipment investment.

D. Adding inventories, consumer durables, and land

In practice, there are not only multiple types of capital goods, but land. We can derive more general steady-state predictions using the same approach as with the three-sector model above.[46]

Specifically, we assume the same production structure as in (29), above:

$$
\begin{aligned}
D &= (K_D)^{\alpha}(AL_E)^{1-\alpha} \\
B &= Q_B(K_B)^{\alpha}(AL_B)^{1-\alpha} \\
C &= Q_C(K_C)^{\alpha}(AL_C)^{1-\alpha}
\end{aligned}
\tag{40}
$$

Now, some durable goods are used for consumption (which raises the weight of durables in final output). We also have inventories in capital. Inventories are goods (in the data, roughly half are durable and half are non-durable), but their relative price movements are less pronounced than for equipment. For generality in derivations, we'll allow both the durable and the non-durable sectors to produce inventories.

The capital aggregate now includes inventories, V, and land, T (for **T**erra), as well as equipment and structures:

$$
K = E^{c_E}S^{1-c_E-c_V-c_T}\left(V_D^{\delta}V_C^{1-\delta}\right)^{c_V}T^{c_T} = K_D+K_B+K_C \tag{41}
$$

Using (40) and (41), we can proceed in the same way as in the three-sector model:

$$
\begin{aligned}
g_D &= \alpha(c_E g_D+(1-c_E-c_V-c_T)g_B+c_V\delta g_D+c_V(1-\delta)g_C+c_T\hat{T})+(1-\alpha)(\hat{a}+n) \\
g_B &= g_D+\hat{q}_B \\
g_C &= g_D+\hat{q}_C
\end{aligned}
\tag{42}
$$

[46] This analysis takes land as exogenous, though not fixed—it can be pulled from other uses, and in the BLS dataset, business use of land grows at about 1-1/2 percent per year. An alternative modeling strategy would be to tie it to the use of structures in some way. That said, the correlation in the BLS dataset between annual changes in structures and land is far from perfect (about 0.4).

TFP growth in each sector is related to the "fundamental shocks" as shown in equation (35). TFP growth for "reproducible investment," $\widehat{TFP_I}$, with user cost (factor share) weights, is then:

$$\begin{aligned}\widehat{TFP_I} &= \left(\frac{c_E + c_V\delta}{1-c_T}\widehat{TFP_D} + \frac{(1-c_E-c_V-c_T)}{1-c_T}\widehat{TFP_B} + \frac{c_V(1-\delta)}{1-c_T}\widehat{TFP_C}\right) \\ &= \widehat{TFP_D} + \frac{(1-c_E-c_V-c_T)}{1-c_T}\hat{q}_B + \frac{c_V(1-\delta)}{1-c_T}\hat{q}_C\end{aligned} \tag{43}$$

Solving the system of equations in (42) yields

$$g_D = \left(\frac{1-\alpha}{1-\alpha(1-c_T)}\right)(\hat{a}+n) + \frac{\alpha c_V(1-\delta)}{1-\alpha(1-c_T)}\hat{q}_C + \frac{\alpha(1-c_E-c_V-c_T)}{1-\alpha(1-c_T)}\hat{q}_B + \left(\frac{\alpha c_T}{1-\alpha(1-c_T)}\right)\hat{T} \tag{44}$$

Adding and subtracting $\widehat{TFP_D}$, rearranging, and substituting from (43), yields:

$$\begin{aligned}g_D &= \widehat{TFP_D} + \left[\frac{1}{1-\alpha(1-c_T)} - 1\right]\widehat{TFP_D} + \frac{\alpha c_V(1-\delta)}{1-\alpha(1-c_T)}\hat{q}_C + \frac{\alpha(1-c_E-c_V-c_T)}{1-\alpha(1-c_T)}\hat{q}_B + \left(\frac{\alpha c_T}{1-\alpha(1-c_T)}\right)\hat{T} + \left(\frac{1-\alpha}{1-\alpha(1-c_T)}\right)n \\ &= \widehat{TFP_D} + \left[\frac{\alpha(1-c_T)}{1-\alpha(1-c_T)}\right]\left[\widehat{TFP_D} + \frac{(1-c_E-c_V-c_T)}{1-c_T}\hat{q}_B + \frac{c_V(1-\delta)}{1-c_T}\hat{q}_C\right] + \left(\frac{\alpha c_T}{1-\alpha(1-c_T)}\right)\hat{T} + \left(\frac{1-\alpha}{1-\alpha(1-c_T)}\right)n \\ &= \widehat{TFP_D} + \left[\frac{\alpha(1-c_T)}{1-\alpha(1-c_T)}\right]\widehat{TFP_I} + \left(\frac{\alpha c_T}{1-\alpha(1-c_T)}\right)\hat{T} + \left(\frac{1-\alpha}{1-\alpha(1-c_T)}\right)n\end{aligned} \tag{45}$$

Growth in reproducible capital per worker can be expressed as:

$$\begin{aligned}\hat{K}^{\mathrm{R}} - n &= \left(\frac{1}{1-c_T}\right)\big((c_E + c_V\delta)g_D + (1-c_E-c_V-c_T)g_S + c_V(1-\delta)g_S\big) - n \\ &= g_D + \left(\frac{c_V(1-\delta)}{1-c_T}\right)\hat{q}_C + \left(\frac{1-c_E-c_V-c_T}{1-c_T}\right)\hat{q}_B - n\end{aligned}$$

If we substitute for g_D from (44), define $\alpha^R = \alpha(1-c_T)$, and rearrange, we find:

$$\hat{K}^{\mathrm{R}} - n = \left[\frac{1}{1-\alpha^R}\right]\widehat{TFP_I} + \left(\frac{\alpha c_T}{1-\alpha^R)}\right)(\hat{T}-n) \tag{46}$$

Overall capital deepening is

$$\begin{aligned}\alpha\left(\hat{K}-n\right) &= \alpha(1-c_T)\left(\hat{K}^{\mathrm{R}}-n\right) + \alpha c_T(\hat{T}-n) \\ &= \left[\frac{\alpha^R}{1-\alpha^R}\right]\widehat{TFP_I} + \left(\frac{\alpha c_T}{1-\alpha^R}\right)(\hat{T}-n)\end{aligned} \tag{47}$$

From (19), output per worker is:

$$\begin{aligned} g-n &= \widehat{TFP}+\alpha\left(\hat{K}-n\right) \\ &= \widehat{TFP}+\left[\frac{\alpha^R}{1-\alpha^R}\right]\widehat{TFP_I}+\left(\frac{\alpha c_T}{1-\alpha^R}\right)(\hat{T}-n) \end{aligned} \tag{48}$$

This equation is a natural extension of the one- and two-sector models. If land's share, c_T, is zero, then this equation exactly matches (28) and (39). If $\widehat{TFP_I}=\widehat{TFP}$, then the equation matches (23).

In terms of comparing model projections, land is a complicating factor. Some comparisons are easier, however, since land affects the predictions equally. First, the predictions of the one-sector model with land are the case where $\widehat{TFP_I}=\widehat{TFP}$, so the difference in predictions is just:

$$\left(g^{\text{Multi-Sector}}-n\right)-\left(g^{\text{One Sector}}-n\right)=\left[\frac{\alpha^R}{1-\alpha^R}\right]\left(\widehat{TFP_I}-\widehat{TFP}\right).$$

Second, recall from the second line of equation ?? that, by the definition of chained GDP, that $g=g_D+s_B\hat{q}_B+(1-s_D-s_B)\hat{q}_C$. It follows that components of the capital-output ratio are:

$$\begin{aligned} g_D-g &= s_B\hat{q}_B+(1-s_D-s_B)\hat{q}_C \\ g_B-g &= (g_D+\hat{q}_B)-g=(1-s_B)\hat{q}_B+(1-s_D-s_B)\hat{q}_C \end{aligned}.$$

Third, from equation ?? for growth in reproducible capital, and from the chain-GDP equation, it follows that the growth rate of the reproducible-capital-to-output ratio is:

$$\hat{K}^{\mathrm{R}}-g=\left(\frac{1-c_E-c_V-c_T}{1-c_T}-s_B\right)\hat{q}_B+\left(\frac{c_V(1-\delta)}{1-c_T}-s_C\right)\hat{q}_C$$

Note that the inventory share of non-land capital payments is under 10 percent, whereas s_C is about 75 percent. Since $\hat{q}_C$ is negative in the data, the second piece tends to push growth in the reproducible-capital to output ratio positive. On the other side, the weight on building-specific TFP growth is the difference between structure's weight in reproducible capital (which averages about 45 percent), and building's share of GDP (which averages 5 percent). Since $\hat{q}_B$ is negative in the data, the building component tends to push this piece negative.

Table 1
Industry Data on Productivity

		Pre-1995	1995-2000	2000-2004	2004-2007	2007-2011	Chng after 2004 ((4)-(3), i.e., 04-07 less 00-04)	*VA Weight (Avg., 1988-2011)*
		(1)	(2)	(3)	(4)	(5)	(6)	*(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)	0.30	0.45	3.92	0.42	1.11	-3.50	*34.3*
(10)	Non-IT intensive (ex NR-C-F and IT-prod)	0.66	1.08	1.03	1.32	-0.03	0.29	*34.6*
(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, exc 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*
(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)	0.53	1.27	0.60	0.02	0.64	-0.58	*33.9*
(21)	Non-fin. intensive (ex NR-C-F and IT-prod)	0.47	0.31	4.53	1.75	0.56	-2.78	*35.0*

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

Table 2
Number of states with slowdowns in labor productivity growth

		# Slowing 2004-07 fr. 1997-04	Median 04-07 change	# Slowing 2004-12 fr 1997-04	Median 04-12 change
		(1)	(2)	(3)	(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, D.C.) 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.

Table 3
Home Prices and State Labor Productivity Slowdowns

Indep. var. \ Dep var.	Panel A: $\Delta LP^{2004\text{-}07} - \Delta LP^{1997\text{-}04}$						
	Private	Excl. NR-F-C+IT Prod	IT intensive	Not IT intensive	Constr	FIRE	NR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
constant	-2.06	-1.36	-2.66	-0.61	-4.89	-1.66	-14.50
	(0.27)	(0.28)	(0.33)	(0.40)	(0.69)	(0.53)	(2.32)
ΔHPI (2001-06)	-0.19	0.10	0.36	-0.024	0.08	-0.12	3.16
	(0.15)	(0.13)	(0.13)	(0.19)	(0.30)	(0.28)	(1.06)
R^2	0.02	0.01	0.05	0.01	0.01	0.02	0.01

Indep. var. \ Dep var.	Panel B: $\Delta LP^{2005\text{-}12} - \Delta LP^{1997\text{-}05}$						
	Private	Excl. NR-F-C+IT Prod	IT intensive	Not IT intensive	Constr	FIRE	NR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
constant	-0.71	-1.00	-1.88	-0.28	3.67	-1.18	-1.95
	(0.22)	(0.20)	(0.34)	(0.32)	(0.54)	(0.57)	(2.31)
ΔHPI (2006-09)	0.60	0.15	0.11	0.13	1.38	0.79	2.63
	(0.13)	(0.11)	(0.21)	(0.20)	(0.33)	(0.36)	(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 U.S. 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 2004-07 from 1997-04; the bottom panel 2005-12 from 1997-05. NR is natural resources, C is construction, F or FIRE is finance, insurance, and real estate. ΔHPI (2001-06) is the change in state home-price indices from 2001Q1 through 2006Q1; ΔHPI (2006-09) is change from 2006:Q1-2009:Q2. ΔHPI is normalized by the cross-sectional standard deviation. The Saiz (2010) housing-supply elasticity instruments for the housing-price change.

Table 4
Historical Predictions of Growth Models

A. No Land

	Overall TFP	Invest. TFP	One-Sector Predicted Y/L	Multi-Sector Predicted Y/L	Actual Output per Unit Labor	*Memo: Labor Quality*	*Memo: Actual Output/Hour (5)+(6)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Full Sample	1.3	1.8	1.9	2.2	**2.0**	*0.4*	*2.4*
pre-1973Q2	2.1	2.2	3.2	3.2	**2.9**	*0.3*	*3.2*
1973Q2-1995Q4	0.4	1.0	0.7	0.9	**1.0**	*0.4*	*1.4*
1995:Q4-2007:Q4	1.4	2.9	2.1	2.8	**2.4**	*0.4*	*2.4*

B. Adding Land as a Factor of Production

	Overall TFP	Invest. TFP	One-Sector Predicted Y/L	Multi-Sector Predicted Y/L	Actual Output per Unit Labor	*Memo: Labor Quality*	*Memo: Actual Output/Hour (5)+(6)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Full Sample	1.3	1.8	1.9	2.1	**2.0**	*0.4*	*2.4*
pre-1973Q2	2.1	2.2	3.1	3.1	**2.9**	*0.3*	*3.2*
1973Q2-1995Q4	0.4	1.0	0.6	0.8	**1.0**	*0.4*	*1.4*
1995:Q4-2007:Q4	1.4	2.9	2.0	2.6	**2.4**	*0.4*	*2.8*

Notes: Column (3) shows predictions of one-sector growth model for output per unit of (quality-adjusted) labor. In panel A, that prediction depends on column (1) according to $\widehat{TFP}\,/\,(1-\alpha)$. Column (4) shows predictions of multi-sector growth model. In top panel, that depends on columns (1) and (2) according to $\widehat{TFP} + \alpha \cdot \widehat{TFP_I}\,/\,(1-\alpha)$. See text for how land is incorporated as a factor of production in bottom panel. The predictions are compared with actual output per unit of quality-adjusted labor in Column (5). The more typical output per hour is shown in Column (7). All calculations take capital's share α=0.33, which is the full-sample average in the Fernald dataset. Investment TFP averages equipment TFP and structures TFP, where the weight on equipment includes the weight of inventories.

Table 5
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	3.21	2.72	3.23	3.89	3.02
(2)	Buildings TFP	-0.38	-0.45	-0.37	-0.58	-0.63
(3)	Consumption TFP	0.35	0.37	0.36	0.50	0.22
(4)	Overall TFP	0.94	0.83	0.96	1.19	0.75
(5)	Investment TFP	2.19	1.82	2.20	2.61	1.98
(6)	Labor prod. projection	**1.91**	1.63	1.93	2.35	1.62
(7)	GDP projection	**2.14**	1.93	2.16	2.48	1.92
(8)	*Lab. prod. proj., 2012 cap. share*	*2.08*	*1.78*	*2.11*	*2.56*	*1.78*
(9)	*GDP proj., 2012 cap. share*	*2.27*	*2.04*	*2.29*	*2.64*	*2.04*

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 2013:Q4, with starting quarters for the windows that range from 1973:Q2 through 2007:Q4. The remaining columns show selected windows. Labor productivity projections in rows (6) and (8) assume that capital's share in "reproducible" (non-land) capital as well as the weight on durables and buildings in total "investment" TFP is its average from 2001:Q4 through 2007:Q4. Line (8) assumes that (reproducible) capital's share remains at its estimated 2013:Q4 level.

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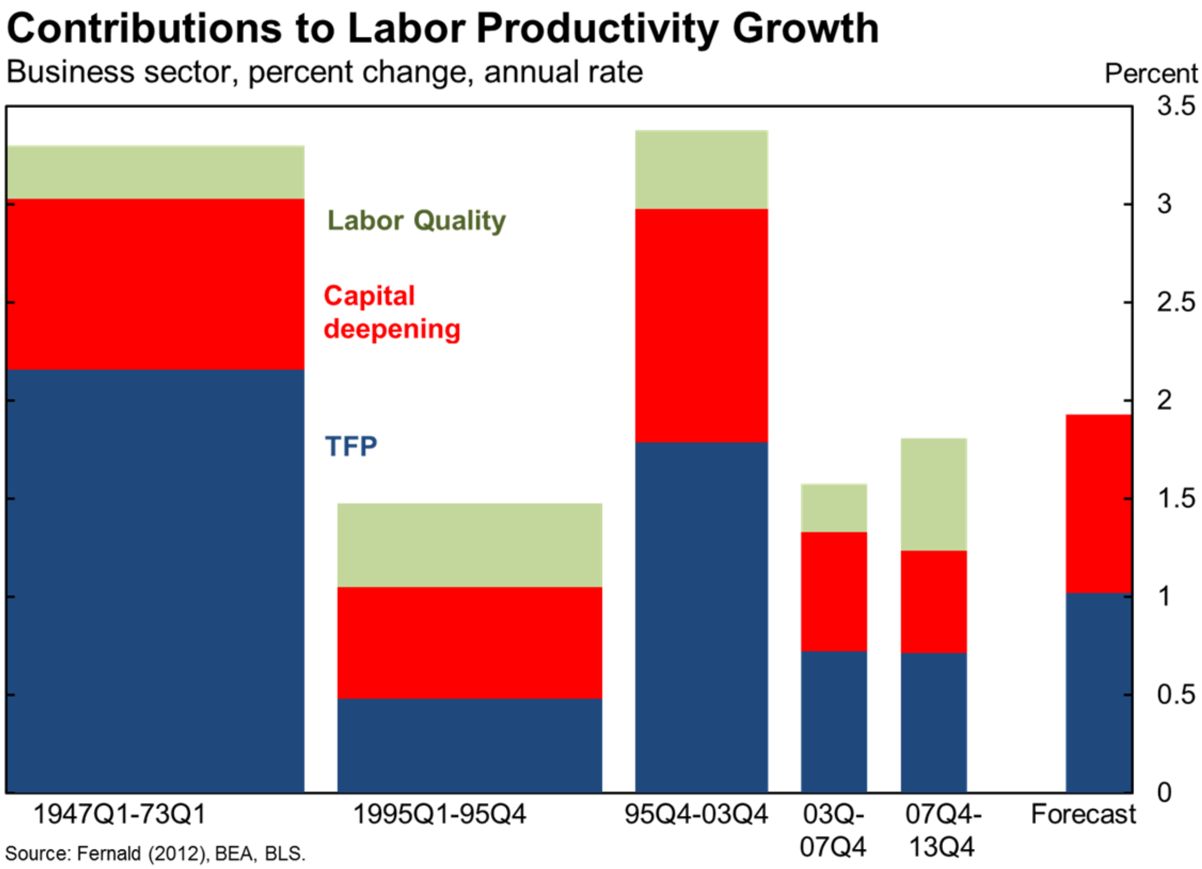
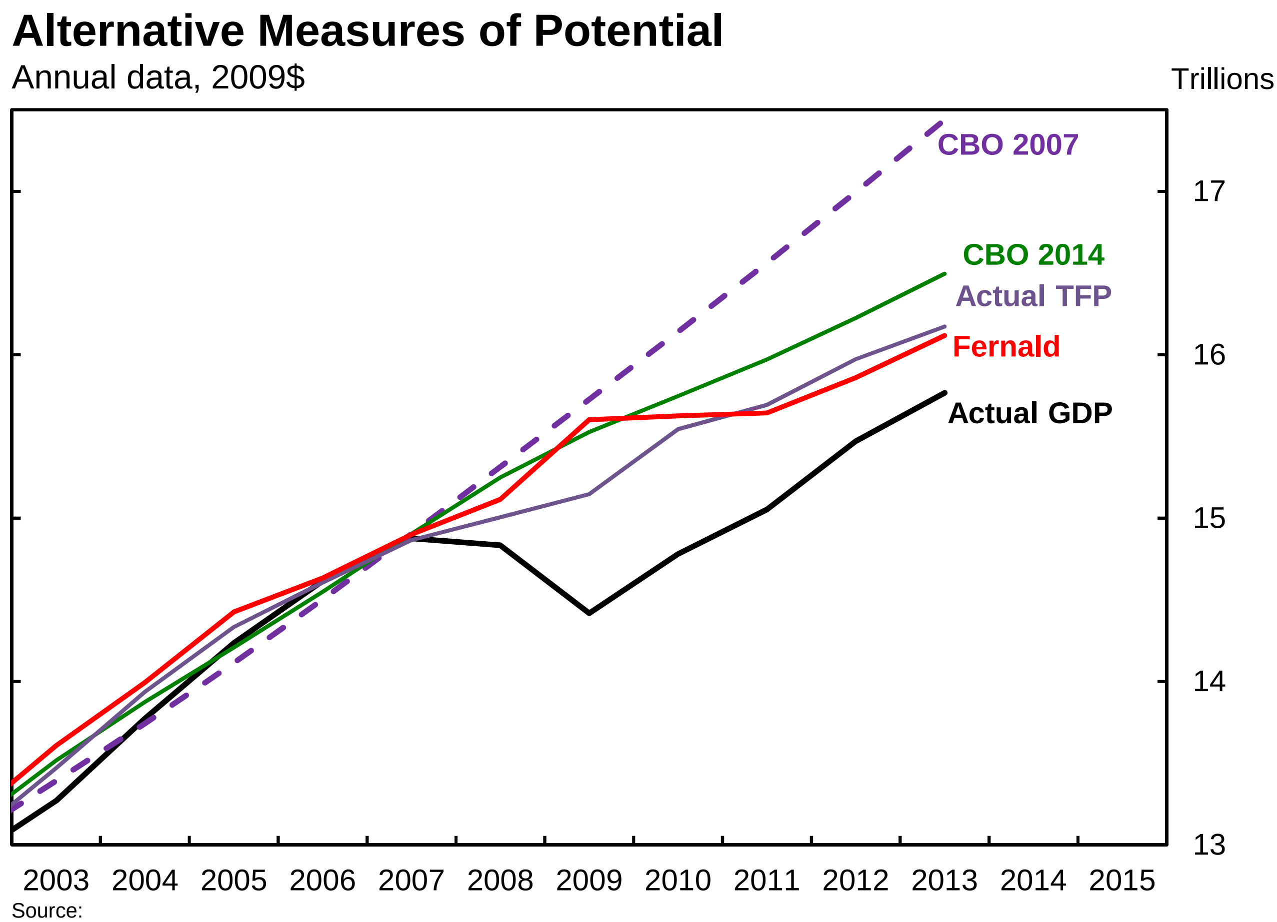
Figure 1
Productivity growth by sub-period



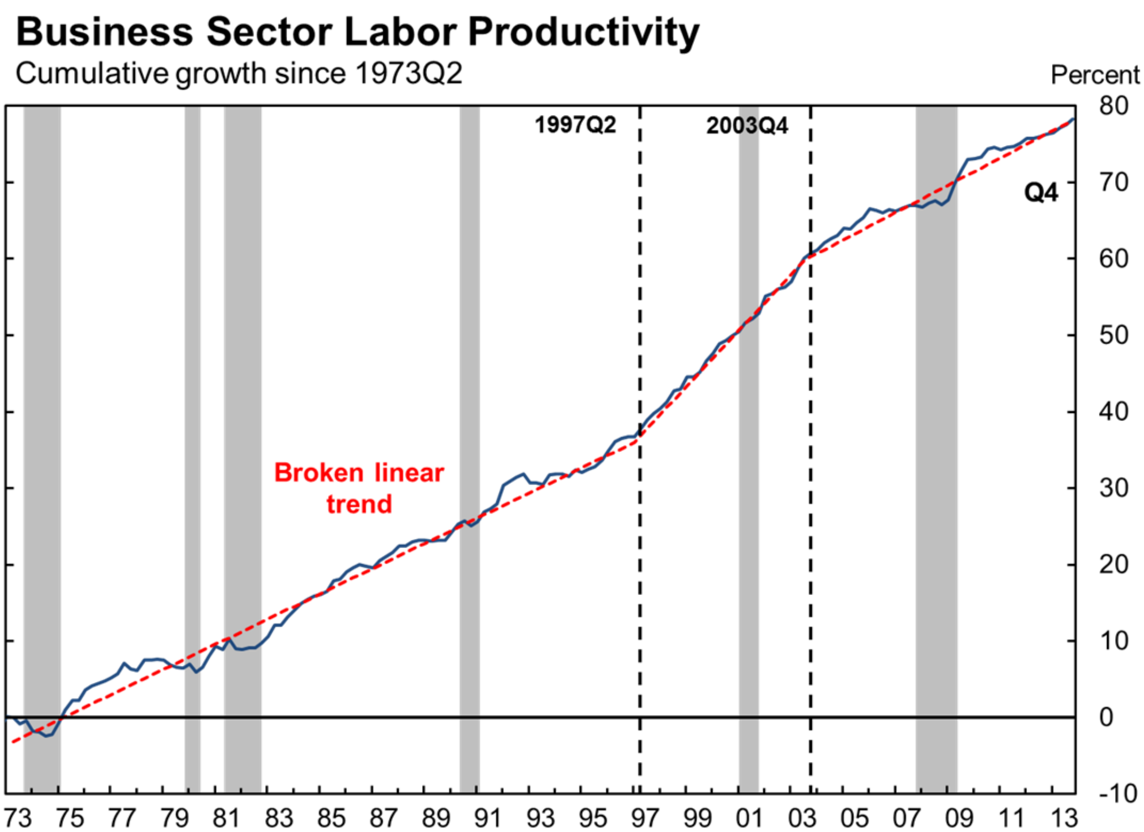
Source: BLS and Fernald (2012)

Figure 2
Potential output and its pre-crisis trend



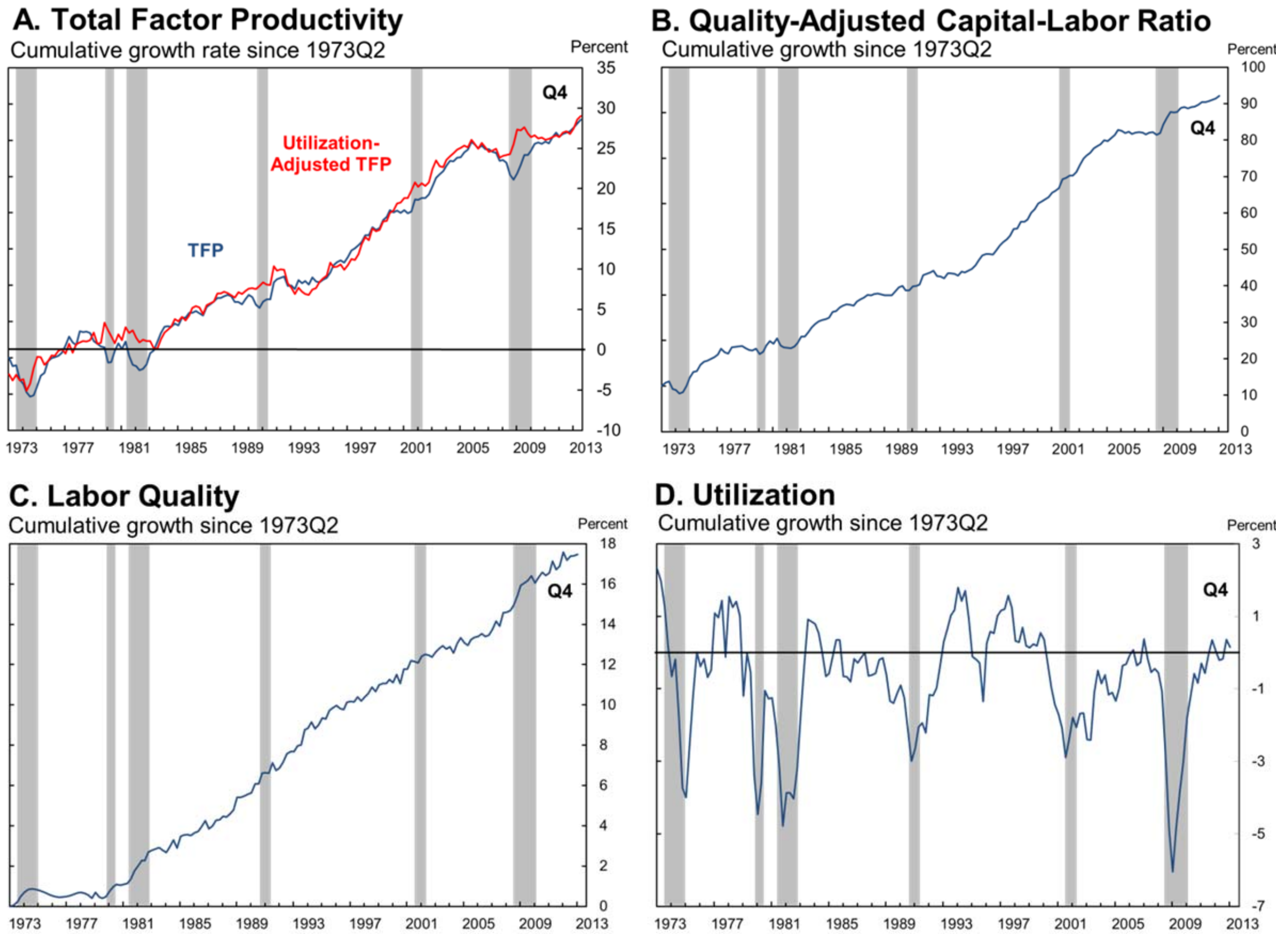
Notes: Figure compares actual real GDP to the CBO's projections for potential prior to the Great Recession (the 2007 line) to CBO's February 2014 projection, as well as the author's calculation of potential following the CBO methodology but with different assumptions. "Actual TFP" assumes utilization is constant, so that actual TFP measures technology, but uses CBO's estimated hours gap. "Fernald" uses estimated utilization and labor-quality gaps along with CBO hours gap. The "2007" CBO estimates are from January 2008, but are based on data through 2007:Q3. Those estimates have been rescaled to 2009$ so that the 2007 value equals the level in CBO (2014a).

Figure 3
Labor productivity since 1973



Source: BLS and Fernald (2012)

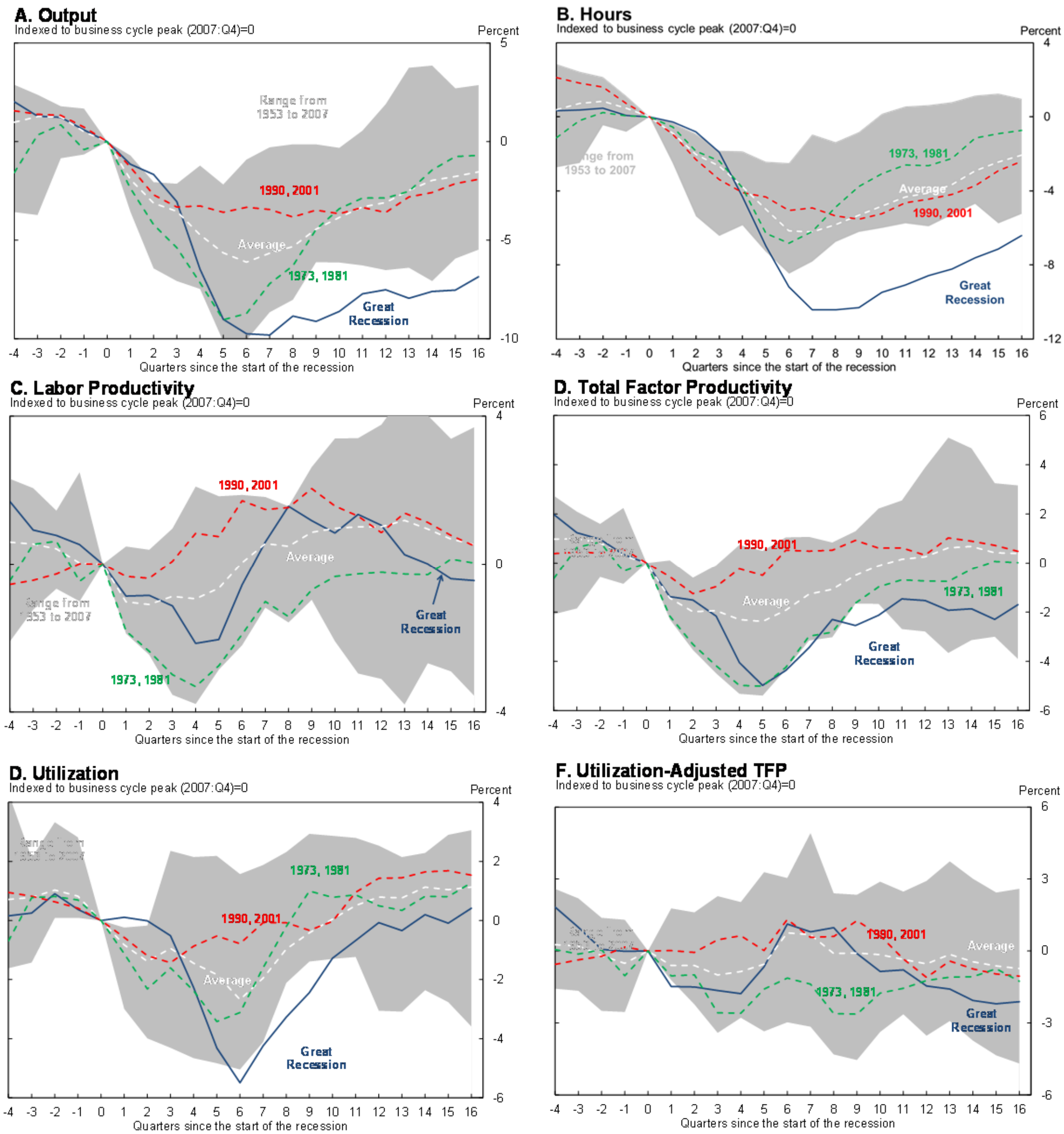
Figure 4
Evolution of Key Growth-Accounting Variables



Notes: Level of utilization is set to zero in 1987:Q4, roughly consistent with the CBO's estimate that the output gap was close to zero at that point.

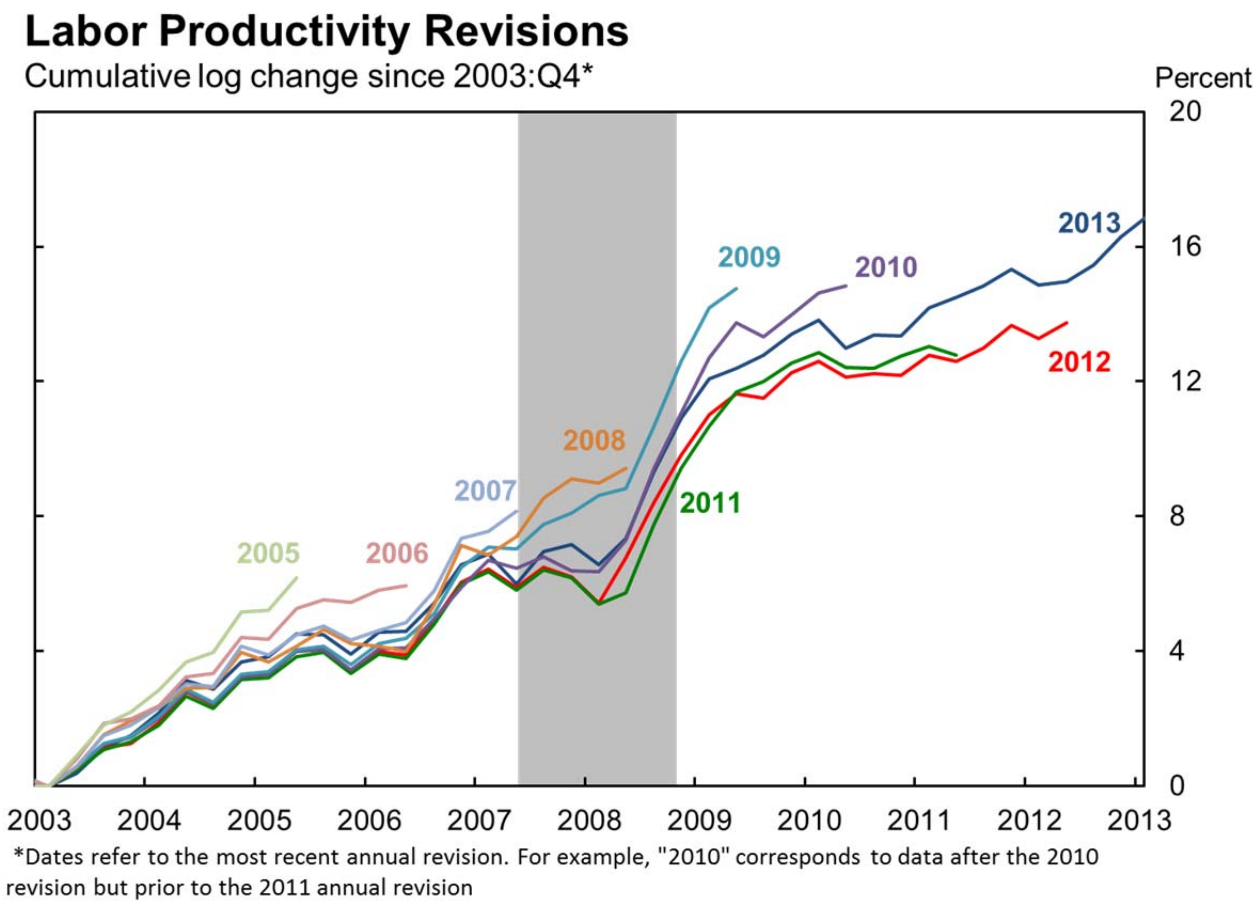
Source: Fernald (2012).

Figure 5
Comparing recessions (indexed to peak)



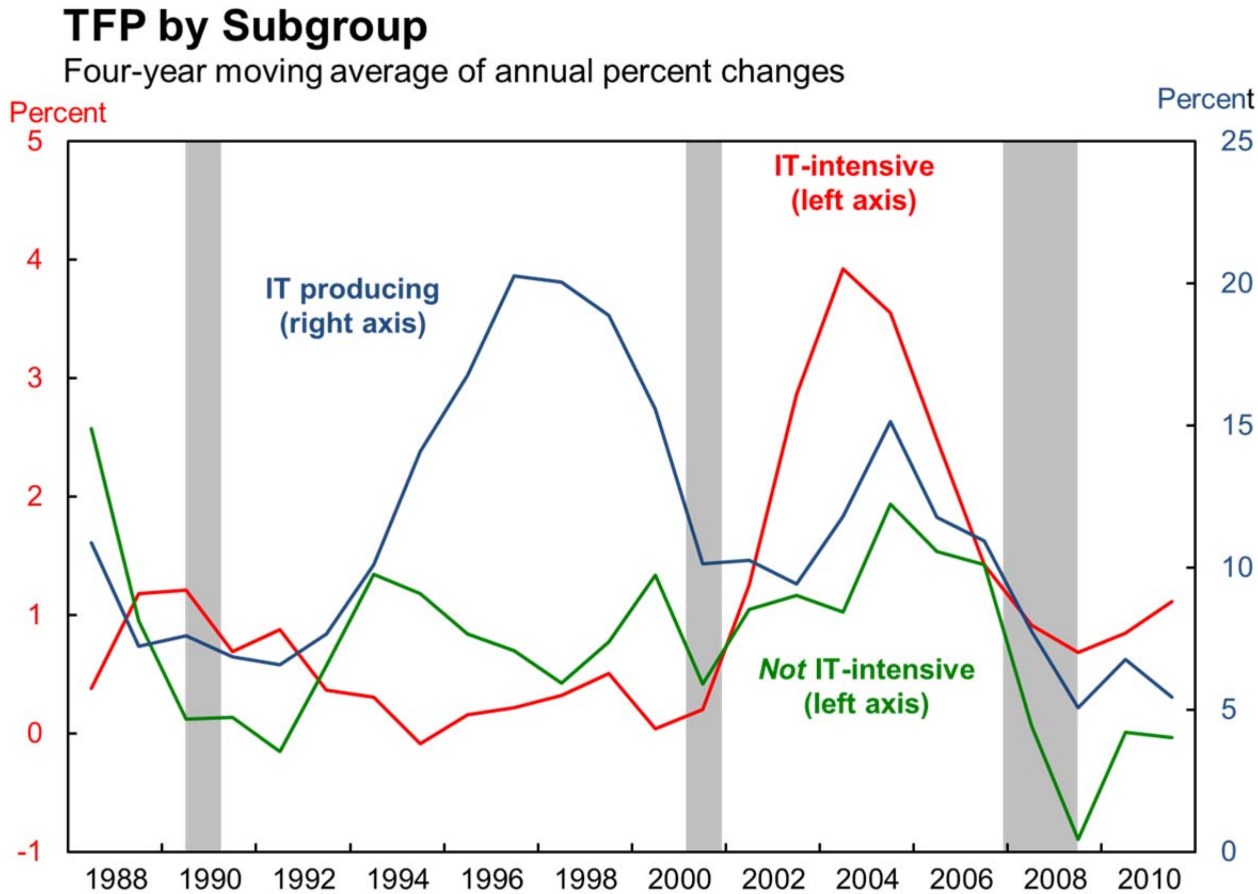
Note: For each plot, quarter 0 is the NBER business-cycle peak which, for the Great Recession, corresponds to 2007:Q4. The shaded regions show the range of previous recessions since 1953. Local means are removed from all growth rates prior to cumulating, using a biweight kernel with bandwidth of 48 quarters. Source is Fernald (2012).

Figure 6
Labor productivity revisions



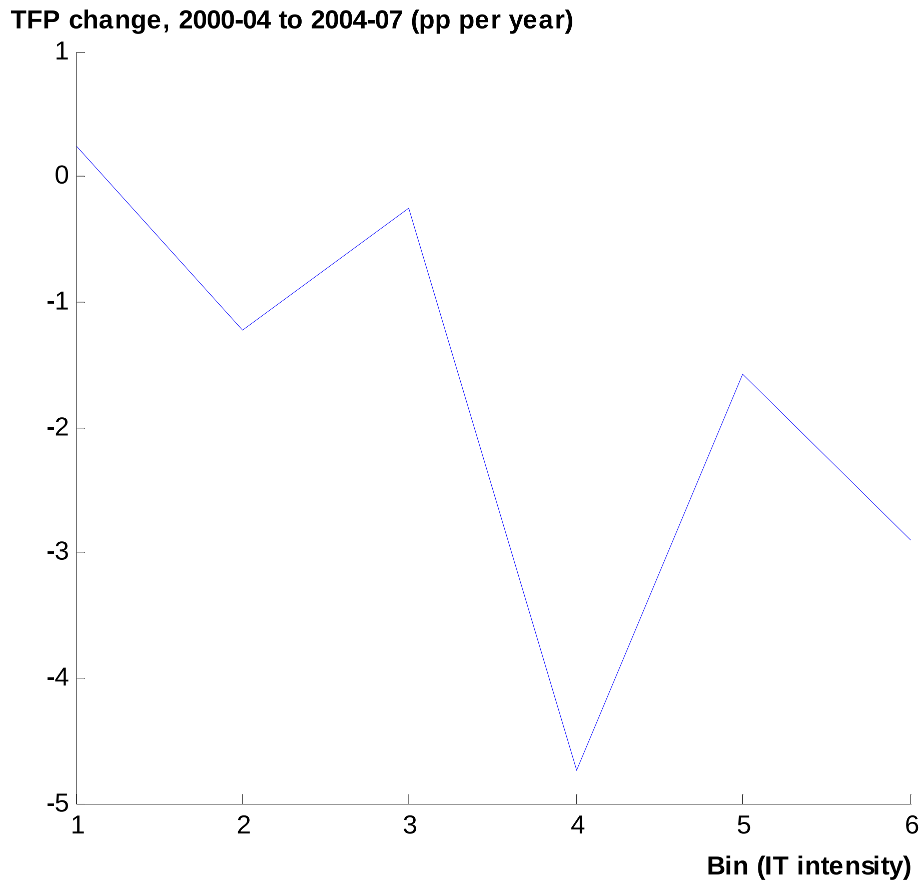
Source: BLS Productivity and Cost releases, and Haver. Output in these series correspond to the expenditure side of the national accounts rather than the average of the expenditure and income sides.

Figure 7
Industry TFP Growth by Subgroup



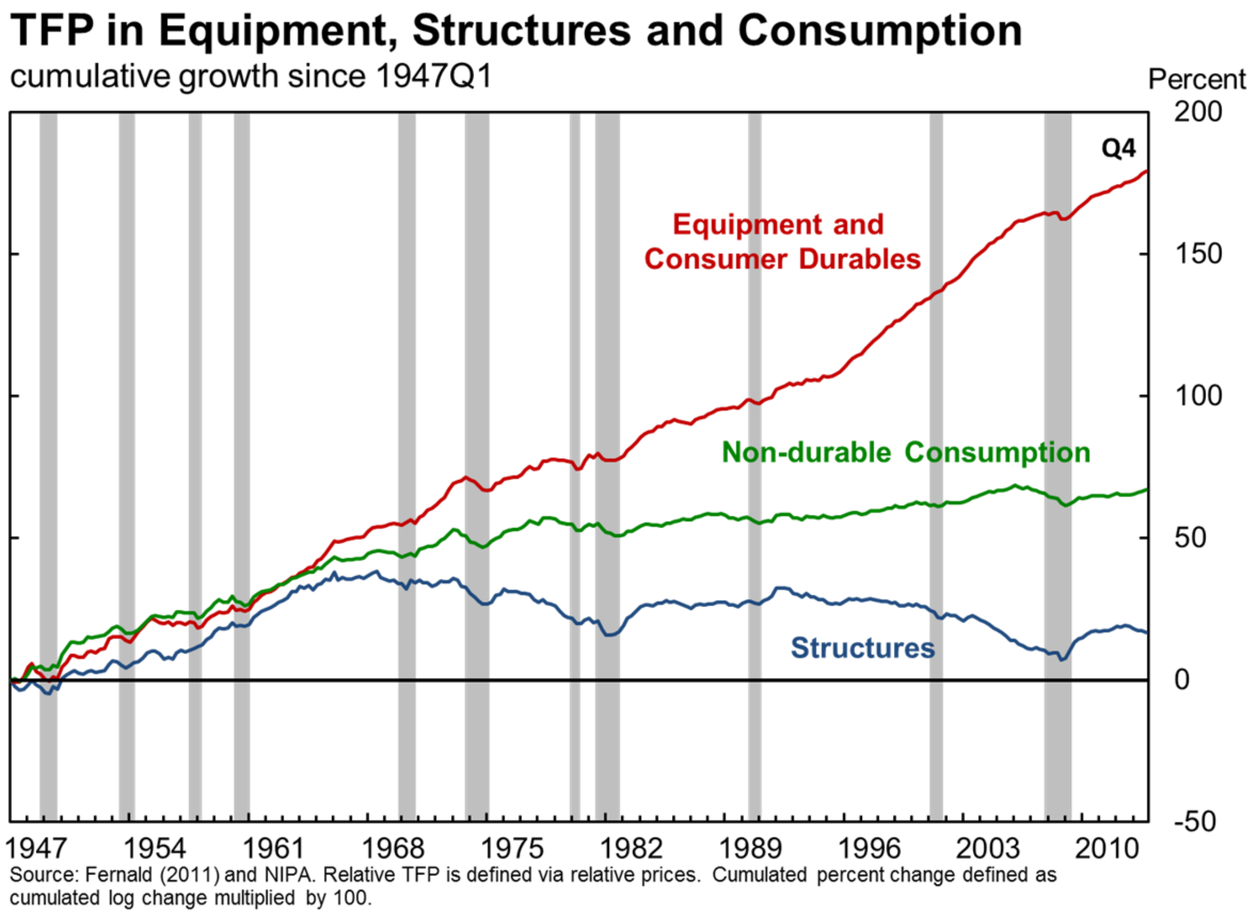
Source: BLS and author's calculations.

Figure 8
Slowdown in TFP Growth and IT Intensity



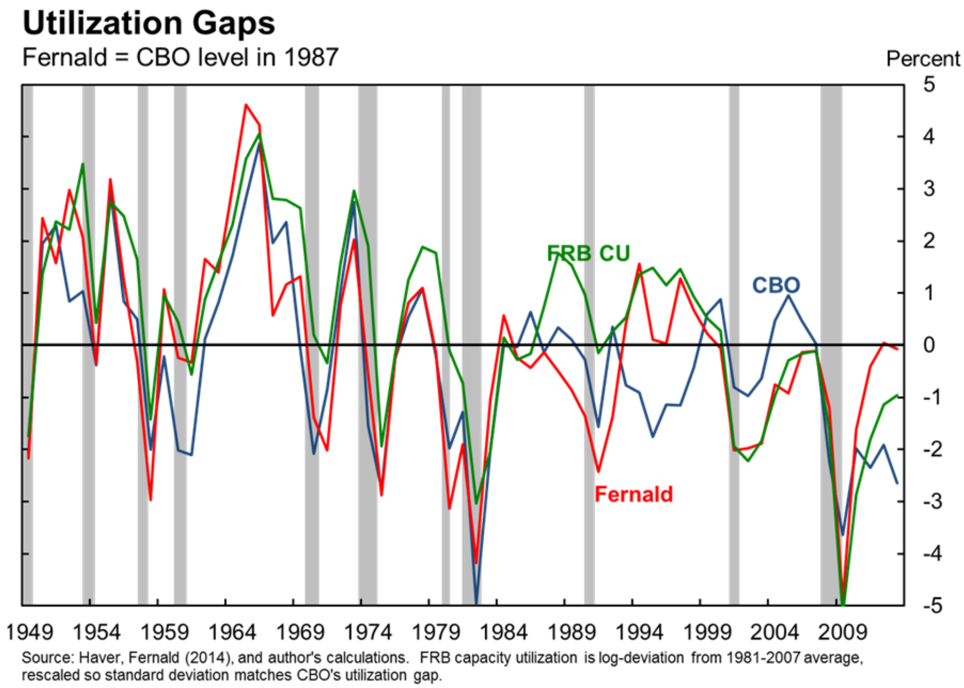
Notes: Figure shows slowdown in TFP growth after 2004 (2000-2004 average relative to 2004-2007 average, vertical axis) plotted against “bins” based on IT intensity (so bin 1 is the least IT-intensive, bin 6 is the most IT-intensive).

Figure 9
TFP by final use sector



Source: Fernald (2012), BEA (for relative prices), and author's calculations.

Figure 10
A. Alternative Utilization Measures



B. CBO and Fernald estimates of TFP

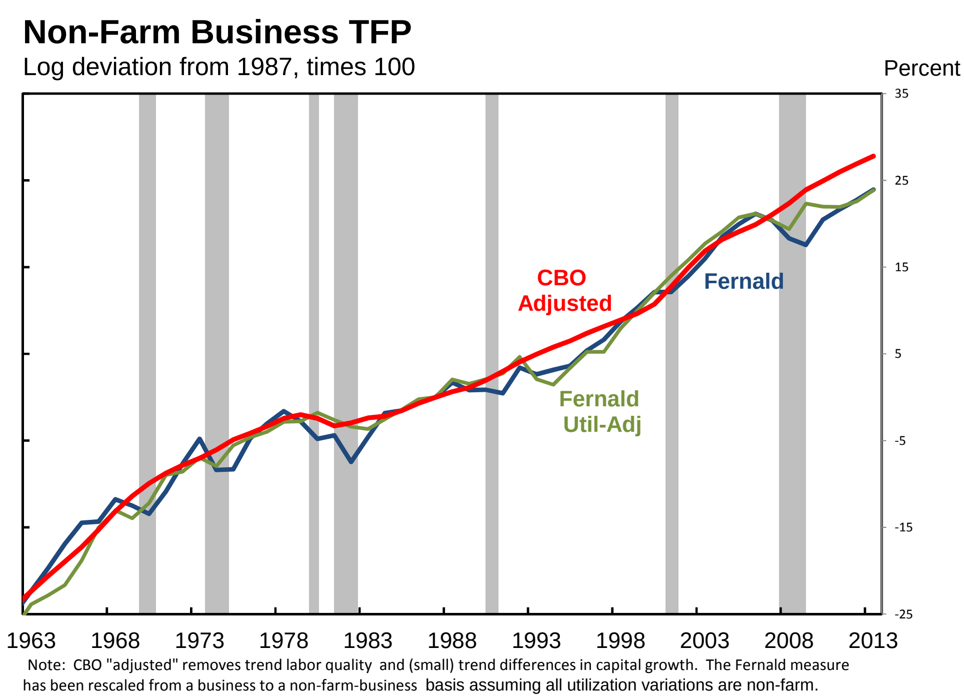
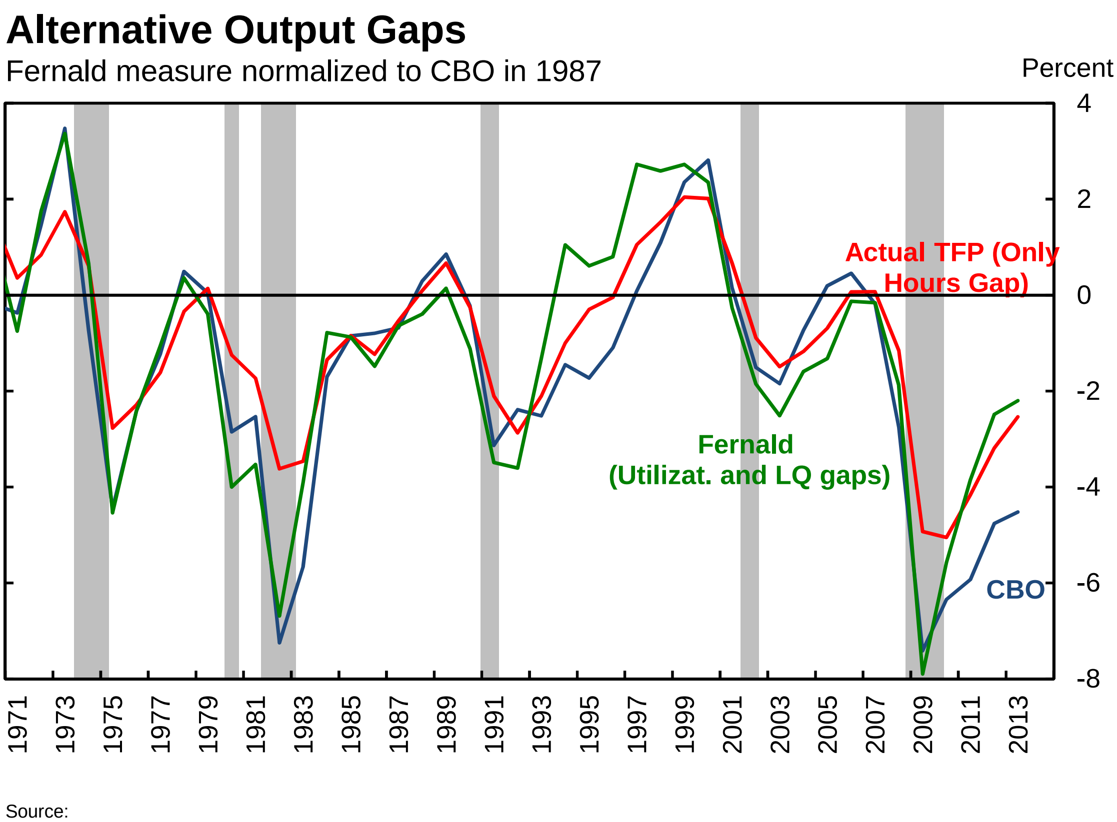


Figure 11
Output Gaps under Different Assumptions



Notes: "Actual TFP" uses the CBO's (2014a) hours gap but sets the utilization gap to zero. "Fernald" uses the utilization gap estimated in Fernald (2012).