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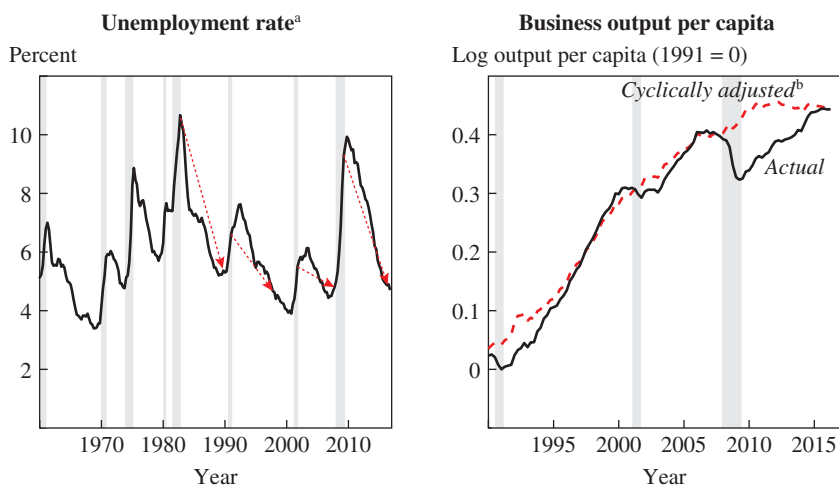
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The Disappointing Recovery of Output after 2009

ABSTRACT U.S. output has expanded only slowly since the recession trough in 2009, even though the unemployment rate has essentially returned to a pre-crisis, normal level. We use a growth-accounting decomposition to explore explanations for the output shortfall, giving full treatment to cyclical effects that, given the depth of the recession, should have implied unusually fast growth. We find that the growth shortfall has almost entirely reflected two factors: the slow growth of total factor productivity, and the decline in labor force participation. Both factors reflect powerful adverse forces that are largely unrelated to the financial crisis and recession—and that were in play before the recession.

Why did U.S. output grow so slowly in the post-2009 recovery, especially relative to the recovery of the unemployment rate? The unemployment rate fell at a pace within the range of the previous three cyclical expansions—see figure 1, left panel, where the dashed arrows

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Figure 1. Unemployment and Output, 1960–2016

Source: U.S. Bureau of Labor Statistics.

a. The unemployment rate measures the number of unemployed persons as a percentage of the labor force age 16 years and older on a quarterly frequency. The arrows connect the unemployment rate at the troughs with the rate 28 quarters later, or the next peak, whichever comes first.

b. These data are cyclically adjusted using Okun's law, and are normalized to equal the actual data at 2007:Q3.

show changes in the unemployment rate from the troughs of recent recessions. In contrast, the figure's right panel shows that the growth of output since 2009 has fallen far short. Output per person—the solid line, in logs—fell sharply during the recession and, as of this writing, remains below any reasonable linear trend line extending its prerecession trajectory.

The dashed line in the right panel of figure 1 provides an alternative output path that removes the normal cyclical effects of the deep recession in a simple way, using Okun's (1962) law, as described later in this paper. The picture is striking: This line is nowhere close to a straight-line projection from the 2007 peak. Rather, cyclically adjusted output per person rose only slowly after 2007, and it then plateaued.

We argue for taking this dashed line seriously as the counterfactual path of output in the absence of the recession. Viewed relative to this path, what appears to be a slow recovery of output reflects something quite different: The U.S. economy suffered a deep recession superimposed on a sharply slowing trend.

We use Solow-style growth accounting to tease out the various components underlying the flattening of the dashed line. Two components explain nearly all the growth gap: slow growth in total factor productivity (TFP),

and falling labor force participation. The participation decline causes cyclically adjusted hours worked per person to fall sharply. Slowly rising TFP and falling hours per person together imply flat cyclically adjusted output per person.

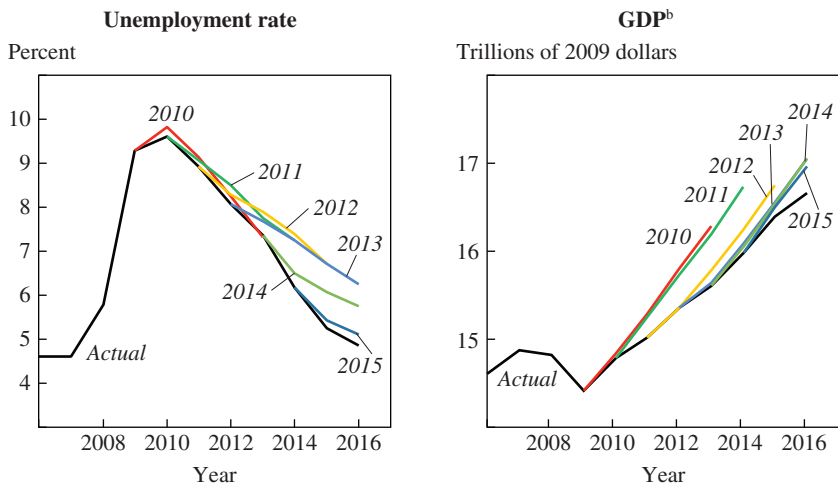
In this paper, we do not focus directly on the collapse of demand that began at the end of 2007 and worsened a great deal after the financial crisis at the end of 2008. *This is not because we believe that the demand effects were small.* In our estimates, the collapse in demand led to a very large cumulative loss in output, as measured by the area between the dashed, cyclically adjusted line and the solid line in the right panel of figure 1. But by 2016, the economy had returned to full employment, so the disappointing level of output at that point reflected nondemand factors.

The crucial question that arises from the growth accounting is whether the factors explaining the shortfall in some way reflect lasting effects of the recession on output—in other words hysteresis, for which three channels are the leading candidates: TFP, labor force participation, and the capital stock. We examine these three channels in detail to discern whether the endpoints of the corresponding variables in 2016 were influenced by the post-2007 experience of recession and slow recovery. Our answer is no. Instead, these factors reflect powerful adverse forces that are largely—if not entirely—*unrelated* to the financial crisis and recession.

The forces of slow growth of the labor force and of TFP were in play before the recession. The Congressional Budget Office (CBO 2006) and Stephanie Aaronson and others (2006) forecasted declines in participation as the baby boom generation retired and the 1960s to 1980s surge of women into the labor force plateaued. Also, before the recession, Stephen Oliner, Daniel Sichel, and Kevin Stiroh (2007) and Dale Jorgenson, Mun Ho, and Stiroh (2008) noted that TFP growth had slowed, though that slowdown is now more easily seen with the benefit of subsequent data as well as data revisions.

This said, it took time for these slow-growth trends to be appreciated. Figure 2 shows that, during the recovery, professional forecasters regularly overpredicted output growth, even while they were being too pessimistic about the recovery of the unemployment rate. These forecasts are representative of other real-time forecasts by the CBO, the Federal Open Market Committee (Lansing and Pyle 2015), and the Council of Economic Advisers. These overly optimistic GDP forecasts constitute an alternative framing of the disappointing recovery of output.

Although the broad trends in both participation and TFP appear to be essentially exogenous to the business cycle, investment is inherently

Figure 2. Forecasts of GDP and Unemployment, 2010–15^a

Sources: Survey of Professional Forecasters; U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis; Congressional Budget Office.

a. Forecasts from the Survey of Professional Forecasters are from the first quarter of the year indicated.

b. The figure assumes the previous year's revised GDP level is known, and projects published forecasts for annual growth rates, following Lansing and Pyle (2015).

endogenous. As many have noted, capital accumulation was lower than in previous recoveries. But we attribute this shortfall to the forces responsible for slower trend output growth. By mid-2016, the *capital–output* ratio was close to its prerecession trend line.

Under standard growth theory, slower TFP growth and falling participation should raise the capital–output ratio, because less investment is needed simply to keep pace with technology and the labor force. This higher capital–output ratio reduces the marginal product of capital and lowers the equilibrium real interest rate. By 2016, the cyclically adjusted capital–output ratio had returned to its trend growth path, but not above that path, as growth theory would suggest. Possibly, additional capital deepening lies ahead. Or other factors might have depressed the steady-state capital–output ratio. Germán Gutiérrez and Thomas Philippon (2016) argue that investment has been held back by rising market power, which lowers the marginal revenue product of capital and thus discourages capital formation. Lewis Alexander and Janice Eberly (2016) attribute part of the decline in investment to the relocation of capital-intensive manufacturing industries from the United States to other countries. It is particularly important that neither of these hypotheses is obviously related to the recession.

Although our account—like that of the CBO (2012)—leaves little room for demand-side explanations of persistently slow growth, we do investigate demand-side forces. Two quantitatively important factors are the unusually slow growth of federal government purchases from 2012 to 2014, which we associate in part with the 2013 U.S. federal budget sequester; and the delay in the usual rebounding of state and local government purchases, which we associate with the housing market collapse and the financial crisis. Absent such delays, output growth would have been higher early during the recovery. The solid line in the right panel of figure 1 would have intersected the dashed line sooner, implying less cumulative loss in output (and employment). However, looking over the entire recovery, the seeds of the disappointing growth in output were sown before the recession in the form of a declining labor force participation rate and slow TFP growth. Indeed, the scaling back of consumption and investment plans in response to slowing TFP growth could induce its own recessionary pressures beyond those from the financial crisis alone. Olivier Blanchard, Guido Lorenzoni, and Jean-Paul L’Huillier (2017) show that this effect could be large, especially with interest rates at the zero lower bound.

Turning now to the details of our analysis, we use counterfactual, cyclically adjusted paths that variables would have followed, absent the recession. We use two methods of cyclical adjustment. The first, which we use for the counterfactual output path in figure 1, measures the cycle using the unemployment rate and adjusts the variables in the growth-accounting identity using a version of Okun’s law. The second, which we use primarily for our analysis of sources of slow demand growth and the timing of the recovery, is conditioned instead on the state of the economy at the cyclical trough in 2009 to compute a baseline forecast from a dynamic factor model. The first method measures slow growth, relative to the recovery of the unemployment rate; the second measures slow growth, relative to a “normal recovery” forecast made at the trough. As discussed in section III, after adjusting for these differences, the two methods provide similar estimates of the growth decomposition, so our growth-accounting analysis focuses on the Okun’s law method.

The Okun’s law method implies that growth of business output per person during the recovery fell short of its average in the three earlier recoveries by 1.8 percentage points per year, cumulating in a total shortfall during the recovery of 13.5 percent. The TFP shortfall contributed nearly 1 percentage point per year, or 7 percentage points for the cumulative output shortfall. The participation shortfall accounted for 0.9 percentage point per year of the output shortfall, or 6.1 percentage points for the cumulative

shortfall. The centrality of the decline in TFP growth and the fall in the labor force participation rate leads us to examine them in greater detail in sections IV and V.

TOTAL FACTOR PRODUCTIVITY Time series methods date the slowdown in cyclically adjusted TFP growth to before the recession. Regime-shift detection methods estimate a break date in early 2006. Alternative Bayesian estimates and standard low-pass filtering, neither of which assumes a sharp break, place the slowdown even earlier. The timing matters: If the slowdown in TFP growth occurred before the recession, the recession cannot be its cause.

In addition, weak investment and capital growth were not important independent contributors to weak output growth during this recovery. Actual investment was almost exactly in line with our simulated forecast at the beginning of the recovery. Furthermore, as noted above, by 2016, the capital–output ratio was in line with its long-term trend. As a result, the shortfall in labor productivity is almost entirely explained by weak TFP growth.

Given the importance for the recovery of the prerecession slowdown in TFP growth, we review a number of candidate explanations for the mid-2000s TFP slowdown and provide some new evidence against one, namely, changes in regulations. We lean toward the hypothesis that the slowdown reflects a slackening in the broad-based, transformative effects of information technology—a productivity boom that began in the mid-1990s and ended in the mid-2000s.

THE LABOR FORCE PARTICIPATION RATE In 2016, the labor force participation rate, at 62.7 percent, was 3 percentage points below its value at the trough. Although different methods for estimating the cyclical component of the participation rate provide different estimates of its cyclical decline early in the recovery, by 2016 that cyclical contribution was small.

Baby boom retirements are an important factor behind the decline in labor force participation. Less widely recognized is that other factors partially push the other way—notably the increasing education levels of the newly older workers. We construct an annual index that allows for shifting population shares in age, education, gender, and marital status. These demographic effects account for 1.2 percentage points of the overall decline of 1.8 percentage points from 2010 to 2016. Changes in participation rates within detailed demographic groups account for the remaining 0.6 percentage point, or roughly one-third of the decline.

There is no consensus about the sources of the persistent unexplained component of labor force participation. We argue that it is not plausibly just

a consequence of the increase in unemployment during the 2007–09 recession. For example, the twin recessions of the early 1980s did not lead to comparable declines in participation relative to the trend. Our review of the evidence supports the less optimistic view that the nondemographic part of the decline represents a continuation of preexisting trends with a variety of sources that are likely to persist.

TIMING OF THE RECOVERY AND DEMAND CONSIDERATIONS In our story, the economy's underlying growth rate would have slowed sharply even without the deep recession. Nevertheless, it took some nine years from the beginning of the recession for the unemployment rate to return to normal. Deficient demand in the recovery (including from the zero lower bound) plausibly slowed the return to its sharply slowing trend. The dynamic factor model sheds light on the sources of deficient demand. As in our earlier analysis, we calculate a simulated forecast as of 2009 and study its subsequent errors. The errors are stated as percentage-point contributions to an overall forecast error of 0.57 percent of GDP per year, which is close to the Okun's law shortfall, after adjusting for slower trend growth and normal cyclical movements.

Weak government spending restrained the expansion. The shortfall in government purchases explains more than half the forecast error (0.31 percentage point per year, of which 0.20 is federal and 0.12 state and local). Government consumption expenditures plus transfer payments would normally have grown by 2.9 percent per year, but in fact grew by only 0.7 percent.

Total household consumption—by far the largest component of total spending—contributed 0.26 percentage point per year to the shortfall in output growth. Durable and nondurable goods behaved almost exactly as forecasted during the expansion. Roughly half the shortfall arose from housing and financial services, which is consistent with the view that housing and finance were key sectors for explaining the special features of the recession and recovery. The real value of financial services, however, is a particularly poorly measured component of output. The shortfall in this sector, and in the even more poorly measured sector of nonprofit institutions serving households, contributes fully 0.10 percentage point to the 0.57 percentage point underforecasting of output. So a small part of the slow measured growth could be due to mismeasurement.

These forecasts suggest that there was little role for several weak demand explanations. The absence of any significant shortfall in consumption growth outside housing is evidence against deleveraging and increasing inequality contributing to the slow recovery. Weak exports exerted a

small drag on output growth, mainly during the years 2011–13. And business investment was in line with forecasts—which is consistent with our view that business investment, a highly cyclical, endogenous variable, was not an exogenous contributor to the weakness of the recovery.

I. Growth Decomposition and Data

Subsection I.A describes our general objective and our data. Subsection I.B then lays out the Solow-style growth-accounting framework we use to analyze the slow recovery of output.

I.A. Focus and Data

We focus on explaining the disappointingly slow recovery that started in mid-2009, which was when the recession ended, according to the National Bureau of Economic Research. We end seven years later, in mid-2016. When we make comparisons with the preceding three recoveries, we use the comparable seven-year periods following the troughs, except for the period following 2001, for which we truncate the business-cycle peak at the end of 2007 (six years).

The slow recovery of output can be examined through the lens of production (since output is produced) or expenditures (since output is purchased). Here, we discuss growth-accounting identities related to production. The production framework is natural for addressing the role of structural trends such as productivity and the labor force. We apply this accounting to the business sector. Growth accounting is less applicable to government, household, and nonprofit production, where output is often not measured independent of inputs.

Our measure of output is the geometric average of income- and expenditure-side measures, as recommended by Jeremy Nalewaik (2010) and subsequent literature (see the online data appendix).¹ Both sides of the accounts provide information about true growth but are subject to measurement error, so a combination improves the signal-to-noise ratio. At an economy-wide level, we follow the Council of Economic Advisers (2015) and refer to this average of gross domestic product and gross domestic income as gross domestic output (GDO) or, where the context is clear, as simply output. Unless noted otherwise, we scale output by the population eligible for employment, age 16 years and above, denoted *Pop*.

1. The online appendixes for this and all other papers in this volume may be found at the *Brookings Papers* web page, www.brookings.edu/bpea, under “Past BPEA Editions.”

John Fernald (2014) describes our quarterly business sector growth-accounting data. Broader output data come from the U.S. Bureau of Economic Analysis; additional labor market data come from the U.S. Bureau of Labor Statistics. The online data appendix provides further details.

1.B. Accounting for Growth

Although our growth accounting focuses on the business sector, we also need to consider the overall economy because labor market indicators, such as the unemployment rate, are economy-wide. An identity links economy-wide gross domestic output, GDO , and business output, Y_t^{Bus} :

$$(1) \quad \left(\frac{GDO_t}{Pop_t} \right) = \left(\frac{GDO_t}{Y_t^{Bus}} \right) \times \left(\frac{Y_t^{Bus}}{Pop_t} \right).$$

The identities in this section are sometimes expressed as ratios of levels and sometimes as growth rates, depending on which one is clearer. Empirical estimation is in growth rates.

Growth accounting decomposes output growth into a set of components that help to show how the second term on the right-hand side of equation 1 evolves. Modern growth accounting follows Jorgenson and Zvi Griliches (1967), which in turn expanded and clarified the work of Robert Solow (1957). Growth in business output, Y_t^{Bus} , depends on growth in capital, K , and labor input, $Labor$. Labor, in turn, depends on $Hours$ and labor quality, LQ : $\Delta \log Labor_t^{Bus} = \Delta \log LQ_t + \Delta \log Hours_t^{Bus}$. Labor quality, LQ , captures the contribution of rising education and experience. Our measure of LQ assumes that relative wages capture relative productivities of workers with different attributes—see Canyon Bosler and others (2016). In per-person terms, we write:

$$(2) \quad \Delta \log \left(\frac{Y_t^{Bus}}{Pop_t} \right) = \Delta \log TFP_t + \alpha_t \Delta \log \left(\frac{K_t}{Pop_t} \right) \\ + (1 - \alpha_t) \Delta \log \left(\frac{LQ \cdot Hours_t^{Bus}}{Pop_t} \right).$$

The time series α_t is capital's share of income.

It is useful to rewrite equation 2 to separate endogenous and exogenous factors. For example, suppose hours growth falls because of demographics. Equation 2 multiplies that change by labor's share. But if the same force leads to an endogenous reduction in capital, we may want to incorporate

this effect. We consider an alternative decomposition of (Y_t^{Bus}/Pop_t) as business sector hours per person times labor productivity (output per hour of work):

$$(3) \quad \left(\frac{Y_t^{Bus}}{Pop_t} \right) = \left(\frac{Hours_t^{Bus}}{Pop_t} \right) \times \left(\frac{Y_t^{Bus}}{Hours_t^{Bus}} \right).$$

The first term on the right-hand side, business hours per person, can be expanded as

$$(4) \quad \left(\frac{Hours_t^{Bus}}{Pop_t} \right) = \left(\frac{Hours_t^{Bus}}{Emp_t^{Bus}} \right) \times \left(\frac{Emp_t^{Bus}}{Emp_t^{CPS}} \right) \\ \times \left(\frac{Emp_t^{CPS}}{LabForce_t} \right) \times \left(\frac{LabForce_t}{Pop_t} \right).$$

The terms on the right-hand side of equation 4 are as follows:

— $\left(\frac{Hours_t^{Bus}}{Emp_t^{Bus}} \right)$ is business sector hours per employee.

— $\left(\frac{Emp_t^{Bus}}{Emp_t^{CPS}} \right)$ is the ratio of business employment, measured (primarily)

from the establishment survey, to household employment, measured from the Current Population Survey (the household survey).

— $\left(\frac{Emp_t^{CPS}}{LabForce_t} \right)$ is employment relative to the labor force, and is by

definition equal to $1 - U_t$, where U_t is the unemployment rate. Over the long run, the contribution of the U term is zero because the unemployment rate reverts to a mean value.

— $\left(\frac{LabForce_t}{Pop_t} \right)$ is the labor force participation rate.

Now consider labor productivity, the second term on the right-hand side of equation 3. With some manipulation, growth-accounting equation 2 yields the useful expression:

$$(5) \quad \Delta \log \left(\frac{Y_t^{Bus}}{Hours_t^{Bus}} \right) = \frac{\Delta \log TFP}{(1 - \alpha_t)} + \left(\frac{\alpha_t}{1 - \alpha_t} \right) \\ \times \Delta \log \left(\frac{K_t}{Y_t^{Bus}} \right) + \Delta \log LQ_t.$$

In this expression, output per hour depends on the capital–output ratio, and labor quality, both expressed in a labor-augmenting form. This is useful, because capital deepening is endogenous. Slower growth in technology and labor lead to a lower path of capital—but a roughly stable capital–output ratio. Thus, the capital–output ratio is useful for assessing whether there are special influences on capital from, say, unusual credit constraints or heightened uncertainty.

In the one-sector neoclassical growth model, the capital–output ratio is pinned down by an Euler equation. If trend technology were constant, the steady-state ratio would be stationary. In models with investment-specific technical change—and in the data—this ratio has a relatively slow-moving trend (see the online appendix to Fernald 2015).

Of course, the capital–output ratio is not necessarily dispositive. Slower trend growth tends to raise the steady-state capital–output ratio. Other factors, such as an increase in market power (Gutiérrez and Philippon 2016), could work in the other direction. Nevertheless, in cyclically adjusted data, the trend capital–output ratio has been remarkably smooth since the 1970s, despite the mid-1990s speedup in growth and the mid-2000s slowdown. Thus, we interpret the capital–output ratio as informative about the possibility of a capital shortfall.

II. Estimation of Cyclical Components and Low-Frequency Trends

As the unemployment rate declines during an expansion, output grows faster than it would with constant unemployment. The deeper the recession, the greater is the recovery in the labor market and the greater is the cumulative above-normal growth of output. Thus, in determining whether the recovery from the 2007–09 recession was slow, we need to control for the depth of the recession. Moreover, the calculation needs to control for underlying systematic changes in the U.S. economy, such as changes in workforce demographics, that affect the underlying mean growth rates of employment and output.

In this paper, we use two complementary methods for controlling for the depth of the 2007–09 recession and thus for assessing the recovery’s speed. The first method is conditioned on the path of the unemployment rate. This method asks: What would the normal cyclical path of output and the other variables in the growth decomposition have been, given the 2009–16 recovery of the unemployment rate? In practice, this amounts to estimating the normal cyclical movements using Okun’s law, extended to variables in addition to output.

The second method controls for the depth of the recession by conditioning on the state of the economy at the 2009 trough, as measured by a large number of time series. This method asks: What would the normal, cyclical path of macroeconomic variables have been, given the depth of the recession? Calculating the normal path entails simulating forecasts of multiple time series, given data through 2009, for which we use a large dynamic factor model.

Both methods allow for low-frequency changes in the mean growth rates, that is, for trends in the growth rates. We adopt a statistical decomposition of the growth rate of a given time series into a trend, a cycle, and an irregular part. Let y_t be the percentage growth rate of a variable at an annual rate, computed using logs (for example, for GDO, $y_t = 400\Delta\log GDO_t$). The decomposition is

$$(6) \quad y_t = \mu_t + c_t + z_t,$$

where μ_t is a long-term trend, c_t is a cyclical part, and z_t is called the irregular part—it describes the higher-frequency movements of the variable that are not correlated with the cycle.

Following convention in the time series literature, we refer to equation 6 as a trend/cycle/irregular decomposition. Because y_t is a growth rate, the trend μ_t is the long-term mean growth rate of the series. In the special case that this mean is constant, in log levels the series would have a linear time trend, with a shifting intercept that depends on c_t and z_t . As explained below, we estimate the long-term trend as the long-run average of y , after subtracting the cyclical part. This long-run average typically evolves for reasons such as changing demographics.

The irregular term, z_t , is the variation in y_t net of the trend and cyclical fluctuations. This irregular term represents the growth in a given variable, above and beyond what would be expected given low-frequency changes in the economy and the normal cyclical movements. We find that large, negative, irregular parts play important roles in the weak recovery.

II.A. Method 1: Using Okun's Law to Account for the Cycle

The first method uses Okun's law to estimate the cyclical component. Because we consider many series, and these series can lead or lag the unemployment rate, we extend Okun's relationship to include leads and lags. The Okun's law definition of c_t thus is

$$(7) \quad c_t = \sum_{j=-p}^q \beta_j \Delta U_{t+j} = \beta(L) \Delta U_t,$$

where U_t is the unemployment rate and $\beta(L)$ is the distributed lag polynomial, with q leads and p lags in the summation. The choices of p and q and other estimation details are described in the next subsection. The sum of the lag coefficients, $\beta(1)$, measures the cyclical variability of y_t . Note that because $E[\Delta U_t] = 0$ over the long run, our cyclical part has a long-run mean of zero.

Okun's original relationship was the reverse of equation 7, regressing changes in the unemployment rate on changes in output with only contemporaneous movements. However, subsequent researchers have often used the specification with unemployment on the right-hand side. Moreover, for output growth and many other series, the leads or lags are statistically significant. Mary Daly and others (2017) discuss growth-accounting micro-foundations of Okun's law and assess its stability over time.

Also, though one could add other measures of labor market slack to equation 7, using the standard unemployment rate (as we do) has several virtues. It is well measured, and it has been measured using essentially the same survey instrument since 1948. Over the long run, it has essentially no trend. And, in any event, the other measures of the state of the labor force are highly correlated with the unemployment rate, once one incorporates leads and lags.

THE CYCLICALLY ADJUSTED TREND A practical problem in estimating the trend μ_t is that persistent cyclical swings can be confused with lower-frequency trends. This problem is particularly acute in estimating trend terms toward the end of our sample, given the severity of the recession and length of the recovery. To address this problem, our estimate of the trend controls for the normal cyclical movements implied by Okun's law.

Substitution of equation 7 into equation 6 yields

$$(8) \quad y_t = \mu_t + \beta(L)\Delta U_t + z_t.$$

The Okun's law "residual" (including μ_t), $y_t - c_t = y_t - \beta(L)\Delta U_t$, is a measure of what the growth rate would have been, consistent with an unchanged unemployment rate. To estimate μ_t , we adopt the framework of the partial linear regression model, which treats μ_t as a nonrandom smooth function of t/T ; see Peter Robinson (1988), James Stock (1989), and Ting Zhang and Wei Biao Wu (2012). In this approach, μ_t is estimated as a long-run, smoothed value of y_t , after subtracting the estimated cyclical part:

$$(9) \quad \hat{\mu}_t = \kappa(L)(y_t - \hat{\beta}(L)\Delta u_t),$$

where $\kappa(L)$ is a filter that passes lower frequencies and attenuates higher frequencies. Because the estimated cyclical part is subtracted before smoothing, we refer to the estimated trend $\hat{\mu}_t$ as a cyclically adjusted trend. The use of a cyclically adjusted trend with a long bandwidth for $\kappa(L)$ helps avoid mechanically attributing the recent slow growth to a declining trend. The online appendix compares the partial linear regression approach to Robert Gordon's (2014) cyclically adjusted state-space (unobserved components) method, and discusses computation of the heteroskedasticity- and autocorrelation-robust standard errors.

ESTIMATION We estimate $\beta(L)$ by regressing y_t on leads and lags of ΔU_t with $p = q = 2$. For some left-hand-side variables, using only contemporaneous ΔU_t suffices; but for others, additional leads and lags are justified statistically. Our estimation period starts at the 1981 peak and ends in the second quarter of 2016. Sensitivity to these choices is discussed below.

For the low-pass filter $\kappa(L)$, we use a biweight filter with truncation parameter of 60 quarters. Tukey's biweight filter $\kappa(L)$ is two-sided, with $\kappa_j = d(1 - (j/B)^2)^2$ for $|j| \leq B$ and $\kappa_j = 0$ otherwise, where B is the bandwidth and d is chosen so that $\kappa(1) = 1$. Endpoints are handled by truncating the filter outside the range of the data and renormalizing. The long truncation parameter was chosen so that changes in $\hat{\mu}_t$ reflect slow multidecadal swings. If there are sharp breaks, this filter will oversmooth, an issue to which we return in section IV.

ADDITIVITY The foregoing method for estimating the trend, cycle, and irregular parts has the useful property of preserving additivity when applied to additive decompositions. Specifically, suppose that $y_t = y_{1t} + y_{2t}$. This additivity is preserved for the estimated cyclical, trend, and irregular parts. That is, $\hat{\mu}_t = \hat{\mu}_{1t} + \hat{\mu}_{2t}$ and $\hat{c}_t = \hat{c}_{1t} + \hat{c}_{2t}$, where the subscripts refer to the parts of y_t , y_{1t} , and y_{2t} . This property is a consequence of using the same cyclical regressors and same filter $\kappa(L)$ for all series, and the property that regression is linear in the dependent variable.

II.B. Method 2: Dynamic Factor Model Estimates of the Cycle

The second method uses a six-factor, dynamic factor model to produce forecasts of the variables under study, where the forecasts are made using data through the 2009 trough. These projections provide an alternative estimate of the cyclical component—specifically, the normal cyclical rebound that would have been expected given the depth of the recession.

The 123 series used to estimate the factor are summarized in table 1. The data set omits high-level aggregates to avoid aggregation identities and double counting—for example, GDP is omitted because its compo-

Table 1. Categories of Quarterly Time Series Used to Estimate the Factors

<i>Category</i>	<i>Number of series</i>
(1) National Income and Product Accounts	12
(2) Industrial production	7
(3) Employment and unemployment	30
(4) Orders, inventories, and sales	8
(5) Housing starts and permits	6
(6) Prices	24
(7) Productivity and labor earnings	5
(8) Interest rates	9
(9) Money and credit	5
(10) International	2
(11) Asset prices, wealth, and household balance sheets	9
(12) Oil market	6
Total	123

Sources: See the online data appendix.

nents are included; consumption of goods is omitted because the consumption of durables and nondurables is included separately; and total employment is omitted because its components are included. The 123 series are transformed into growth rates (for activity variables; see the online appendix for the details of other series); low-frequency trends are extracted, as discussed above; and six factors are then estimated using principal components.

These six factors are forecasted through the second quarter of 2016 using a vector autoregression with four lags, with the 2009 trough as the jumping-off point. Forecasts for a given variable are then computed using the factor loadings from a regression of that variable on the factors. The forecasting regressions are estimated using data from 1984 through the 2009 trough.

Stock and Mark Watson (2016) discuss factor methods and provide empirical results for closely related models and data sets. The online appendix has additional details, including measures of fit.

With one exception, the simulated forecasting approach freezes the growth rate trends in each series at their trough values. The exception is that we allow demographic changes to affect labor force participation. It was clear before the recession that baby boomers' retirements would depress participation. Here, we use the Divisia–Törnqvist index—developed in section V below—to project the effect of changing demographics. This demographic trend in participation feeds through, with share weights as appropriate, into the trends in employment, hours, and output. We leave unchanged the trends in capital, the ratio of business to household employment, and hours

per employee. The result is a projected output trend that incorporates aging and other demographic effects on employment as understood at the trough, with other component trend growth rates frozen at their trough values. Trend growth rates for expenditure components of output are computed as the component's time series trend as of the trough, plus the share-weighted difference between the output trend (inclusive of the participation aging trend) and the trough value of the output trend. This final adjustment, which ensures that share-weighted trend growth rates are additive, is numerically negligible because the trough-quarter participation adjustment to the trend value of output is small.

In the notation of equation 6, the factor model forecast of y_t is the sum of the trend projection μ_t and the projection of c_t computed using the detrended factors. Thus, the forecast error is an estimate of the irregular part z_t ; subtracting this forecast error measures the growth shortfall of y_t .

The dynamic factor model method, like the Okun method, preserves the additivity of the components.

III. Results: Accounting for Slow Growth

We are now ready to quantify the sources, in a growth-accounting sense, of the slow growth in output. We begin with a brief discussion of the cyclical properties of the component variables in the growth-accounting decomposition.

III.A. Cyclical Properties of the Growth-Decomposition Variables

Table 2 provides three summary measures of the cyclicity of the variables entering the growth decomposition and additional broad measures of output. The first column shows the generalized Okun's law coefficient, which provides a natural measure of cyclicity. Specifically, it is the sum of the coefficients, $\beta(1)$, in equation 8; the units are chosen so that the coefficient is the percent change in each variable per percentage point change in the unemployment rate. The sum of the Okun's law coefficients on the components equals the Okun's law coefficient on the sum of the components. For example, the coefficients in lines 7 through 9 add to -2.02 , which is the coefficient in line 6 for real business output per capita.

Of the total cyclical variation in business hours per capita (line 10), as measured by the generalized Okun's law coefficient of -2.3 , nearly half (-1.08) comes from the employment rate (1 minus the unemployment rate), one-sixth (-0.35) comes from variations in hours per worker, and a small amount (-0.16) comes from labor force participation. These results reflect

Table 2. Cyclicalty of Real Output and Its Components^a

Component	Generalized Okun's law coefficient and standard error ^b	Standard deviations from components ^c			<i>R</i> ² from regressing on factors ^d
		Cycle (c)	Trend (μ)	Irregular (z)	
(1) GDP	-1.49 (0.18)	1.90	0.58	1.77	0.66
(2) GDO	-1.53 (0.17)	1.92	0.57	1.61	0.72
(3) Business GDO	-2.03 (0.21)	2.53	0.59	2.11	0.73
(4) GDP per capita	-1.48 (0.17)	1.88	0.52	1.84	0.60
(5) GDO per capita	-1.52 (0.17)	1.89	0.51	1.63	0.67
(6) Business GDO per capita	-2.02 (0.20)	2.51	0.54	2.12	0.70
(7) Total factor productivity	-0.50 (0.19)	1.24	0.24	2.27	0.38
(8) $\alpha \times$ capital / population	-0.09 (0.06)	0.20	0.19	0.32	0.37
(9) $(1-\alpha) \times (LQ \times \text{hours} / \text{population})$	-1.43 (0.14)	1.54	0.26	1.24	0.57
(10) Business labor hours per capita	-2.30 (0.19)	2.54	0.36	1.51	0.74
(11) Business hours per worker	-0.35 (0.10)	0.55	0.04	1.05	0.25
(12) Ratio of business employment to household employment	-0.71 (0.09)	0.73	0.08	1.20	0.24
(13) Household employment rate	-1.08 (0.01)	1.36	0.00	0.10	0.89
(14) Labor force participation rate	-0.16 (0.10)	0.32	0.33	0.87	0.02
(15) Business output per hour	0.28 (0.22)	0.77	0.37	2.23	0.24
(16) TFP / $(1-\alpha)$	-0.75 (0.29)	1.88	0.35	3.41	0.39
(17) Capital-output ratio $\times \alpha / (1-\alpha)$	0.90 (0.09)	1.30	0.07	1.09	0.75
(18) Labor quality	0.13 (0.05)	0.37	0.05	0.99	0.06

Sources: See the online data appendix

a. Indented rows sum to the prior level of aggregation.

b. The Okun's law coefficients are $\beta(1)/4$. They are measured in quarterly percentage points of growth per percentage point change in the unemployment rate. Standard errors are in parentheses.

c. The standard deviations of the components are for quarterly growth rates reported in percentage points at an annual rate.

d. The R^2 is from the regression of the component variable on the factors used in the factor model.

the small procyclicality of the participation rate, which falls as unemployment rises. Of course, a large reduction in participation occurred before and during the recovery. Section V examines the extent to which the recent decline in participation is related to the slack labor market.

One-third of the cyclical variation in business output (-0.71) comes from procyclical variation in the ratio of business employment to household survey employment. Differences in coverage and concept help explain this variation. In terms of coverage, the household survey is broader, covering the entire civilian economy; and the business sector is much more procyclical than the nonbusiness sector (for example, government and non-profits). In terms of concept, a worker holding two jobs counts twice in the establishment survey but just once in the household survey. If this worker loses one of these jobs when the unemployment rate rises, then establishment survey employment falls more than household survey employment. After adjusting for coverage, Fernald and Christina Wang (2016) find that hours worked—number of workers times hours per worker—has almost the same cyclicity in the two surveys.

Labor productivity (line 15) is weakly and insignificantly countercyclical. It combines strongly procyclical TFP (line 7 or, rescaled, line 16) with the strongly countercyclical capital–output ratio (line 17). Research on TFP has discussed the roles of labor hoarding, cyclical changes in capital utilization, and other nontechnological factors that account for the procyclicality of productivity (Basu and Fernald 2001). Investment is procyclical, but the cumulated stock of capital changes only slowly; so the capital–output ratio is strongly countercyclical because of output in the denominator. Finally, the countercyclicality of labor quality (0.13, row 18) supports the hypothesis that when unemployment rises, lower-skilled workers differentially become unemployed.

The remaining columns of table 2 quantify the variation in each variable that is cyclical, as measured first by the standard deviation of the Okun’s law estimate of c_t and second by the fraction of the variance of the series explained by the factors (that is, the R^2 of the common component in the dynamic factor model). By both measures, the most cyclical variable is the employment rate—by construction, for the Okun’s law estimate; and as a result of the factors explaining variation in employment, for the factor model estimate. Although cyclical variation in TFP accounts for one-fourth of the cyclical variation in business output per capita, cyclical variation only accounts for a fraction of the variation in TFP growth. TFP growth has a large amount of high-frequency variation, including measurement noise.

III.B. Growth Components: Trends and Cyclical Parts

Table 3 summarizes the results of the growth-accounting decomposition, where Okun's law is used to estimate the cyclical component conditional on the unemployment rate path. The table compares the mean values of these components in the recent recovery with their mean values in the three previous recoveries. For this table, the three previous recoveries are defined as the first 28 quarters of the recovery (the number of quarters from the first one after the trough to the end of our sample) or the trough-to-peak period, whichever is shorter. Columns a, b, and c in table 3 present actual average historical growth rates, and contributions to growth rates, at annual rates. Columns d, e, and f provide the decomposition after cyclically adjusting these variables using the Okun's law method.

Figures 3, 4, and 5 show (with the solid lines) the log levels of the series in table 3. These figures also plot the cyclically adjusted series, using Okun's law (the dotted lines), and the cyclically adjusted trend (the dashed line). The solid and dotted lines in the right panel of figure 1 and in the top-left panel of figure 3 are the same, but with different time scales and normalizations (see the figure notes).

Table 4 is the counterpart of table 3, in which the cyclical component is computed using the factor-based method, conditional on the state of the economy in mid-2009. The first column, the forecast, is the sum of the cyclical component of the forecast and the trend, averaged over the 2009–16 forecasting period. The second column is the actual average growth of the variable, and the third column is the factor estimate of the irregular part z , which is the shortfall—that is, the gap between forecasted and actual growth. The standard error of the cyclical component (that is, of the common component of the dynamic factor model) is given in parentheses.²

III.C. Components of Expenditure: Trends and Cyclical Parts

Many proposed explanations for the slow recovery appeal to deficient demand or to deficiency in a component of demand. To shed light on these explanations, we undertake the same trend/cyclical/irregular decomposition for variables in the GDP expenditure identity.

2. The shortfall in the third column is the negative of the usual definition of a forecast error. In addition, the standard error of the conditional mean in the third column is not the forecast standard error (which incorporates the uncertainty associated with future values of the factors and shocks), but rather is the sampling standard error arising from estimating the vector autoregression and other regression coefficients.

Table 3. Shortfall of the Postcrisis Recovery Relative to Earlier Recoveries: Growth Accounting Decomposition Using Okun's Law Cyclical Adjustment^a

Component	Historical values			Cyclically adjusted values					
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
	Three previous recoveries ^b	2009:Q2–2016:Q2 ^c	Annual shortfall (a) – (b)	Three previous recoveries ^{b,d}	2009:Q2–2016:Q2 ^{c,d}	Annual shortfall (d) – (e)	Annual shortfall in smooth trend	Residual shortfall (f) – (g)	Current shortfall
(1) GDP	3.60	2.06	1.54	2.95	0.96	1.99	1.26	0.73	14.94
(2) GDO	3.57	2.20	1.37	2.92	1.11	1.81	1.24	0.57	13.54
(3) Business GDO	4.04	2.76	1.29	3.18	1.29	1.89	1.31	0.58	14.14
(4) GDP per capita	2.48	1.02	1.45	1.84	–0.07	1.91	1.13	0.78	14.30
(5) GDO per capita	2.45	1.16	1.29	1.80	0.07	1.73	1.11	0.62	12.90
(6) Business GDO per capita	2.92	1.72	1.21	2.07	0.26	1.81	1.18	0.63	13.49
(7) Total factor productivity	1.30	0.89	0.42	0.99	0.28	0.71	0.36	0.35	5.12
(8) $\alpha \times$ capital / population	0.79	0.24	0.55	0.77	0.24	0.53	0.40	0.13	3.78
(9) $(1-\alpha) \times (LQ \times$ hours / population)	0.83	0.59	0.24	0.30	–0.27	0.57	0.41	0.15	4.04
(10) Business labor hours per capita	0.81	0.63	0.18	–0.06	–0.76	0.70	0.55	0.14	5.00
(11) Business hours per worker	0.07	0.24	–0.17	–0.10	–0.07	–0.03	–0.06	0.03	–0.24
(12) Ratio of business employment to household employment	0.12	0.37	–0.25	–0.11	0.01	–0.12	0.06	–0.18	–0.83
(13) Household employment rate	0.43	0.68	–0.25	0.00	0.00	0.00	0.00	0.00	0.02
(14) Labor force participation rate	0.19	–0.66	0.85	0.15	–0.69	0.85	0.56	0.29	6.11
(15) Business output per hour	2.11	1.09	1.03	2.12	1.01	1.11	0.62	0.49	8.09
(16) TFP / $(1-\alpha)$	1.95	1.44	0.51	1.48	0.51	0.96	0.48	0.48	6.98
(17) Capital–output ratio $\times \alpha / (1-\alpha)$	–0.26	–0.69	0.42	0.16	0.07	0.08	0.11	–0.02	0.59
(18) Labor quality	0.43	0.33	0.09	0.49	0.43	0.06	0.03	0.03	0.44

Sources: See the online data appendix.

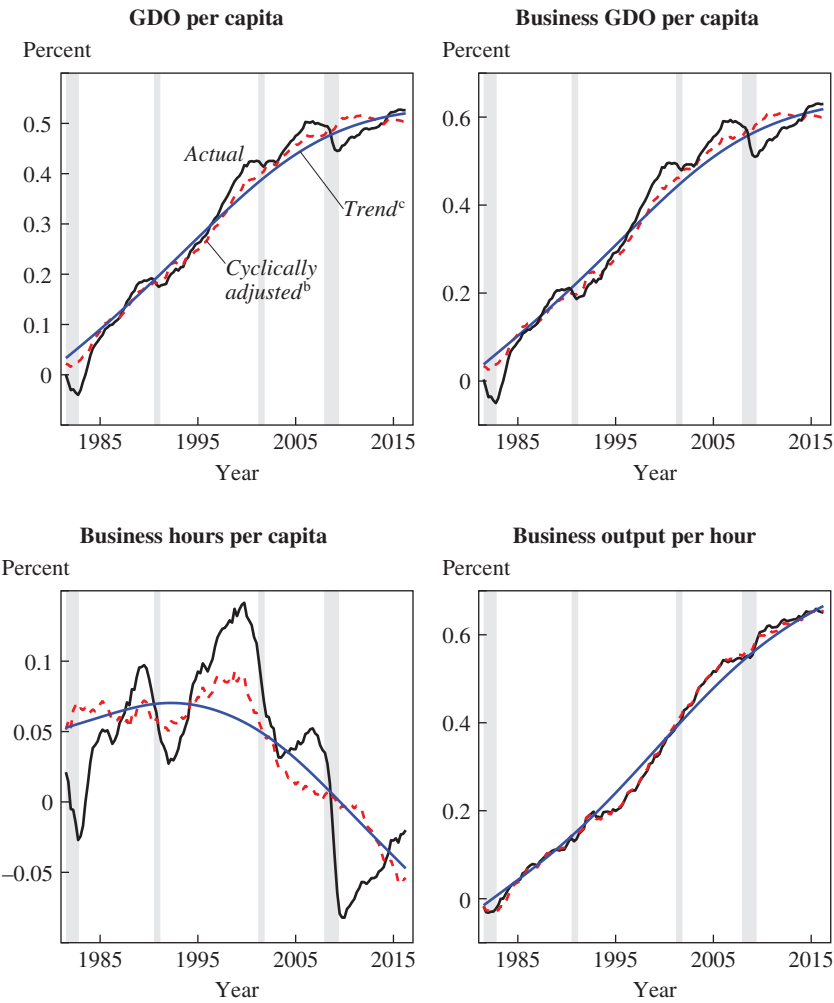
a. Units are average annual percent changes or percentage point differences. Indented rows sum to the prior level of aggregation.

b. The three previous recoveries are the averages during the first 28 quarters from the troughs of 1982 and 1991, and the 24 quarters of expansion after the 2001 trough.

c. The postcrisis recovery period is 2009:Q2 through 2016:Q2 (28 quarters).

d. The cyclically adjusted entries in these columns are residuals from Okun's law regressions.

Figure 3. Output and Labor Productivity, 1981–2016^a



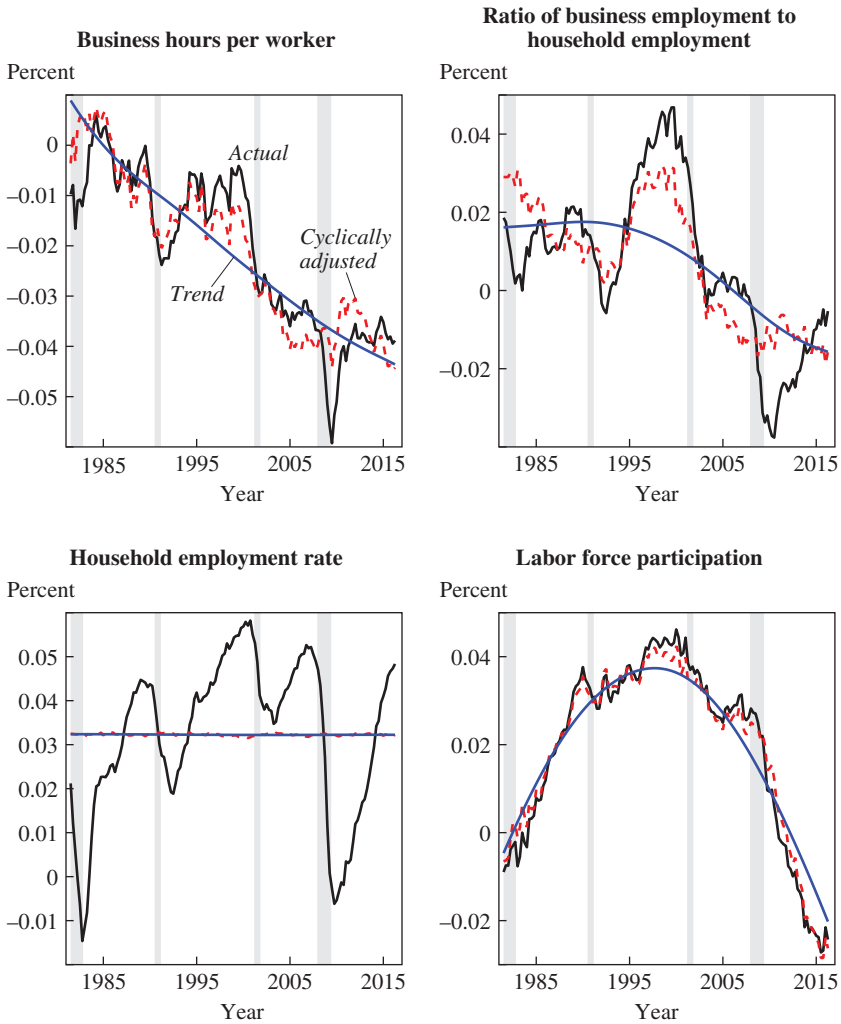
Sources: U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis; authors' calculations.

a. The figures show cumulated growth rates. Levels are normalized to have the same means over the sample shown.

b. The cyclically adjusted data are residuals (including constant terms) from Okun's law regressions.

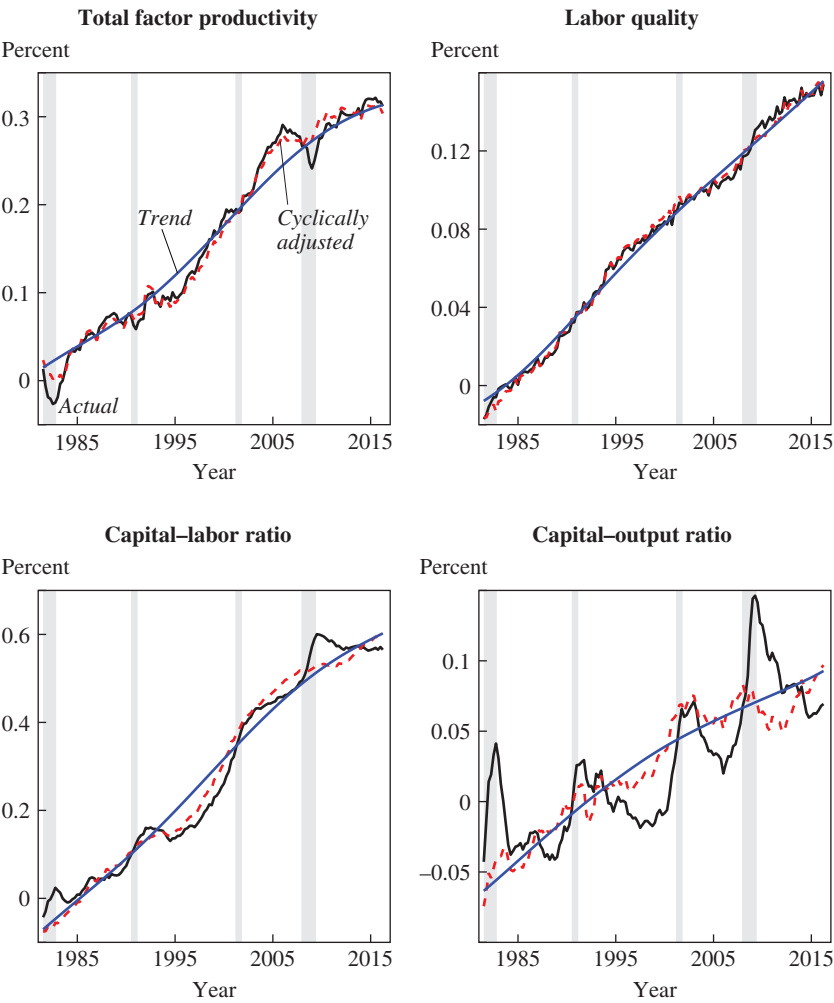
c. The trend lines are biweight-filtered with a bandwidth of 60 quarters fitted to the Okun's law residuals.

Figure 4. Labor Market Variables, 1981–2016^a



Sources: U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis; authors' calculations.
a. See the notes to figure 3.

Figure 5. Productivity, Capital Ratios, and Labor Quality, 1981–2016^a



Sources: U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis; authors' calculations.
a. See the notes to figure 3.

Table 4. Shortfall of the Postcrisis Recovery Relative to 2009:Q4 Forecasts: Growth Accounting Decomposition Using Forecast-Based Cyclical Adjustment

<i>Component</i>	<i>Forecast^a</i>	<i>Actual</i>	<i>Shortfall (SE)^b</i>
(1) GDP	2.63	2.06	0.57 (0.07)
(2) GDO	2.63	2.20	0.43 (0.07)
(3) Business GDO	3.11	2.76	0.35 (0.08)
(4) GDP per capita	1.51	1.02	0.48 (0.09)
(5) GDO per capita	1.51	1.16	0.35 (0.07)
(6) Business GDO per capita	1.99	1.72	0.27 (0.09)
(7) Total factor productivity	1.40	0.89	0.52 (0.09)
(8) $\alpha \times \text{capital} / \text{population}$	0.43	0.24	0.19 (0.01)
(9) $(1-\alpha) \times (LQ \times \text{hours} / \text{population})$	0.15	0.59	-0.44 (0.05)
(10) Business labor hours per capita	-0.08	0.63	-0.72 (0.06)
(11) Business hours per worker	0.08	0.24	-0.16 (0.03)
(12) Ratio of business employment to household employment	-0.16	0.37	-0.53 (0.06)
(13) Household employment rate	0.26	0.68	-0.42 (0.02)
(14) Labor force participation rate	-0.27	-0.66	0.40 (0.03)
(15) Business output per hour	2.07	1.09	0.98 (0.08)
(16) TFP / $(1-\alpha)$	2.15	1.44	0.72 (0.12)
(17) Capital-output ratio $\times \alpha / (1-\alpha)$	-0.43	-0.69	0.26 (0.03)
(18) Labor quality	0.34	0.33	0.01 (0.04)

Sources: See the online data appendix.

a. The forecasts are computed using the factor model and the values of the factors through 2009:Q2.

b. The shortfall is the negative of the forecast error. The standard error is of the shortfall arising solely from sampling error in the estimated model parameters.

Table 5 shows these decompositions using (share-weighted) contributions to growth. The first column of numbers shows the average growth contributions from 2009 to 2016. Because the forecasts and forecast errors are additive, the trend values, forecasts, and forecast errors in the remaining columns also add to their respective aggregates. The first block of columns on the second page presents results using the Okun's law cyclical adjustment, and the final block presents results using the dynamic factor model; the shortfall is the negative of the forecast error.

Figure 6 presents plots of selected dynamic factor model forecasts, their actual value, and their trend. For these plots, series that appear as components in tables 4 and 5 are not share-weighted. Plots for all the variables presented in tables 4 and 5 are given in the online appendix.

III.D. Discussion

A key difference between our two methods concerns the counterfactual cyclical path of labor market variables. The Okun method is conditioned on the unemployment rate path; thus, by construction, there is no irregular part

for the unemployment rate, and the irregular part for closely related labor market variables is small. In contrast, the forecasting exercise projects a normal cyclical path for all the variables, conditional on the state of the economy at the trough in 2009; in principle, the actual path of any variable, including labor market variables, can depart arbitrarily from its forecasted path. The factor forecasts capture two key features of the recovery, in that they underpredict the labor market recovery and overpredict output growth. We return to this and other implications of the factor forecasts at the end of this section.

Aside from this major difference in forecasts of output and unemployment in the recovery, the two methods generally yield quantitatively similar estimates of the irregular part, and lead to similar conclusions about the behavior of the components of output growth during the recovery. For clarity, we therefore focus primarily on results using the Okun method.

We begin with the first group of columns in table 3, which summarizes the shortfall of output and the growth decomposition components without cyclical adjustment. GDO grew 3.57 percent per year in the previous three recoveries (column a), but only 2.20 percent in the current recovery (column b), for a shortfall of 1.37 percentage points (column c). Similarly, business output per capita grew 2.92 percent in the previous three recoveries, but only 1.72 percent per year in the current one, for a shortfall of 1.21 percentage points. Looking down column c, many of the rows are nonzero, but a few stand out. These include a decline in the growth of capital per person (capital shallowing, row 8), a decline in the growth rate in TFP (rows 7 and 16), and a decline in the labor force participation rate (row 14).

This comparison of actual growth rates understates the output shortfall, however, because it does not account for how deep the recent recession was relative to the three previous ones on average. The second group of estimates presents the same decomposition after removing the cyclical component using Okun's law—that is, conditioning on the unemployment rate.

This cyclical adjustment creates a different, starker picture of the slow growth situation. The shortfall in business output per person is much larger, at 1.81 percentage points, reflecting the depth of the 2007–09 recession. The cumulative shortfall in output is 13.5 percent (final column). After cyclical adjustment, the only element that is quantitatively important for explaining hours is labor force participation (row 14), and the only element that is quantitatively important for labor productivity is TFP (row 16). Shortfalls in the direct contribution of capital input per person are also large (row 8), but when scaled by output (row 17) the contribution is small.

We now discuss selected elements of the growth accounting.

Table 5. Expected and Unexpected Contributions to GDP Growth: Demand Components^a

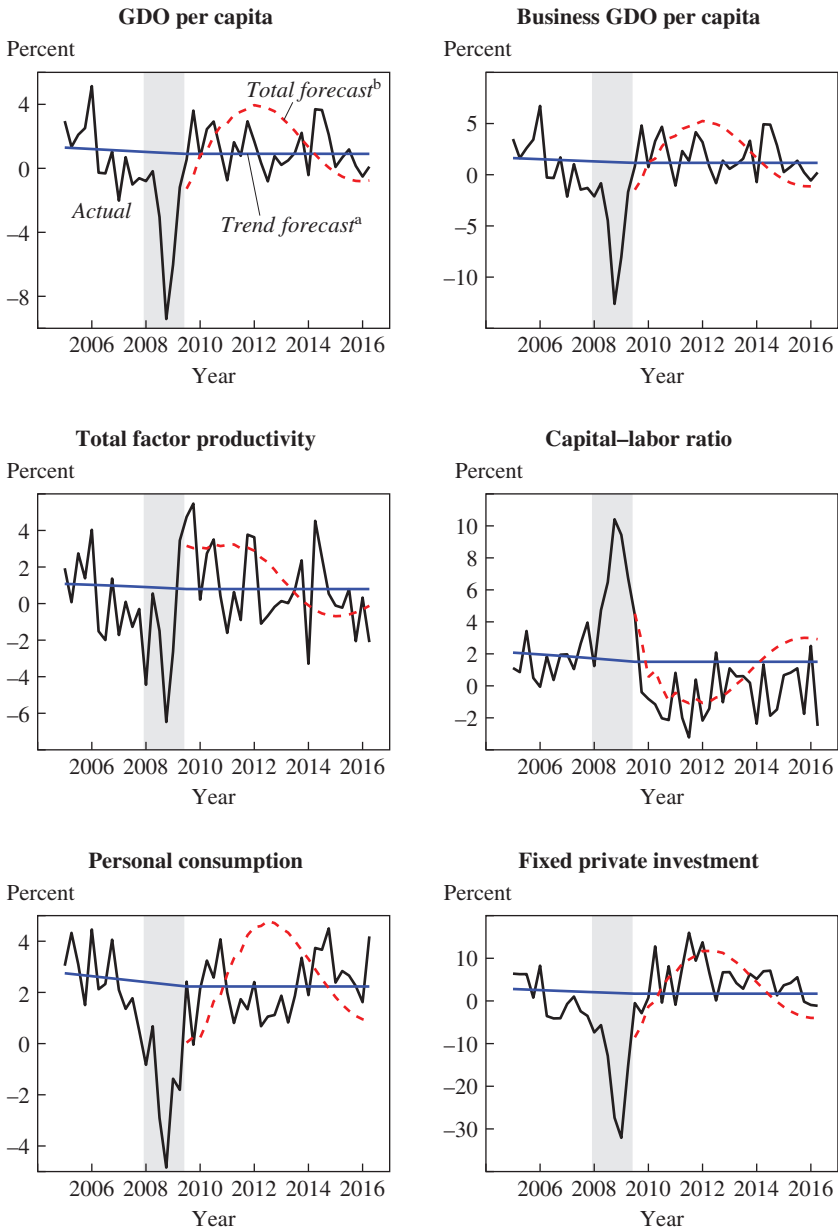
<i>Component</i>	<i>Growth rate, 2009:Q2– 2016:Q2</i>	<i>Average share</i>
Real GDP	2.06	1.00
Personal consumption expenditures	1.54	0.68
Goods	0.78	0.23
Durables	0.47	0.07
Motor vehicles and parts	0.11	0.02
Furniture and durable household equipment	0.11	0.02
Recreational goods and vehicles	0.20	0.02
Other durables	0.05	0.01
Nondurables	0.32	0.15
Food and beverages off premises	0.06	0.05
Clothing and footwear	0.06	0.02
Gasoline and energy	0.00	0.02
Other nondurables	0.19	0.06
Services	0.76	0.46
Housing and utilities	0.13	0.13
Health care	0.31	0.11
Transportation services	0.04	0.02
Recreational services	0.04	0.03
Food service and accommodations	0.11	0.04
Financial services and insurance	0.00	0.05
Other services	0.10	0.06
Nonprofit institutions serving households	0.03	0.02
Gross private domestic investment	0.91	0.15
Fixed private investment	0.70	0.15
Nonresidential	0.50	0.12
Structures	−0.01	0.03
Equipment	0.38	0.06
Intellectual property products	0.14	0.04
Residential	0.20	0.03
Structures	0.20	0.03
Equipment	0.00	0.00
Government expenditures	−0.19	0.19
Federal	−0.09	0.08
State and local	−0.10	0.12
Exports	0.58	0.13
Imports	−0.76	−0.16
Addendum: Government consumption expenditures plus transfer payments	0.66	n.a.

Sources: See the online data appendix.

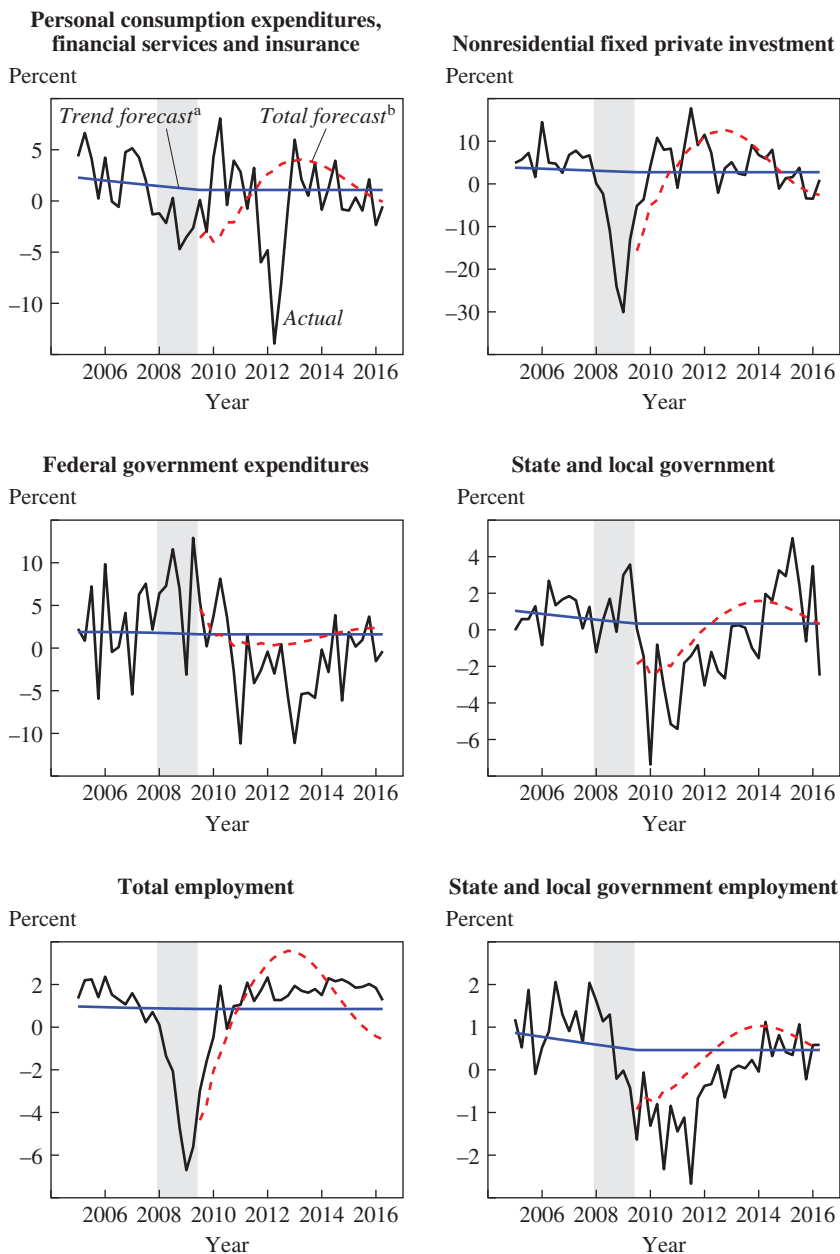
a. Indented rows sum to the prior level of aggregation.

<i>Okun's law coefficient (SE)</i>	<i>Okun's law cyclical adjustment</i>					<i>Dynamic factor model forecast</i>		
	<i>Growth rate</i>					<i>Fore- cast</i>	<i>Short- fall</i>	<i>SE</i>
	<i>Three previous recoveries</i>	<i>Postcrisis recovery</i>	<i>Total short- fall</i>	<i>Trend short- fall</i>	<i>Irregular (z) shortfall</i>			
-1.49 (0.18)	2.95	0.96	1.99	1.26	0.73	2.63	0.57	0.07
-0.74 (0.14)	2.00	1.04	0.96	0.70	0.26	1.80	0.26	0.04
-0.44 (0.14)	0.80	0.48	0.32	0.24	0.08	0.86	0.08	0.03
-0.25 (0.06)	0.43	0.28	0.15	0.12	0.03	0.50	0.03	0.03
-0.09 (0.04)	0.10	0.04	0.06	0.09	-0.03	0.10	-0.01	0.02
-0.06 (0.01)	0.08	0.06	0.02	0.02	0.00	0.10	0.00	0.00
-0.06 (0.01)	0.21	0.15	0.06	0.02	0.04	0.24	0.04	0.01
-0.03 (0.01)	0.05	0.03	0.02	0.00	0.01	0.06	0.01	0.00
-0.19 (0.03)	0.38	0.20	0.18	0.13	0.05	0.37	0.05	0.01
-0.03 (0.02)	0.08	0.03	0.04	0.03	0.01	0.08	0.02	0.00
-0.05 (0.01)	0.12	0.03	0.09	0.07	0.02	0.08	0.02	0.01
-0.03 (0.01)	0.03	-0.02	0.04	0.02	0.02	0.00	0.00	0.01
-0.07 (0.01)	0.15	0.15	0.00	0.00	0.00	0.19	0.00	0.01
-0.30 (0.08)	1.21	0.57	0.64	0.46	0.18	0.93	0.18	0.02
-0.06 (0.02)	0.28	0.10	0.18	0.12	0.07	0.20	0.07	0.01
0.00 (0.03)	0.23	0.31	-0.08	-0.07	-0.01	0.31	0.00	0.01
-0.08 (0.01)	0.07	0.00	0.07	0.06	0.01	0.03	-0.01	0.00
-0.04 (0.01)	0.09	0.02	0.07	0.05	0.03	0.06	0.02	0.00
-0.06 (0.02)	0.09	0.08	0.01	0.01	0.00	0.11	0.00	0.01
-0.02 (0.04)	0.18	-0.03	0.21	0.16	0.05	0.06	0.07	0.01
-0.06 (0.02)	0.15	0.06	0.09	0.07	0.02	0.11	0.01	0.01
0.02 (0.01)	0.12	0.05	0.07	0.05	0.02	0.06	0.03	0.01
-1.11 (0.14)	0.63	0.03	0.60	0.45	0.15	0.89	-0.02	0.04
-0.94 (0.07)	0.53	0.09	0.43	0.41	0.03	0.59	-0.11	0.03
-0.69 (0.08)	0.47	0.13	0.34	0.26	0.08	0.48	-0.02	0.02
-0.19 (0.03)	-0.01	-0.06	0.05	0.02	0.03	0.00	0.01	0.01
-0.44 (0.05)	0.30	0.09	0.20	0.17	0.03	0.33	-0.05	0.02
-0.06 (0.01)	0.19	0.11	0.07	0.06	0.02	0.15	0.01	0.01
-0.25 (0.05)	0.07	-0.03	0.10	0.15	-0.05	0.12	-0.08	0.02
-0.25 (0.05)	0.07	-0.03	0.10	0.15	-0.05	0.11	-0.08	0.02
0.00 (0.00)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.10 (0.06)	0.45	-0.11	0.56	0.31	0.25	0.12	0.31	0.03
0.11 (0.05)	0.18	-0.04	0.22	0.07	0.15	0.11	0.20	0.02
-0.01 (0.03)	0.26	-0.07	0.34	0.24	0.10	0.02	0.12	0.01
-0.27 (0.08)	0.60	0.36	0.24	0.10	0.14	0.60	0.03	0.04
0.54 (0.09)	-0.70	-0.34	-0.36	-0.29	-0.08	-0.77	-0.01	0.03
1.22 (0.52)	3.67	1.33	2.34	0.91	1.44	2.86	2.20	0.23

Figure 6. Forecasted and Actual Paths from the Factor Model: Selected Variables, 2005–16



(continued)

Figure 6. Forecasted and Actual Paths from the Factor Model: Selected Variables, 2005–16 (*Continued*)

Sources: U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis; authors' calculations.

a. Trend forecast is the long-term growth trend.

b. Total forecast is the forecast based on six factors estimated by principal components.

BUSINESS OUTPUT Figure 3 above, which shows the cumulative parts of the growth of business output per capita, conveys a basic finding of this paper. For the period of the recovery from the crisis recession, the consistent improvement in the labor market should have been associated with a dramatic recovery of output, based on historical, cyclical patterns. But two powerful forces opposed the cyclical part: the low-frequency trend and the high-frequency irregular part. Moreover, the downward slopes of the two parts are almost the same, and our breakdown of the noncyclical behavior of output gives equal roles to the high- and low-frequency parts.

HOURS PER WORKER Figure 4 above shows the levels of the three statistical parts of weekly hours per worker. Consistent with the coefficient of -0.35 given in table 2, the cyclical part of hours rose smoothly during the recovery, as in the three earlier recoveries. The slope of the low-frequency trend plotted in the figure, μ , rose slightly, though the high-frequency irregular part fell slightly. Unlike many other indicators, weekly hours behaved fairly normally in the postcrisis recession.

LABOR FORCE PARTICIPATION Figure 4 shows that the low-frequency trend in participation grew at a declining rate until 1998, and then began to shrink. The rate of shrinkage declined slightly in the last years shown. The cyclical part grew during the recovery, but both the high- and low-frequency parts declined. The net effect was a substantial decline in labor force participation during the recovery, in contrast to the pattern of low but positive growth in recoveries through the 1990s. Section V pursues explanations of the labor force's recent anomalous behavior.

LABOR QUALITY Although labor quality contributes to low-frequency growth in productivity (figure 5), it explains little of the post-2009 cyclically adjusted growth shortfall.

CAPITAL INPUT At first glance, capital input (table 3, row 8) appears to contribute a moderate amount to the shortfall in output. However, as we noted above, capital input is jointly determined with TFP, the labor force, employment, and other endogenous variables. Row 17 of table 3 shows that when measured relative to output, there was essentially no shortfall in the cyclically adjusted growth rate of capital. Figure 5 shows that the low-frequency part, and to a lesser extent the high-frequency part, started to decline somewhat before the crisis.

SENSITIVITY ANALYSIS In the online appendix, we report results for table 3 estimated using different numbers of lags in the Okun's law equation 8, and using different estimation samples. Most of the Okun's law coefficients in table 2—including the headline coefficients on GDP, GDO,

and business output—are insensitive to these changes. For the labor force participation rate, the generalized Okun's coefficient decreases from -0.16 to -0.37 when 12 lags are used, but using 12 lags somewhat reduces this coefficient for TFP. It is particularly important that the overall cyclically adjusted shortfall is quite robust to these changes, as is our decomposition. The reason for this robustness is that although the Okun's law coefficients change somewhat for some series, by mid-2016 the decline in the unemployment rate had slowed down as the economy approached full employment, so the net cyclically adjusted contributions did not change substantially.

COMPARING THE OKUN'S LAW AND FACTOR MODEL ESTIMATES Table 4 shows that compared with what would have been expected based on the data through 2009, actual GDP growth fell short by 0.57 percentage point, GDO growth fell short by 0.43 percentage point, and business output fell short by 0.35 percentage point. These cyclically adjusted shortfalls are smaller than their counterparts in table 3 because the recovery of employment was stronger than expected based on the factor forecasts: The Okun's law method in table 3 is conditioned on the unemployment rate path, but the factor model forecast has a shortfall in the household employment rate of -0.42 ; that is, the factor model predicts a less rapid fall in the unemployment rate. This feature of the factor forecasts—an unexpectedly strong recovery of the labor market, and an unexpectedly weak recovery of output—is consistent with the real-time errors of professional forecasters given in figure 2. As a back-of-the-envelope comparison, using the per capita business output shortfall from the factor model of 0.27 percentage point, the negative shortfall in the employment rate of 0.42, and the Okun's law coefficient of 2.02 for business output per capita yields an adjusted estimate of $1.12 (= 2.02 \times 0.42 + 0.27)$ of the shortfall in business output per capita from the factor model, adjusted for the fact that the factor model underpredicts employment. This is roughly comparable to the 0.91 sum of the irregular component computed using Okun's law (0.63) plus the error forecasting the trend growth rate. As another example, though the factor model overpredicts the average growth rate of the capital–output ratio (see table 4), this ratio is countercyclical, and its growth rate exceeds the factor model forecast after adjustment for the forecast error in employment.

In summary, this section documents that slow growth since 2009 is essentially entirely accounted for by slow TFP growth and declining labor force participation. The crucial issue for interpreting these results is the extent to which the slowdown in TFP and the fall of participation

were independent of or, alternatively, a consequence of the recession and its aftermath.

IV. Why Have Capital Accumulation and Productivity Fallen Short?

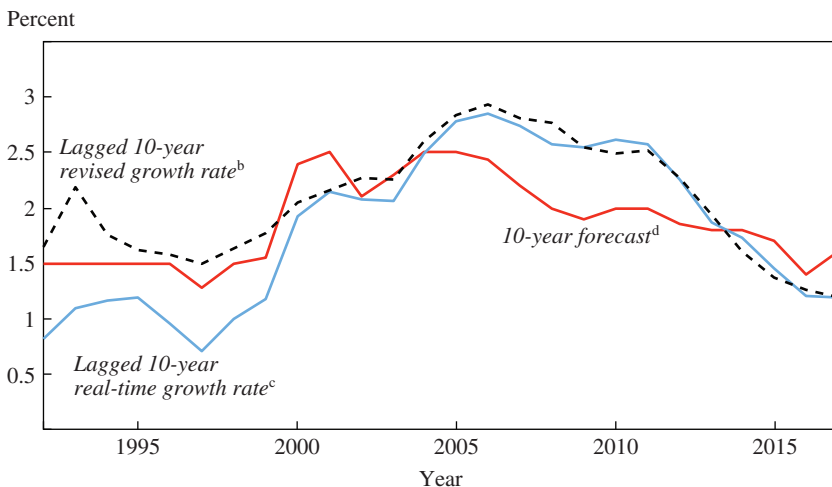
Why has cyclically adjusted productivity growth been slow, and, relatedly, has there been an unusual shortfall in capital deepening? We reach two conclusions.

First, according to both aggregate and industry-level data, the decline in productivity occurred before the recession. This observation strongly suggests that the recession was not the cause of the slowdown in cyclically adjusted productivity growth. Upon considering several candidate explanations for the productivity slowdown, including mismeasurement and an increasing regulatory burden, we are left to conclude that productivity growth slowed after the early 2000s because of a pause in or an end to the broad-based, transformative effects of information technology.

Second, weak capital formation was not an important *independent* contributor to weak output growth. Although investment was low during this recovery relative to earlier recoveries, capital growth was not low relative to output growth: By 2016, the capital–output ratio was in line with its long-term trend. If investment had been as strong as in the three earlier recoveries, the capital–output ratio would have grown by an improbably large amount. Using this ratio as the benchmark recognizes that businesses acquire capital to produce output. A long line of research using the investment accelerator recognizes this principle. This output benchmark inherently incorporates the fall of the underlying growth rate of output from the decline in cyclically adjusted productivity growth and the decline in labor force participation.

IV.A. When Did Productivity Growth Slow?

Even before the financial crisis, professional forecasters had noticeably lowered their estimates of the trend in the growth of labor productivity. Figure 7 plots the median forecasts from the Survey of Professional Forecasters for productivity growth over the next 10 years. The forecasts broadly track the lagging 10-year average growth of actual labor productivity computed using both real-time and final revised data. Forecasts rose sharply between 1999 and 2000. They remained close to 2.5 percent through the 2006 survey. They have since fallen by about a percentage point. Half that decline occurred before the financial crisis, between 2006 and early 2008.

Figure 7. Real-Time Estimates of Prospective 10-Year Growth in Labor Productivity, 1992–2017^a

Sources: Survey of Professional Forecasters; Archival Federal Reserve Economic Data; U.S. Bureau of Labor Statistics.

a. The figure shows the annual average growth rate of labor productivity for the nonfarm business sector.

b. The revised actual data are from February 2, 2017.

c. The real-time growth rate shows the average growth rate for the 10 years ending in the previous calendar year. The data are from the first data release of each year shown.

d. The 10-year forecast is from the Survey of Professional Forecasters. Surveys are from the first quarter of the year, and are annual averages over the next 10 years.

The slowdown is also evident in the time series data on TFP. The top-left panel of figure 5 shows that TFP growth picked up in the mid-1990s and slowed before the recession. The statistical question is whether those were persistent changes in trend growth, or more transient variations.

We undertake two sets of analyses of the timing and persistence of the slowdown in productivity growth. The first entails computing tests for a break or for a slower time variation in the mean of cyclically adjusted productivity growth. The second provides Bayesian posterior inference on whether the decline in the mean occurred before the 2007–09 recession began.

Table 6 summarizes five tests for the null hypothesis that there is no time variation in the mean growth rate of TFP. Let y_t^{ca} denote the cyclically adjusted growth rate of productivity, so that, following equation 6, $y_t^{ca} = \mu_t + z_t$, where μ_t is the local mean (or trend) value of y_t^{ca} , and z_t is the mean-zero irregular component. Table 6 shows results for two sample periods: the 35-year sample from 1981 through 2016 that has been the primary focus of this paper; and, to increase power, a 60-year sample from 1956 through

Table 6. Test Statistics for a Break in the Mean Growth Rate in Total Factor Productivity^a

	<i>Quandt likelihood ratio^b</i> <i>(sup-Wald) test</i>			<i>Nyblom</i> <i>test^c</i>	<i>Low-</i> <i>frequency</i> <i>stationary</i> <i>test^d</i>
	<i>1 break</i>	<i>2 breaks</i>	<i>3 breaks</i>		
<i>1956–2016</i>					
<i>p</i> value for $H_0: \mu_t = \mu$	0.01	0.06	0.01	0.02	0.03
Estimated break dates	1973:Q1	1973:Q1 2006:Q1	1973:Q1 1995:Q4 2006:Q1		
$\hat{\sigma}_{\Delta\mu}^e$	0.11			0.11	
90% CI for $\sigma_{\Delta\mu}^f$	(0.03, 0.36)			(0.02, 0.04)	
<i>1981–2016</i>					
<i>p</i> value for $H_0: \mu_t = \mu$	0.38	0.14	0.25	0.35	0.31
Estimated break dates	2006:Q1	1995:Q1 2006:Q1	1988:Q1 1995:Q4 2006:Q1		
$\hat{\sigma}_{\Delta\mu}^e$	0.05			0.05	
90% CI for $\sigma_{\Delta\mu}^f$	(0.00, 0.15)			(0.00, 0.27)	

Sources: See the online data appendix.

a. All tests are of a constant mean against a nonconstant alternative, and are heteroskedasticity- and autocorrelation-robust.

b. The nonconstant alternative for the Quandt likelihood ratio test is the regime changes.

c. The nonconstant alternative for the Nyblom test is the random walk drift.

d. The nonconstant alternative for the low-frequency stationary test is general martingale variation.

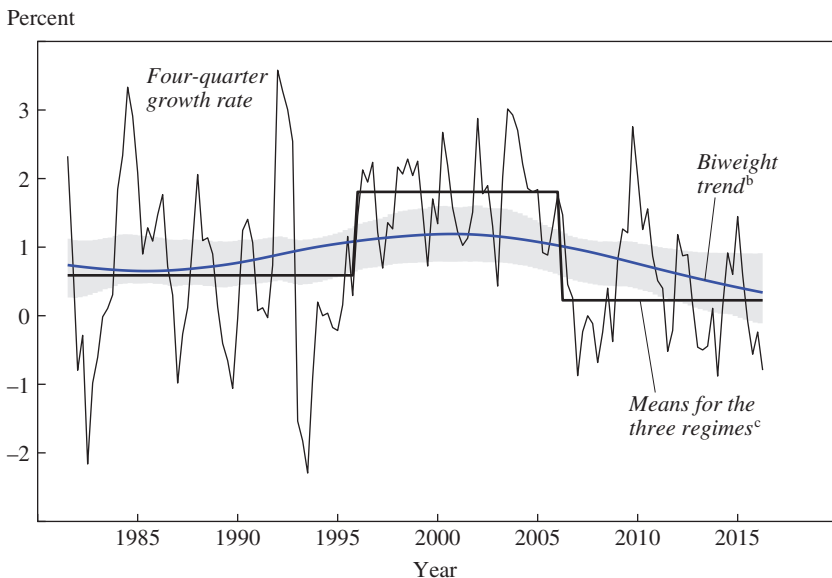
e. This row is a point estimate of the standard deviation of a random walk drift in the mean, $\sigma_{\Delta\mu}$.

f. This row is the 90 percent confidence interval of a random walk drift in the mean, $\sigma_{\Delta\mu}$, based on inverting the test statistic.

2016. The first three tests are the sup-Wald (the autocorrelation-robust Quandt likelihood ratio) break test of a constant mean against the alternative of, respectively, one, two, or three breaks. Along with the test statistic, this test yields estimates of the break dates themselves. The remaining two tests are the Nyblom (1989) tests that focus power on a small martingale variation in μ_t , and the low-frequency stationary test (Müller and Watson 2008), a low-frequency, point-optimal test for a martingale variation.

All five tests reject the null hypothesis that μ_t is constant using the 1956–2016 sample, but not using the shorter-duration 1981–2016 sample. This primarily reflects the inclusion of the early-1970s productivity slowdown in the longer sample. The three-break, full-sample test identifies break dates in 1973, 1995, and 2006, with a *p* value (for the null of no breaks) of 0.01, which accords with the conventional view of a high-growth period before 1973; a lower-growth period until 1995; and the high-growth period

Figure 8. Cyclically Adjusted TFP Growth and Estimated Low-Frequency Means, 1981–2016^a



Sources: U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis; authors' calculations.

a. The figure shows cyclically adjusted total factor productivity growth. The shaded area is the 67 percent Bayesian posterior interval.

b. The biweight trend is cyclically adjusted using a biweight filter with a bandwidth of 60 quarters.

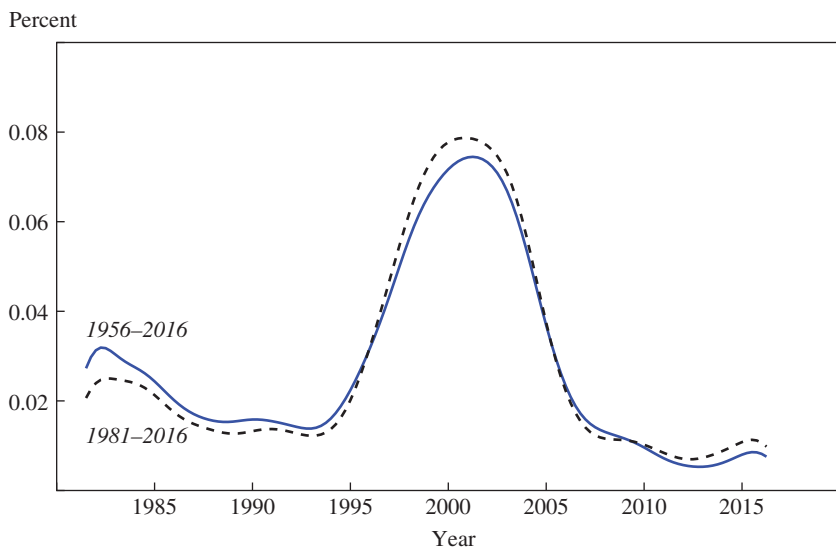
c. Means are estimated for three regimes using break tests with breaks at 1995:Q4 and 2006:Q1.

of the technology boom. Notably, for our purposes the test does not find a break during or after the 2007–09 recession.

To gain additional insight into possible persistent changes in cyclically adjusted productivity growth, we use a latent variable state-space model for the trend and irregular components μ_t and z_t , in which μ_t is modeled as a Gaussian random walk and z_t is modeled as Gaussian white noise. By adopting a Bayesian framework, we are able to undertake posterior inference on the timing of a peak in trend productivity growth and the magnitude of its decline before the recession. Details are given in the online appendix.

The results are summarized in figures 8 and 9. Figure 8 shows the four-quarter growth rate of cyclically adjusted TFP growth and three different estimates of μ_t : the cyclically adjusted biweight estimate (equation 9); the three-regime estimate, with estimated break dates in 1995 and 2006; and a 67 percent posterior interval for μ_t , from the Bayesian implementation of the random walk plus noise model. Figure 9 provides the posterior

Figure 9. The Posterior Density of the Date of Maximum Trend Growth in Total Factor Productivity, 1981–2016^a



Sources: U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis; authors' calculations.

a. The figure shows cyclically adjusted total factor productivity growth, computed using a Bayesian implementation of the random walk plus noise model for productivity growth.

distribution of the date of the maximum of the local mean of productivity growth between 1981 and 2016.

Taken together, we interpret table 6 and figures 8 and 9 as providing coherent evidence that the decline in productivity growth started before the recession. The posterior distribution in figure 9 dates the peak of μ_t in the late 1990s or early 2000s, with little of the mass after 2006. The frequentist tests do not provide strong evidence of a break post-1981; but to the extent that they do suggest breaks, they occurred before the 2007–09 recession. Using the Bayesian approach, we can compute the posterior probability of the magnitude of the decline between the peak of μ_t in about 2000 and its value in 2007; this calculation yields a posterior median estimate of 0.72 percentage point using the full sample, and a 67 percent posterior interval of (0.32, 1.27). These estimates, which suggest a significant decline before the cyclical peak, are also consistent with the decline in the biweight estimate and the Bayesian posterior sets shown in figure 8.

The discussion above focuses on measured TFP growth. A complementary perspective comes from looking at inputs to innovation, where a change in the trend is apparent in about 2000—even earlier than for

productivity. Productivity grows as the economy accumulates better ways to produce output. The national accounts measure some investments in innovation—namely, in intellectual property products, which include software; research-and-development spending by businesses, universities, and nonprofits; and the production of books, movies, television shows, and music. Investment in these products grew at an annual rate of 8.1 percent from 1975 to 2000. After the tech collapse in 2000, that high growth rate slowed precipitously to only 3.5 percent from 2000 to 2007, close to its post-2007 pace of 3 percent. Recent research adds additional intangible investments in innovation, training, reorganizations, and the like. Estimates of these additional intangible investments by Carol Corrado and Kirsten Jäger (2015) also show a slower pace of growth after 2000.

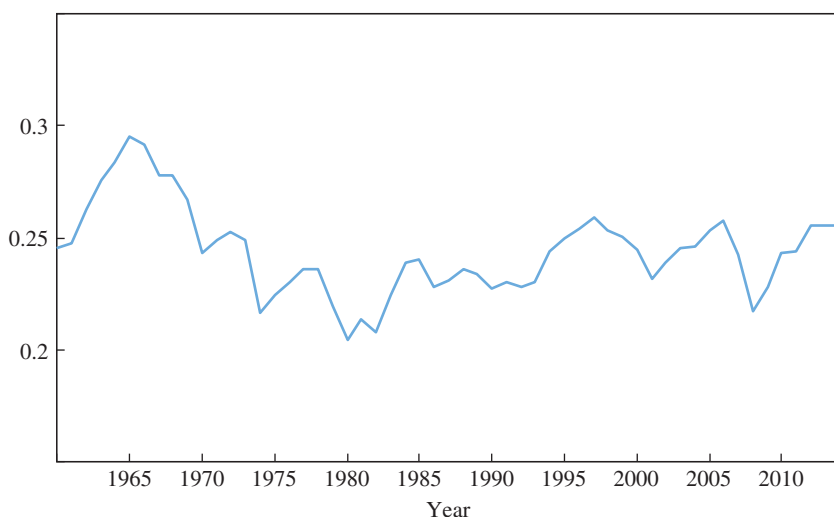
In sum, in the U.S. data since the early 1970s, the unusual period for productivity growth was roughly the 10 years from 1995 to 2005, when growth was faster than before or since.³ Measured spending on innovation also shows a slowdown much earlier than the recession.

IV.B. Why Has Capital Fallen Short?

On its face, concerns about weak investment seem appropriate; after cyclical adjustment, nonresidential investment growth contributed 0.47 percentage point to GDP growth during the previous three recessions, but only 0.13 percentage point during the recent recovery (table 5). This apparent shortfall in capital formation could reflect special features of the recession and recovery—such as tighter credit, increased financial frictions, and heightened uncertainty; potential longer-term factors include heightened regulatory barriers, increased market power, and shifts in industry composition.

Explaining this apparent shortfall requires a model of capital formation. The core of such a model is a demand function for productive capacity, which in turn depends on demand for output as well as the cost of capital. Jorgenson (1963) refined the principle by deriving the capital demand function from business optimization, conditional on the level of output and proportional to output. James Tobin (1969) refined the theory by incorporating adjustment costs.

3. Kahn and Rich (2007) use a complementary, somewhat more structural, regime-switching model on labor productivity and other variables, and date the shift to a low-productivity-growth regime in late 2004 or early 2005. Their most recent model update is available at https://www.newyorkfed.org/medialibrary/media/research/national_economy/richkahn_prodmod.pdf.

Figure 10. Ratio of Business Earnings to the Value of Capital, 1960–2014

Source: Authors' calculations.

Capital demand theory suggests benchmarks that would allow us to diagnose the role of special crisis and recession factors. Line 8 of table 3 shows that using only population as a benchmark—in effect, treating investment as exogenous—implies a substantial shortfall in the capital–population ratio in the recent recovery compared with the three earlier recoveries. However, line 17 of table 3 and the bottom-right panel of figure 5 show that using output as the benchmark reverses the impression of a shortfall—the capital–output ratio in the recent recovery behaved in line with its average in the earlier recoveries. According to the output benchmark, the shortfall in investment is the natural companion of the shortfall in output. Investment theory assigns a major role to the demand for output as a driver of capital demand and therefore of investment.

Investment theory does include other determinants along with output. One is the return to capital, a measure that Jorgenson (1963) brought into formal investment theory. An important determinant of business investment is the payoff to owners of capital. Some accounts of weak investment imply that capital was not earning as much as in normal times. Others imply that the return would be above normal, because a force limiting investment resulted in extra profitability for the smaller amount of capital. But, as figure 10 shows, the earnings of capital—measured as the sum of business

profits, interest paid, and depreciation—have been remarkably steady since the crisis. Earnings per \$1 of capital fell in 2009, but rebounded to normal in 2010 and have remained normal since then. The behavior of the return to capital supports our finding that investment was behaving normally, given the shortfall in output.

Gutiérrez and Philippon (2016) use Tobin's (1969) q theory of adjustment cost to provide a benchmark. The variable q , a normalized measure of the value of firms recorded in the stock and bond markets, has risen to high levels during the recovery. So why has investment not been stronger? Jorgenson's optimization model implies that firms invest until the marginal revenue product of capital equals its rental price. Gutiérrez and Philippon cite evidence such as rising concentration ratios to argue that rising market power has increased the gap between average and marginal revenue products. Market power rationalizes weak investment with a strong stock market.

Gutiérrez and Philippon (2016) consider only the relation with adjustment cost (Tobin's q), not the investment function. In the investment- q plane, the q curve slopes upward (the "supply" of investment), the demand for investment slopes downward, and their intersection determines investment and the value of q . An increase in market power shifts the q curve to the left, riding up the demand curve, resulting in lower investment and a higher value of q . Higher market power would reduce the capital-output ratio.

Alexander and Eberly (2016) find a shortfall in plant and equipment investment relative to a standard investment model. But the shortfall began in 2000, long before the recession of 2007–09, so their work supports our view that the capital-output ratio was not depressed by the recession itself. They attribute the shortfall to a shift toward investment in intellectual property and other intangibles. In manufacturing, firms tend to relocate physical production and its associated capital offshore, while retaining the intellectual property in the United States. Our measure of capital includes (some) intangible capital, so our finding of stability of capital input relative to output is consistent with Alexander and Eberly's (2016) findings.

The stability of the capital-output ratio is not conclusive evidence that there was no shortfall in capital resulting from the recession itself. Productivity growth has been low, and the labor force participation rate fell, so the trend in output growth fell. Accordingly, the capital-output ratio should have risen, according to standard growth theory. But because, in fact, it did not rise, there has been a shortfall in the ratio. Conversely, rising

market power would be a source of a decline in the ratio. It is beyond the scope of this paper to sort out quantitatively which effect dominates for the capital–output ratio. Our empirical evidence that the ratio is on its previous trend is consistent with the two forces roughly offsetting each other. In any case, in terms of investment, they point in the same direction—the level of investment itself should, at least for a time, be unusually weak for reasons unrelated to the recession or slow recovery, but rather because of lower productivity growth, declining participation, and possibly rising market power.

IV.C. Explanations for Slow Productivity Growth

Why has productivity growth been so slow if it is not the result of the financial crisis? Our conclusion is that the slowdown is plausibly a pause in—if not an end to—the information technology revolution. Our related conclusion is that the slowdown was not mainly the result of the recession. In this subsection, we review several hypotheses about the productivity slowdown. We begin with three nonrecession explanations and then return to the recession story.

MISMEASUREMENT Perhaps the problem of slow growth in both productivity and output is illusory. Plausibly, we could have missed many of the gains of from technology-related hardware, software, and digital services. But for mismeasurement to explain the productivity slowdown and its timing, growth must be mismeasured by more since the recession than in the previous 10 years.

Neither David Byrne, Fernald, and Marshall Reinsdorf (2016) nor Chad Syverson (2016) find evidence that, on balance, the mismeasurement of technology-related real output growth has in fact worsened since the early 2000s. In addition, the steady shift of economic activity toward poorly measured, slow-productivity-growth services, such as health care, does not change the picture, since the mid-2000s slowdown in productivity growth spread broadly across industries. Hence, changes in weighting matters relatively little. Philippe Aghion and others (2017) find a modest increase since the early 2000s in missing growth from creative destruction and increases in varieties. But the increase in bias is small relative to the measured slowdown in productivity growth.

RISING REGULATION AND THE LOSS OF DYNAMISM A rising regulatory burden could have slowed productivity growth (Barro 2016), and differing regulatory barriers do seem to matter across countries (Fatás 2016; Cetto, Fernald, and Mojon 2016). Indeed, regulation could be a reason why, by many measures, the U.S. economy’s dynamism has declined

over time (Decker and others 2016a, 2016b). Job creation and destruction have slowed; the business startup rate has fallen; and young firms have grown less in recent years. Ryan Decker and others (2016b) suggest that the character of declining dynamism changed after 2000, which would match the view that there were structural shifts in trend growth independent of the 2007–09 recession. This lack of dynamism could be a symptom of a lack of available or exploitable ideas. But some observers assert that its source is regulatory burdens, so we examine the link between regulation and productivity.

In the United States, a rising federal regulatory burden does not appear to explain the medium-frequency variations in productivity. First, although some commentators have pointed specifically to post-2008 federal regulatory changes, the timing does not fit because the peak in productivity growth occurred before that time.

Second, even for the post-2008 period, the industries where regulation increased the most did not for the most part show a decline in productivity growth. Omar Al-Ubaydli and Patrick McLaughlin (2015) apply text-analysis methods to the U.S. *Code of Federal Regulations* to construct industry-level indexes of regulations from 1975 through 2014. Their Reg-Data database covers 42 private industries that match industries for which we have productivity data from the U.S. Bureau of Labor Statistics for 1987 through 2014. (The online appendix describes the data in detail.) Industries with substantial increases in regulation after 2008 include, most notably, (i) finance, (ii) energy (pipelines, oil and natural gas extraction, and utilities), (iii) construction, and (iv) transportation (especially trucking, water, and rail).

Table 7 presents selected cuts of the Bureau of Labor Statistics' industry-level TFP data. The slowdown for the entire private business economy (line 1) after 2004 is marked. Finance slows sharply after 2004 and shows no further slowdown after 2007, the period of Dodd–Frank and other regulatory restrictions. With fracking, energy industries experienced *faster* productivity growth after 2007, so recent regulatory restraints on energy do not explain slow productivity growth. Construction also has experienced less negative productivity growth. Of heavily regulated industries, only transportation (2.5 percent of value added) has seen lower TFP growth.

Finance could matter, of course, as an intermediate provider of services. Using the input–output tables, we divided industries into finance-intensive (row 8) and non-finance-intensive (row 9) industries, defined by the expenditure share of financial services in industry gross output. Both groups slow sharply after 2004, but the finance-intensive grouping actually improves

Table 7. Industry Growth by Subperiod^a

	(a)	(b)	(c)	(d)	(e)	(f)	(g)
<i>Component</i>	<i>Pre- 1995</i>	<i>1995– 2000</i>	<i>2000– 04</i>	<i>2004– 07</i>	<i>2007– 14</i>	<i>Change after 2004 (d) – (c)</i>	<i>Value- added weight</i>
(1) Private business	0.62	1.35	2.05	0.32	0.26	–1.73	100.0
(2) Finance and insurance	–0.48	3.37	0.89	0.27	0.22	–0.63	8.3
(3) Energy ^b	3.15	–3.47	5.55	–3.51	3.14	–9.06	5.9
(4) Transportation (excluding pipelines)	3.47	2.34	2.57	2.78	0.40	0.21	2.5
(5) Construction	0.17	–1.29	–0.82	–5.50	–0.62	–4.67	6.0
(6) IT production	8.47	14.46	7.23	6.78	2.49	–0.45	5.7
(7) Business, excluding finance	0.71	1.17	2.17	0.34	0.28	–1.84	91.7
(8) Finance-intensive	0.22	0.24	1.35	–0.03	0.57	–1.37	44.7
(9) Non-finance-intensive	1.16	2.03	2.95	0.67	–0.03	–2.28	47.0
(10) Business, excluding finance and IT production	0.25	0.23	1.84	–0.10	0.12	–1.93	68.0
(11) IT-intensive	0.39	0.96	2.19	0.86	–0.22	–1.33	42.8
(12) Non-IT-intensive	0.11	–0.52	1.49	–0.99	0.45	–2.49	43.2

Sources: See the online data appendix.

a. Industry and aggregate growth are based on the U.S. Bureau of Labor Statistics' 60-industry multi-factor productivity data. Units are percent change per year, except for the value-added weight, which is the average percentage share from 1988 to 2014.

b. Energy includes oil and gas production, pipelines, refining, and utilities.

after 2007, despite increasing financial regulation. During the entire post-2004 period, the slowdown is larger for non-financial-intensive industries. Thus, it does not appear that post-2008 financial restrictions were a major impediment to productivity growth.

Third, we find little evidence of a broader regulatory effect. Table 8 shows panel regressions of industry productivity growth on current and lagged values of growth in industry regulatory restrictions. All regressions include industry fixed effects; the second column includes year effects. Columns 1 and 2 show that, with one and two lags, growth in regulatory restrictions is statistically insignificant and the explanatory power is tiny. Columns 3 and 4, which average lagged values, also show small and statistically insignificant effects. These negative findings are consistent with

Table 8. Panel Regressions of Industry TFP Growth on Regulatory Restrictions^a

	(1)	(2)	(3)	(4)
	<i>Industry TFP growth</i>			
<i>Regulation</i> _{<i>i,t</i>}	0.032 (0.032)	0.033 (0.033)		
<i>Regulation</i> _{<i>i,t-1</i>}	-0.023 (0.027)	-0.011 (0.026)		
<i>Regulation</i> _{<i>i,t-2</i>}	-0.045 (0.039)	-0.036 (0.035)		
<i>Regulation</i> _{<i>i,t-3</i>}	0.022 (0.023)	0.036 (0.034)		
<i>Regulation</i> _{<i>i,t-2</i>} ^b			-0.018 (0.040)	-0.009 (0.036)
<i>Regulation</i> _{<i>i,t-3:t-5</i>} ^c				0.060 (0.050)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes
<i>F</i> statistics for <i>Regulation</i> (<i>p</i> value)	0.36 (0.83)	0.44 (0.78)	0.19 (0.67)	0.86 (0.43)

Sources: See the online data appendix.

a. Data are annual observations of industry TFP growth and regulations for 42 industries for which Reg-Data has an index of regulation for 1987–2014. Standard errors clustered by industry are in parentheses.

b. This term denotes the average value of *Regulation* for lags $t = 0, 1, 2$.

c. This term denotes the average value of *Regulation* for lags $t = 3, 4, 5$.

those of Nathan Goldschlag and Alexander Tabarrok (2014), who find that changes in U.S. federal regulations have little or no effect on industry entrepreneurial activity or dynamism.

The lags might be long and uncertain; the data could be too noisy; or the regulations that matter could mainly be at the state and local levels (for example, land use restrictions and occupational licensing). However, at a first cut, we find no evidence that federal regulation is a first-order issue.

A PAUSE IN THE INFORMATION TECHNOLOGY REVOLUTION The hypothesis that information technology (IT) was the culprit is natural. A large body of literature links the mid-1990s speedup in productivity growth to the exceptional contribution of computers, communications equipment, software, and the Internet. IT has had a broad-based and pervasive effect on the economy through its role as a general-purpose technology (Bresnahan and Trajtenberg 1995; David and Wright 2003; Basu and others 2004). Businesses throughout the economy became more efficient by reorganizing to take advantage of an improved ability to manage information. However, by the early 2000s, industries like retailing had already been substantially

reorganized, so the gains from further innovation might have become more incremental (Gordon 2016; Fernald 2015).

Table 7 suggests some evidence consistent with this hypothesis. IT-producing industries (line 6) grew much more slowly after 2000 and even more slowly after 2007. Industries that use technology intensively showed a larger slowdown after 2007 relative to the 2000–04 period. But it is fair to say that this slowdown was broad-based. All industries use IT, and increasingly so. If that is the story, one might see another such period in the future, perhaps reflecting artificial intelligence, cloud computing, the Internet of Things, and the radical increase in mobility from smartphones. But we have not yet seen such gains in the data.

This story rings true in a number of ways. First, it is consistent with the large body of literature on the role of IT in the productivity acceleration of the late 1990s. Second, it is consistent with the view in the general-purpose-technology literature that the gains are, essentially, a series of drawn-out level effects. The gains might ebb and flow (Syverson 2013), and it is hard *ex ante* to know when the transformative gains will cease.

FALLOUT FROM THE RECESSION AND FINANCIAL CRISIS Our use of cyclically adjusted productivity growth corrects for normal cyclical movements in productivity and allows us to focus on the magnitude and timing of the more persistent, secular slowdown that has been the focus of this section so far. But a large body of literature argues that deep recessions, and especially financial crises, might reduce the level or growth rate of TFP.⁴ For example, a crisis might reduce investment in innovation or raise capital misallocation. If these channels are important, then a high-pressure economy might help reverse these effects and lead to faster growth in innovation (Yellen 2016)

Nevertheless, theory suggests that effects could go in either direction. For example, reallocation effects could raise higher productivity in a credit crisis (Petrosky-Nadeau 2013), as could cleansing effects (Caballero and Hammour 1994). Nicholas Bloom (2014) points out that higher uncertainty can stimulate longer-run innovation.

Overall, there is limited empirical evidence for the United States that historical downturns in the business cycle, financially related or otherwise, permanently cut the level or growth rate of productivity. An obvious counterexample is the depressed 1930s, which were an extraordinarily

4. For an early review, see Fatás (2000). For more recent discussions, see Reifschneider, Wascher, and Wilcox (2015) and Adler and others (2017).

innovative period, by all accounts (Field 2003; Alexopoulos and Cohen 2011; Gordon 2016). More broadly, Yu-Fan Huang, Sui Luo, and Richard Starts (2016) find that the level of TFP bounces back quickly from recessions, including after 2009. This evidence is consistent with the view that lower-frequency swings in productivity growth rates are largely exogenous to the business cycle.

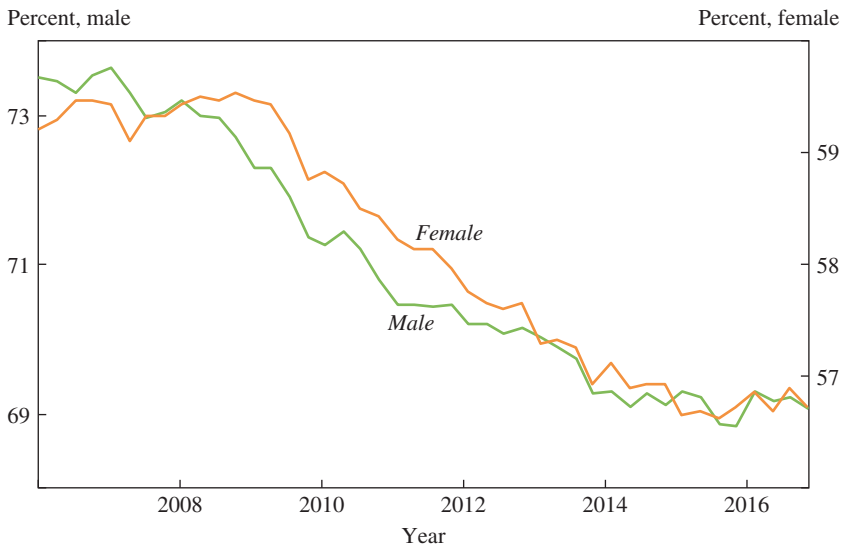
The biggest challenge for explaining the recent U.S. data is the timing: Productivity growth slowed before the recession. Diego Anzoategui and others (2016) suggest that there might have been a prerecession shock to exogenous growth followed by the large shock from the recession. Yet, as noted above, measured U.S. investments in research and development and other intellectual property slowed markedly after 2000, with a much smaller effect during the recent recession.

In sum, it is difficult to measure counterfactual productivity growth absent the recession, or absent the regulatory tightening. But we find that the weight of the evidence suggests that the slow pace of growth since the mid-2000s is real, and has contributed substantially to the disappointing recovery, and—with roots in the temporary, IT-spurred productivity boost of the 1990s—may even continue.

V. Changes in the Labor Market

The trends in labor force participation for men and women were very different than in earlier years, with women rising and men falling. As shown in figure 11, however, both have moved together since 2006 and both have fallen sharply since 2008. This decline has exerted a large negative force on output growth. Table 3 above shows that the contribution of participation to output, after cyclical adjustment, was -0.69 percentage point per year (column e), compared with an increase of 0.15 point per year averaged over the three previous recoveries (column d), for a shortfall of 0.85 point per year (column f). Cumulated over the recovery period through 2016, the shortfall was 6.11 percentage points (column i), almost as large as for TFP.

Before the crisis, recessions depressed labor force participation, though there were forces on both sides. Higher unemployment discouraged participation because it took longer to find a job. On the flip side, declines in income and wealth raised participation by inducing more people to seek and take jobs. The cyclical coefficient given in table 2 is small (-0.16) over a sample period that includes the rise in unemployment and fall in participation during and after the recession. This generalized Okun's coefficient increases in specifications allowing for slower adjustment; with

Figure 11. Labor Force Participation Rates by Sex, 2006–16

Source: U.S. Bureau of Labor Statistics.

three years of lags, it is -0.37 . Regardless of the lag specification, however, by 2016 the normal cyclical component of the participation rate was essentially zero.

Our estimate of the cyclical sensitivity of participation is *larger* if we end our sample before the crisis. Although the period of rising unemployment saw declines in participation, the recovery involved falling unemployment and falling participation, and that experience outweighed the contribution from the contraction. Key to our conclusions about participation is the fact that, until recently, participation continued to fall as unemployment declined from its peak of 10 percent to normal levels below 5 percent. This episode would be hard to explain if cyclical developments dominated participation toward the end of the recovery.

Many researchers ascribe part of the decline in participation to demography, specifically to the rising fraction of the population age 55 and above. Older individuals are more likely to retire. But adjusting for age composition alone, or just age and sex, misses countervailing demographic forces that reduce the propensity to retire. In particular, the people who moved into the 55+ age group during the recovery are better educated than their predecessors, and better-educated workers tend to retire later than less-educated workers. Estimates of pure aging declines in participation,

which use historical rates for older workers, could overstate the contribution of aging during the recent recovery. Instead, we calculate indexes that adjust for five demographic dimensions of heterogeneity in the working-age population.

The measured overall labor force participation rate can be written as $L = \sum_i s_i L_i$, where s_i is the population share and L_i is the participation rate of demographic group i . The change in the overall participation rate thus satisfies

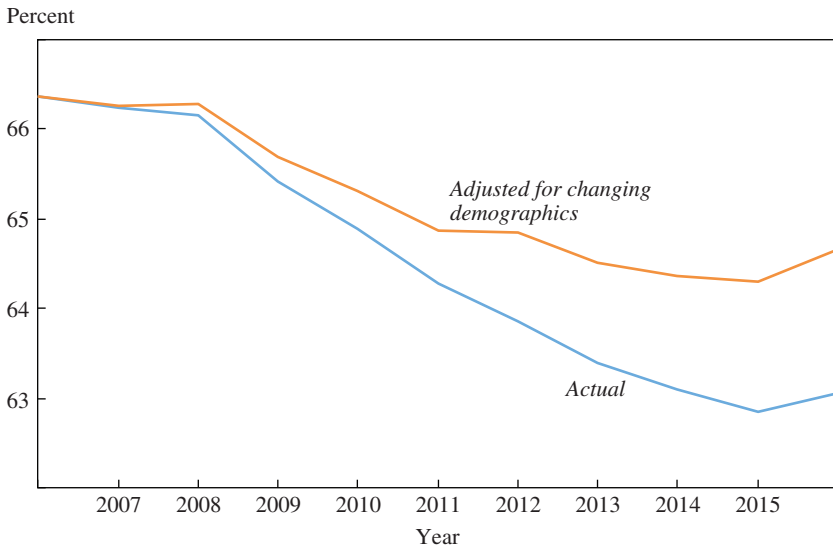
$$(10) \quad \Delta L = \sum_i s_i \Delta L_i + \sum_i L_i \Delta s_i$$

to a high degree of accuracy, especially if s_i in the first term and L_i in the second are measured as equally weighted values from the earlier and current periods. The cumulation of the first term is the component of the level of participation attributable to changes in participation within demographic groups and the cumulation of the second term is the component attributable to composition changes in the population. We call these the *rate* and *share* effects. Indexes calculated this way are named after François Divisia, and the refinement of measuring shares as equally weighted averages is named after Leo Törnqvist. The variation in the rates during the period is large enough to make any share index with fixed rates misleading. Counterfactual calculations based on holding rates at, say, the 2006 or 2016 levels are effectively fixed-rate indexes.

We implement the decomposition in equation 10 with annual data from the Current Population Survey for about 6,100 detailed cells defined by 67 age categories; two sexes; four education groups; four race groups; and three marital status groups. A few hundred cells in each year are empty. Figure 12 shows the overall labor force participation rate and our *rate* index. The difference between the two indexes is effectively our index of the *share* effect, that is, the effect of changing demographics. During the recovery, from 2010 through 2016, the reported participation rate across the population age 16 and older fell by 1.8 percentage points. Of this, 0.6 point came from the rate effect—the result of lower participation, on average, within demographic groups—and 1.2 points came from compositional change. During the period from 2007 to 2016, the two components fell by 1.6 percentage points. In other words, forces other than demography accounted for about one-third of the overall decline during the recovery, and for about half the decline since the cyclical peak in the fourth quarter of 2007.

The key question is: What explains the large nondemographic decline in the participation rate? Some specifications suggest that the cyclical

Figure 12. Labor Force Participation Rate Adjusted for Changing Demographics, 2006–16



Sources: U.S. Bureau of Labor Statistics; authors' calculations.

component of the participation rate is larger than in our specification here (see Erceg and Levin 2014; or see our longer-lag results reported in the online appendix). Even with a large cyclical coefficient, however, by the middle of 2016, the unemployment rate had returned to a normal or near-normal range, leaving only a very small normal cyclical component by mid-2016.

If the nondemographic participation gap as of 2016 is not part of a normal cyclical pattern, could it reflect unusual features of this recession and recovery? We think not. The 5.5 percentage point increase in the unemployment rate from its 2006 trough to its 2009 peak was comparable to the 5 percentage point increase from its 1979 trough to its 1982 peak spanning the twin recessions of the early 1980s. As shown in figure 1, the unemployment rate initially fell more sharply in the first 18 months following its peak in 1982 than following its 2009 peak; but the rate then plateaued. During the five years following its 2009 peak, the unemployment rate fell by 0.9 percent per year, nearly as fast as the 1.0 percent per year decline following the 1982 peak. Because the cyclical movements of the early 1980s are part of the data used to estimate the Okun's law coefficients,

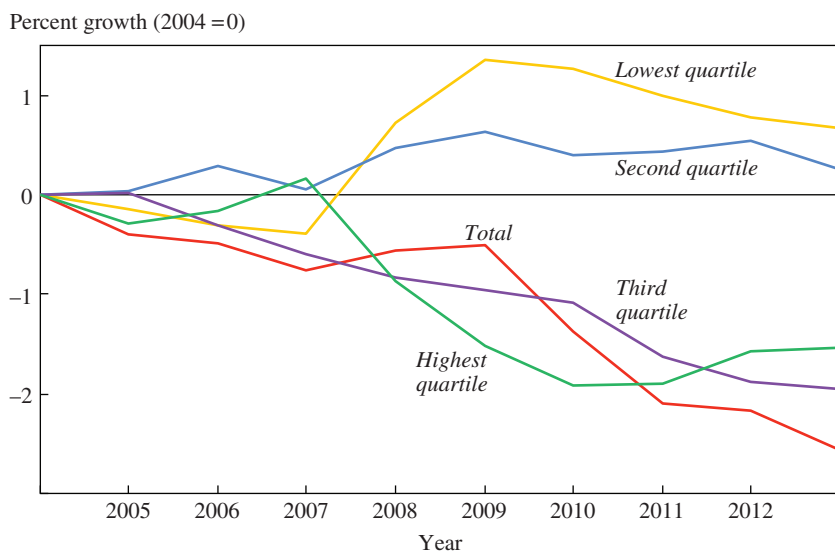
explanations that appeal to hysteresis must therefore argue that the correlations from previous cycles do not translate to the current cycle. It is not possible to estimate these coefficients precisely using only the current cycle; but, if anything, the unemployment coefficients are smaller when the current cycle is included in the data set. Finally, a related concern could be that the Okun coefficients are different for increasing than decreasing rates of unemployment, so our cyclical estimate is misspecified; but we find no evidence of such an asymmetry.

Aaronson and others (2014) report a variety of results for labor force participation. They find that their forecasts of participation published in 2006 were remarkably accurate as of 2014, suggesting that the entirely unforeseen recession and recovery that began at the end of 2007 had little net effect on participation. Their overall conclusion is that the sources of the decline in participation are partly demographic and partly a change that is not much related to conditions in the labor market. Though they do not specifically discuss the post-2009 expansion, it appears that their results (and others' they cite) confirm our conclusion that the dramatic improvement in the labor market during the recovery had little net effect on participation.

Our conclusion is that the roots of the nondemographic participation gap as of 2016 lie somewhere other than in the recession. Research has so far been inconclusive about the sources.

Figure 13 shows labor force participation rates for people age 25 through 54 by family income. Between 2004 and 2013, participation rose among members of the poorer half of families, and fell substantially in the upper half, the third and fourth quartiles. Essentially, all the decline in participation occurred in families with higher incomes. This finding contradicts the hypothesis that the decline in participation reflects the marginalization of poorer families in the labor market.

Table 9 investigates how people spent the time freed up by reduced work hours. It compares time allocations in 2015 with those in 2007. Market work, including time spent on job searches, fell by 1.6 hours a week for men and by 1.4 hours for women. The two categories with increases were personal care and leisure, which include a large amount of TV watching and other video-based entertainment, especially for men. The drop in hours devoted to other activities included a decline in housework for women. Basically, time use shifted toward enjoyment and away from work and investment activities. There was no substitution from market work to either nonmarket work or investment in human and household capital.

Figure 13. Growth in Labor Force Participation by Family Income, 2004–13^a

Sources: U.S. Bureau of Labor Statistics; Hall and Petrosky-Nadeau (2016).

a. The figure shows the growth in labor force participation for people age 25 to 54 by income quartiles, indexed to 2004 = 0.

The surprising, large, and persistent decline in labor force participation is a phenomenon that deserves and will receive intensive study. Although there is room for disagreement about the extent to which the early-recovery decline in labor force participation reflected a weak labor market, that cyclical component was gone by mid-2016. Similarly, although demographic shifts are and will continue to be an important part of the decline in the participation rate, demographics provide only a partial explanation. The complete explanation will also consider changes in family structure, real wages, taxes, benefits, and the value of time spent outside the labor market.

Table 9. Changes in Weekly Hours of Time Use for People Age 15 and Older, 2007–15

	<i>Personal care, including sleep</i>	<i>Market work</i>	<i>Education</i>	<i>Leisure</i>	<i>Other</i>
Men	2.0	-2.4	0.5	0.7	-0.8
Women	2.4	-1.5	0.1	0.7	0.8

Source: American Time Use Survey.

VI. Other Explanations for Slow Output Growth

So far, our discussion has highlighted the noncyclical role of slow TFP growth and declining participation in explaining slow output growth. Our forecasting model, however, provides some evidence on the large number of other explanations that have been proposed.

Our analysis takes demand into account through the use of unemployment as a cyclical indicator and through the use of a factor model with a multivariate statistical characterization of the cycle. If unemployment rates below 5 percent imply an economy in a cyclically normal condition, then this rules out explanations based on permanent or highly persistent weak demand. Moreover, explanations based on temporary demand deficiency need to be reconciled to the fact that the recovery of the unemployment rate was not abnormally slow—indeed, was faster than expected (figure 2). Sponsors of explanations based on weak demand need to couple their explanations with a parallel explanation of the behavior of labor market indicators.

VI.A. Empirical Evidence from the Forecasting Exercise

Figure 6, complemented by the full set of factor model forecasts shown in the online appendix, shows three periods in the history of the recovery. From mid-2009 through 2010, the economy grew vigorously, with output, consumption, private fixed investment, and employment all growing at or above the forecasted path. From 2011 through 2013, employment growth, though strong, was below its predicted path, and the associated predicted strong growth in output failed to materialize. This large growth gap reflected the lack of sustained output growth in the 3 to 4 percent range that was typical of earlier recoveries. After an initial surge, the growth of productivity was well below its predicted path. In the third period, since 2014, growth in many aggregates, including output and especially employment, has been stronger than the forecasted path, and—notably—the slow productivity growth over this period is consistent with the cyclical prediction. This picture is one of a recovery delayed; the slow-growth puzzle is largely the absence of strong growth in productivity and output in 2011 through 2013.

The demand decomposition given in table 5 indicates that most of the demand components tracked their forecasted paths, on average. Although exports were unexpectedly weak, so were imports; after share-weighting, their contributions to the average shortfall in output growth were negligible, at 0.03 and −0.01 percentage point per year, respectively. Table 5

indicates that the average forecast error for GDP of 0.57 percentage point is largely attributable to three sources: consumption of services (0.18 percentage point), federal government expenditures (0.15), and state and local government expenditures (0.10).

For federal government purchases, the main shortfall occurred in 2013 and 2014 (figure 6). This period coincides with the fiscal drag associated with the unwinding of American Recovery and Reinvestment Act expenditures and with the sequester. For state and local expenditures, the period of negative contributions was longer, from 2010 through early 2014.

Consumption growth during the recovery was slightly weaker than predicted—a 0.26 percentage point contribution to the output shortfall. Much of this weakness is attributable to two service sectors: housing and utilities (0.07 percentage point) and financial services and insurance (0.07 percentage point). The forecast error in residential investment averaged -0.08 percentage point during the full period, but this masks the housing sector's delayed recovery. Through 2011, the normal, cyclical recovery of housing did not materialize, and housing investment growth did not stabilize on the forecasted path until 2012. The strength of the housing market since 2014 accounts for the negative contribution of residential investment to the output shortfall.

VI.B. Discussion

These forecast errors shed light on some of the explanations for the slow recovery. Explanations in which aggregate demand is held back by unusually retarded growth of consumption—increasing inequality, policy uncertainty, or consumer deleveraging—do not square with the fact that the contribution of consumption growth to the shortfall in output growth was only 0.26 percentage point; rather, consumption growth largely tracked its predicted path during the recovery. Moreover, the largest shortfall in consumption is in services—mainly, housing services, and financial services and insurance—and in the latter case, for only three aberrant quarters in 2011 and 2012. This pattern does not seem to align with any explanation that focuses on shortfalls in aggregate demand that operate through consumption broadly.

Similarly, the evidence does not support theories that operate through slow investment. Nonresidential investment growth was, in fact, unexpectedly strong early in the recovery, and otherwise largely tracked its predicted path, apart from a slow spell in 2013 (figure 6).

The fact that the growth of consumption and investment largely tracked their historical, cyclical patterns suggests that the unusual features of the

current recovery that might have restrained aggregate demand are not, in fact, key drivers of the slow recovery. Moreover, one would expect slow aggregate demand to be reflected in sluggish revival of employment and the unemployment rate, but that is evidently not the case because employment growth exceeded the 2009 prediction on average. Growth was strong early and late in the recovery.

Our examination of the expenditure components revealed one part of demand that made a contribution to the slow recovery: weakness in federal, state, and local government purchases. The timing of the forecast errors suggests that the unwinding of the American Recovery and Reinvestment Act spending combined with the sequester provided substantial headwinds to the recovery. In addition, the persistently slow growth of state and local government purchases through 2013, along with the slow growth during this period of state and local government employment, points to an unusually severe fiscal drag imparted by restrained state and local purchases associated with balanced budget requirements and the prolonged effect on real estate tax receipts of the fall in house prices during the recession. These measures do not include transfers, which, unlike direct government purchases, were growing; thus transfers may have somewhat supported consumption. Nevertheless, as shown by the addendum line in table 5, there was a large shortfall in government expenditures plus transfers. This composite category was forecasted to grow by 2.86 percent per year, but in fact it only grew at a 0.66 percent pace.

Finally, we find some room for explanations associated with a poor or missed measurement of real output. Gross domestic income growth averaged 2.34 percent from 2009 to 2016, while GDP grew at 2.06 percent. Table 5 suggests that some of this difference may come from unexpected sources. In particular, half the unexpected decline in services consumption in 2013 is attributable (in a national accounting sense) to a decline in one of the most poorly measured sectors of consumption: financial services and insurance. Additional investigation of these measurement issues is warranted.

VII. Concluding Remarks

Output grew substantially less during the recovery from the 2007–09 recession than would normally have accompanied the observed, relatively rapid decline in the unemployment rate. It grew less than it would have given its normal relation to an index derived from many macroeconomic indicators. And it grew less than professional forecasters predicted, both at the

time of the trough and throughout the recovery. An explanation for poor output growth needs to start with two key facts: Productivity grew substantially less than its historical growth rate, both in expansions and in general; and labor force participation shrank an atypical and unexpected amount. Research on both topics is active today. We conclude in this paper that the large movements in both factors were in train before the recession, and cyclical effects contributed at most modestly to them.

Will growth pick up in the future, or slow further? The median respondent in the Survey of Professional Forecasters for the first quarter of 2017 forecasts growth in the next 3 years, and the next 10 years, to exceed its average pace during the recovery so far. Although changes in technology trends are hard to predict, the analysis in our paper does not support such optimism. The disappointing average pace of growth since 2009 included a large cyclical component that has, as of this writing, largely gone away. The remaining slow underlying pace of growth reflected underlying non-cyclical trends that predated the recession. To date, those trends have been persistent, and are not a mismeasurement mirage. Although a turnaround in productivity growth could happen again, such a turnaround does not appear to be on the horizon. This observation, combined with labor force participation that is persistently declining for both demographic and non-demographic reasons, suggests subdued steady-state output growth for the foreseeable future.

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References

- Aaronson, Stephanie, Tomaz Cajner, Bruce Fallick, Felix Galbis-Reig, Christopher Smith, and William Wascher. 2014. "Labor Force Participation: Recent Developments and Future Prospects." *Brookings Papers on Economic Activity*, Fall: 197–255.
- Aaronson, Stephanie, Bruce Fallick, Andrew Figura, Jonathan Pingle, and William Wascher. 2006. "The Recent Decline in the Labor Force Participation Rate and Its Implications for Potential Labor Supply." *Brookings Papers on Economic Activity*, no. 1: 69–134.
- Adler, Gustavo, Romain Duval, Davide Furceri, Sinem Kiliç Çelik, Ksenia Koloskova, and Marcos Poplawski-Ribeiro. 2017. "Gone with the Headwinds: Global Productivity." Staff Discussion Note no. 17/04. Washington: International Monetary Fund.
- Aghion, Philippe, Antonin Bergeaud, Timo Boppart, Peter J. Klenow, and Huiyu Li. 2017. "Missing Growth from Creative Destruction." Working Paper no. 2017-04. Federal Reserve Bank of San Francisco.
- Alexander, Lewis, and Janice Eberly. 2016. "Investment Hollowing Out." Paper prepared for the 17th Annual Jacques Polak Research Conference, International Monetary Fund, Washington, November 3.
- Alexopoulos, Michelle, and Jon Cohen. 2011. "Volumes of Evidence: Examining Technical Change in the Last Century through a New Lens." *Canadian Journal of Economics* 44, no. 2: 413–50.
- Al-Ubaydli, Omar, and Patrick A. McLaughlin. 2015. "RegData: A Numerical Database on Industry-Specific Regulations for All United States Industries and Federal Regulations, 1997–2012." *Regulation & Governance* 11, no. 1: 109–23.
- Anzoategui, Diego, Diego Comin, Mark Gertler, and Joseba Martinez. 2016. "Endogenous Technology Adoption and R&D as Sources of Business Cycle Persistence." Working Paper no. 22005. Cambridge, Mass.: National Bureau of Economic Research.
- Barro, Robert J. 2016. "The Reasons behind the Obama Non-Recovery." *Wall Street Journal*, September 20.
- Basu, Susanto, and John Fernald. 2001. "Why Is Productivity Procyclical? Why Do We Care?" In *New Developments in Productivity Analysis*, edited by Charles R. Hulten, Edwin R. Dean, and Michael J. Harper. University of Chicago Press.
- Basu, Susanto, John G. Fernald, Nicholas Oulton, and Sylaja Srinivasan. 2004. "The Case of the Missing Productivity Growth, or Does Information Technology Explain Why Productivity Accelerated in the United States but Not in the United Kingdom?" *NBER Macroeconomics Annual* 18: 9–82.
- Blanchard, Olivier, Guido Lorenzoni, and Jean-Paul L'Huillier. 2017. "Short-Run Effects of Lower Productivity Growth: A Twist on the Secular Stagnation Hypothesis." Working Paper no. 23160. Cambridge, Mass.: National Bureau of Economic Research.
- Bloom, Nicholas. 2014. "Fluctuations in Uncertainty." *Journal of Economic Perspectives* 28, no. 2: 153–76.

- Bosler, Canyon, Mary C. Daly, John G. Fernald, and Bart Hobijn. 2016. "The Outlook for U.S. Labor-Quality Growth." Working Paper no. 2016-14. Federal Reserve Bank of San Francisco
- Bresnahan, Timothy F., and Manuel Trajtenberg. 1995. "General-Purpose Technologies: 'Engines of Growth'?" *Journal of Econometrics* 65, no. 1: 83–108.
- Byrne, David M., John G. Fernald, and Marshall B. Reinsdorf. 2016. "Does the United States Have a Productivity Slowdown or a Measurement Problem?" *Brookings Papers on Economic Activity*, Spring: 109–57.
- Caballero, Ricardo J., and Mohamad L. Hammour. 1994. "The Cleansing Effect of Recessions." *American Economic Review* 84, no. 5: 1350–68.
- Cette, Gilbert, John Fernald, and Benoît Mojon. 2016. "The Pre-Great Recession Slowdown in Productivity." *European Economic Review* 88: 3–20.
- CBO (Congressional Budget Office). 2006. "The Budget and Economic Outlook: Fiscal Years 2007 to 2016." Washington. <https://www.cbo.gov/publication/17601>
- . 2012. "What Accounts for the Slow Growth of the Economy after the Recession?" Washington. <https://www.cbo.gov/publication/43707>
- Corrado, Carol, and Kirsten Jäger. 2015. "Wealth and Investment in Mature Societies." Presentation given at Milestone 3: Midterm Conference, Smart Public INTANGibles (SPINTAN), London, April 23–24. http://www.spintan.net/wp-content/uploads/public/Carol-Corrado-Wealth-and-Investment_carol-corrado.pdf
- Council of Economic Advisers. 2015. "A Better Measure of Economic Growth: Gross Domestic Output (GDO)." Washington: White House. https://obama.whitehouse.archives.gov/sites/default/files/docs/gdo_issue_brief_final.pdf
- David, Paul A., and Gavin Wright. 2003. "General Purpose Technologies and Surges in Productivity: Historical Reflections on the Future of the ICT Revolution." In *The Economic Future in Historical Perspective*, edited by Paul A. David and Mark Thomas. Oxford University Press.
- Daly, Mary C., John G. Fernald, Fernanda Nechio, and Òscar Jordà. 2017. "Shocks and Adjustments." Working paper.
- Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda. 2016a. "Declining Business Dynamism: What We Know and the Way Forward." *American Economic Review* 106, no. 5: 203–07.
- . 2016b. "Where Has All the Skewness Gone? The Decline in High-Growth (Young) Firms in the U.S." *European Economic Review* 86: 4–23.
- Erceg, Christopher J., and Andrew T. Levin. 2014. "Labor Force Participation and Monetary Policy in the Wake of the Great Recession." *Journal of Money, Credit and Banking* 46, suppl. 2: 3–49.
- Fatás, Antonio. 2000. "Do Business Cycles Cast Long Shadows? Short-Run Persistence and Economic Growth." *Journal of Economic Growth* 5, no. 2: 147–62.
- . 2016. "The Agenda for Structural Reform in Europe." In *After the Crisis: Reform, Recovery, and Growth in Europe*, edited by Francesco Caselli, Mário Centeno, and José Tavares. Oxford University Press.

- Fernald, John G. 2014. "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity." Working Paper no. 2012-19. Federal Reserve Bank of San Francisco.
- . 2015. "Productivity and Potential Output Before, During, and After the Great Recession." *NBER Macroeconomics Annual* 29: 1–51.
- Fernald, John G., and J. Christina Wang. 2016. "Why Has the Cyclicalities of Productivity Changed? What Does It Mean?" *Annual Review of Economics* 8: 465–96.
- Field, Alexander J. 2003. "The Most Technologically Progressive Decade of the Century." *American Economic Review* 93, no. 4: 1399–413.
- Goldschlag, Nathan, and Alexander T. Tabarrok. 2014. "Is Regulation to Blame for the Decline in American Entrepreneurship?" Working Paper in Economics no. 15-11. Fairfax, Va.: George Mason University.
- Gordon, Robert J. 2014. "A New Method of Estimating Potential Real GDP Growth: Implications for the Labor Market and the Debt/GDP Ratio." Working Paper no. 20423. Cambridge, Mass.: National Bureau of Economic Research.
- . 2016. *The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War*. Princeton University Press.
- Gutiérrez, Germán, and Thomas Philippon. 2016. "Investment-Less Growth: An Empirical Investigation." Working Paper no. 22897. Cambridge, Mass.: National Bureau of Economic Research.
- Hall, Robert, and Nicolas Petrosky-Nadeau. 2016. "Changes in Labor Participation and Household Income." Economic Letter no. 2016-02. Federal Reserve Bank of San Francisco.
- Huang, Yu-Fan, Sui Luo, and Richard Startz 2016. "Are Recoveries All the Same: GDP and TFP?" Working paper. <http://econ.ucsb.edu/~startz/Are%20Recoveries%20All%20the%20Same.pdf>
- Jorgenson, Dale. 1963. "Capital Theory and Investment Behavior." *American Economic Review* 53, no. 2: 247–59.
- Jorgenson, Dale W., and Zvi Griliches. 1967. "The Explanation of Productivity Change." *Review of Economic Studies* 34, no. 3: 249–83.
- 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, no. 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* 54, no. 6: 1670–701.
- Lansing, Kevin J., and Benjamin Pyle. 2015. "Persistent Overoptimism about Economic Growth." Economic Letter no. 2015-03. Federal Reserve Bank of San Francisco.
- Müller, Ulrich K., and Mark W. Watson. 2008. "Testing Models of Low-Frequency Variability." *Econometrica* 76, no. 5: 979–1016.
- Nalewaik, Jeremy J. 2010. "The Income- and Expenditure-Side Estimates of U.S. Output Growth." *Brookings Papers on Economic Activity*, Spring: 71–106.

- Nyblom, Jukka. 1989. "Testing for the Constancy of Parameters over Time." *Journal of the American Statistical Association* 84, no. 405: 223–30.
- Okun, Arthur M. 1962. "Potential GNP: Its Measurement and Significance." Paper no. 190. New Haven, Conn.: Yale University, Cowles Foundation for Research in Economics. <https://www.scribd.com/document/347717593/Potential-GNP-Its-Measurement-and-Significance>
- Oliner, Stephen D., Daniel E. Sichel, and Kevin J. Stiroh. 2007. "Explaining a Productive Decade." *Brookings Papers on Economic Activity*, no. 1: 81–137.
- Petrosky-Nadeau, Nicolas. 2013. "TFP during a Credit Crunch." *Journal of Economic Theory* 148, no. 3: 1150–78.
- Reifschneider, Dave, William Wascher, and David Wilcox. 2015. "Aggregate Supply in the United States: Recent Developments and Implications for the Conduct of Monetary Policy." *IMF Economic Review* 63, no. 1: 71–109.
- Robinson, Peter M. 1988. "Root- N -Consistent Semiparametric Regression." *Econometrica* 56, no. 4: 931–54.
- Solow, Robert M. 1957. "Technical Change and the Aggregate Production Function." *Review of Economics and Statistics* 39, no. 3: 312–20.
- Stock, James H. 1989. "Nonparametric Policy Analysis." *Journal of the American Statistical Association* 84, no. 406: 567–75.
- Stock, James H., and Mark W. Watson. 2016. "Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics." In *Handbook of Macroeconomics, Volume 2A*, edited by John B. Taylor and Harald Uhlig. Amsterdam: North-Holland.
- Syverson, Chad. 2013. "Will History Repeat Itself? Comments on 'Is the Information Technology Revolution Over?'" *International Productivity Monitor* 25: 37–40.
- . 2016. "Challenges to Mismeasurement Explanations for the U.S. Productivity Slowdown." Working Paper no. 21974. Cambridge, Mass.: National Bureau of Economic Research.
- Tobin, James. 1969. "A General Equilibrium Approach to Monetary Theory." *Journal of Money, Credit and Banking* 1, no. 1: 15–29.
- Yellen, Janet L. 2016. "Macroeconomic Research After the Crisis." Speech given at the 60th Annual Economic Conference, Federal Reserve Bank of Boston, Boston, October 14.
- Zhang, Ting, and Wei Biao Wu. 2012. "Inference of Time-Varying Regression Models." *Annals of Statistics* 40, no. 3: 1376–402.

Comments and Discussion

COMMENT BY

ROBERT J. BARRO I learned a lot from this valuable paper about the disappointing recovery of U.S. real GDP since the end of the Great Recession in 2009. The analysis brings out two central elements. First is the low recent growth rate of total factor productivity (TFP). Second is the decline in the labor force participation rate, of which two-thirds is a special post-crisis effect and one-third is a longer-term trend.

The paper features a surprising but effective use of the unemployment rate to filter out cyclical forces. Ex ante, if I had considered two variables—the growth rate of TFP and the level of the unemployment rate—I would have guessed that the former would be more stable over time. But the latter—based on a rudimentary household survey begun in 1948—turns out to be more stable. This finding is surprising, because one would have guessed that many forces could permanently alter the mean unemployment rate derived from this survey. In practice, however, the mean seems to be constant since 1948. The authors use deviations from this mean to gauge cyclical effects, which tend to vanish over time. Moreover, the cyclical behavior of the unemployment rate is highly correlated with that in other variables, including the growth rate of real per capita GDP. Hence, they can effectively use the behavior of the unemployment rate to cyclically adjust the observed growth rates of real GDP and other variables.

A natural question is whether this method of using the unemployment rate data also applies to other countries. A quick inspection of the countries in the Organization for Economic Cooperation and Development suggests that the procedure is likely to work for the United Kingdom, Canada, and Australia, but not for several countries in Western Europe or for Japan. The latter cases seem to feature permanent shifts in the average level of the unemployment rate.

Some of the analysis relies on the conclusion that the recent slowdown in TFP growth rates started in about 2006—one of the authors' three estimated break dates—rather than 2010–11. My main inference from their evidence is that this finding may be correct, but the result is uncertain. The difficulty is clear in their figure 8. The period after 2010 seems to have lower average TFP growth than in the 1996–2006 period. But the period just after 2006 is heavily influenced by the Great Recession and the immediate recovery. These years show volatile TFP growth, which is high early in 2010. Therefore, the break in the TFP growth rate could easily be sometime in 2010, rather than early in 2006.

Another question is what would have happened to the estimated break date in 2006 if TFP growth had turned out to be high from 2010 on. Would the authors still have estimated a break around 2006? Because of the two-sided filter used to gauge the breaks, it seems that the low observed TFP growth starting in 2010 contributed to the setting of the break date in 2006. But this procedure creates a kind of circularity. The low TFP growth as of 2010 contributes to the setting of the break in 2006, and the break in 2006 allows the authors to conclude that the low observed TFP growth since 2006 or 2010 could not have been caused by policies that postdate the 2007–09 recession. In particular, the argument is that low recent TFP growth could not have been caused by increases after 2009 in regulations, transfer payments, taxes, and so on. I think this reasoning is unpersuasive. In any event, a key question is what policies and the like might explain the recently low TFP growth rates and labor force participation rates, and I would not rule out policies that have applied since 2010.

In their table 8, the authors analyze the effects of regulations on U.S. TFP growth rates across industries from 1988 to 2014, using RegData (Al-Ubaydli and McLaughlin 2015). The creators of RegData apply textual analysis to the wording of regulations contained in the *Code of Federal Regulations*. They search for and count numbers of words that indicate constraints on activity, such as “shall,” “must,” “may not,” “prohibit,” and “require.” RegData provides a crude indicator of regulations by industry, though it does seem better than previously used counts of pages in the *Federal Register*. In particular, the *Code of Federal Regulations* is a stock of regulations in effect—which seems relevant for productivity—whereas the *Federal Register* relates to the flow of new ones. The authors' table 8 shows that the indicator from RegData has zero explanatory power for TFP growth rates using annual data for 42 U.S. industries for the years 1988–2014. However, a reasonable explanation for this result is that the textual analysis in RegData does not provide a reliable gauge of regulatory impact.

Therefore, I am not convinced from table 8 that U.S. TFP growth rates are independent of regulatory burden.

I am also skeptical that one can reliably estimate the effects of various government policies on economic growth by studying just one country, even the United States. There is much more information in large country panels (despite many criticisms, some even valid, of cross-country growth regressions). Moreover, even for the United States, the World Bank's ease of doing business measures seem more meaningful than RegData as gauges of regulations that would have an impact on economic growth. These data on the ease of doing business began being collected in 2004 and have become more comprehensive since 2006 and now cover 190 countries. However, most of these data are at the country level and do not include information by sector.

The World Bank's Doing Business project initially stressed indicators related to the costs of opening a business, a measure developed in the 1980s for Lima by Hernando de Soto in his famous 1989 book *The Other Path*. Currently, the analysis applies to 10 categories: starting a business, dealing with construction permits, getting electricity, registering property, getting credit, protecting minority investors, paying taxes, trading across borders, enforcing contracts, and resolving insolvency. A new indicator related to selling to the government will soon be coming. An indicator of labor market regulations is also published, but has been excluded since 2009 from the overall ease of doing business measure.

In compiling its indicators, the World Bank examines the forms of laws and regulations, as well as actual practices. The indexes are compiled from extensive consultations in each country with private sector practitioners, government officials, and World Bank staff members. The measurements rely particularly on legal practitioners and other private sector professionals who regularly undertake the types of transactions being considered.

In 2006, the United States was ranked 3 out of 155 countries for the overall ease of doing business (with a more-or-less cardinal indicator of 0.851 on a 0–1 scale, what the report calls “distance to frontier”). The U.S. ranking was 4 out of 183 from 2010 to 2012, and then slipped noticeably to 8 out of 190 at the start of 2017 (where the cardinal indicator was down to 0.824).

A key question is what these measures of regulatory burden explain for economic growth. In an ongoing project at the American Enterprise Institute, we are considering the overall ease of doing business indicator in the context of panel regressions for per capita GDP growth rates. Preliminary results indicate that a more favorable regulatory climate is conducive to

faster growth. For example, a U.S. shift from its current position to the world best (currently New Zealand, earlier Singapore) raises the estimated growth rate by around 0.3 percent per year on impact. However, the major difficulty in this analysis is that the World Bank data are available only since 2004 and in a fuller context only since 2006. We are, therefore, attempting to supplement these data with longer-term information related to institutional characteristics and measures of structural change.

As mentioned above, this paper by Fernald, Hall, Stock, and Watson finds that a second important factor in the weak economic growth since 2010 has been a decline in labor force participation. In particular, a major part of this decline is independent of long-term demographic trends. Therefore, an important outstanding issue concerns the policies or other variables that explain this unusual recent decline in labor force participation. One possibility is that this decline relates to the expansion in the number of persons, particularly older males, who are on disability insurance.

REFERENCES FOR THE BARRO COMMENT

- Al-Ubaydli, Omar, and Patrick A. McLaughlin. 2015. "RegData: A Numerical Database on Industry-Specific Regulations for All United States Industries and Federal Regulations, 1997–2012." *Regulation & Governance* 11, no. 1: 109–23.
- de Soto, Hernando. 1989. *The Other Path: The Invisible Revolution in the Third World*. New York: Harper & Row.

COMMENT BY

LUCREZIA REICHLIN¹ This rich paper by John Fernald, Robert Hall, James Stock, and Mark Watson provides a very careful analysis of the time series properties of key real economic indicators, with the aim of identifying the causes of the slow recovery of output after the last recession. A slow recovery, defined as a slow path back to the historical trend, cannot be easily distinguished from a situation in which the trend has slowed down, while cyclical characteristics correspond to the average historical experience. In the first case, I have in mind a classical trend-cycle decomposition, with a constant slope trend and temporary fluctuations around the cycle; in the second case, the trend is itself variable.

1. I would like to thank Thomas Hasenzagl and Filippo Pellegrino for very valuable research assistance.

Ex post, with the benefits of many years of postrecession data, one can say with some confidence that the recovery from the 1982 recession corresponds to the classical representation of a stable trend and a stationary cycle. In this case, the recovery can be most likely attributed to cyclical factors, although, given the recovery's unusual length and sluggishness, some inertia mechanisms were surely at work. Can the recovery from the 2007–08 recession be characterized in the same way? Or are the data revealing that it is the trend that has shifted downward (possibly precrisis)?

The difficulty in telling the two cases apart is that two unobserved components—the trend and the cycle—must be identified from one observed time series. Using cross-correlation between different time series can help this identification problem, and this is what the authors do in this paper.

Fernald, Hall, Stock, and Watson address three broad questions: (i) Should the slow recovery be attributed to the trend or to the cycle? (ii) If it is explained by a change in the trend, did this change occur before the Great Recession? (iii) What were the drivers of this change?

They provide an eclectic methodological approach. The key feature of the analysis is that it proceeds in two steps. In the first, each series is “cleaned” of its cyclical component. The residual, including a trend and a noise component, is then used in a growth accounting exercise, by which the main causes of the slowdown are identified.

We should understand this procedure as a sort of counterfactual analysis. In such an analysis, one would compute a forecast of the series of interest for the recovery years, conditioning on a variable or a set of variables that describe cyclical behavior. These counterfactual paths would capture their “typical” cyclical behavior and the difference between the realized paths and the counterfactual paths (the anomalies), which would possibly be explained by changes in trends. The authors suggest a slightly different procedure, in which the typical cycle is extracted through a regression on unemployment (taken as a proxy for the cycle) or through a regression on unobserved factors extracted from a rich data set of detrended series. Once the series are cleaned of the cycle, the analyses focus on what is left, which is modeled as the sum of a trend and a noise component, whose dynamics should reveal the contribution of structural rather than cyclical factors.

The trend is modeled as a deterministic function of time, capturing a low-frequency component, and the noise is what is left after detrending and cyclical adjustment (see the authors' equation 6). For each series y_t , we have:

$$y_t = \mu_t + c_t + z_t,$$

where μ_t is the trend, c_t is the cycle, and z_t is the noise—what the authors call the “irregular part.”

Growth accounting calculations reveal that the output growth shortfall (with respect to previous recoveries) since 2009 is almost entirely explained by the slow growth of total factor productivity (TFP) and the decline in labor force participation, while the shortfall in labor productivity is overwhelmingly explained by TFP. The shortfalls are larger for cyclically adjusted series and are explained by both noise and trend components. Moreover, both cyclically adjusted TFP and labor force participation—the main drivers of the shortfalls—slowed down before the crisis.

These findings suggest that the slow recovery is unrelated to mechanisms associated with the financial crisis that many have emphasized in the literature, and instead must be explained by structural factors originating earlier.

The remainder of my comment focuses on TFP’s role in explaining the slowdown and aims at assessing the robustness of some of the empirical findings.

The authors’ key results are given in their table 3, which reports estimates for the growth accounting exercise based on the series before and after having been cleaned of their cyclical component. The table shows that for the cyclically adjusted series, the growth shortfall with respect to previous recoveries is larger than for the unadjusted series. The difference is attributed to the noise and trend components. Moreover, the shortfall of output and labor productivity is almost entirely due to TFP, with the trend and the noise having equal weights.

To understand this result, it is useful to look at the authors’ figure 3 and the top-left panel of their figure 5, which show the trend/cycle/noise decompositions for different series.

Let us first focus on TFP (top-left panel of figure 5). Throughout the sample, the cyclically adjusted series is very close to the actual series, but oscillates around the trend. These swings are captured by the noise component, which we can interpret as measurement error. During the recession, one sees a sharp contraction of the series itself, which is explained by the cycle; then, the recovery until about 2014 is explained by both the cycle and the noise component. Thereafter, TFP is back at its trend.

Gross domestic output per capita (top-left panel of figure 3) has a larger cyclical component, but the trend and the cyclically adjusted component have a similar pattern. Productivity (bottom-right panel of figure 3) has

historically almost no cycle, but the swings in measurement error seem to be similar to those of TFP.

Overall, these figures point to a persistent slowdown in the mid-2000s that is common to all the series considered and predates the crisis. The decomposition, however, has a puzzling feature: a large and persistent noise component in both TFP and labor productivity, which seems to capture some low-frequency variation. A natural question is whether the latter captures some systematic cyclical components that are not identified by the authors' methodology and are possibly related to demand factors.

In what follows, I use different statistical methodologies to investigate this question.

CYCLES AND NOISE The logic of the exercise proposed by Fernald, Hall, Stock, and Watson relies on the notion that there is a typical cycle and, once we clean the series of it, one can study anomalies of the recent recovery with respect to past history.

I focus on the methodology for cycle extraction based on Okun's law, because this is the one for which the authors present a complete set of results. This method is simple and clever, but relies on the assumption that the relationship between unemployment and output in past recoveries was stable, a fact that is not supported by the data. We know, for example, that in the 1990s—but not in the 1980s—the United States experienced a “jobless” recovery, whereas in the last recovery, unemployment recovered earlier than output. Given this instability, it is difficult to identify the benchmark cycle.

This point leads to an ambiguous interpretation of the residual from the Okun's law adjustment. Let me illustrate this with a counterfactual exercise. Rather than relying on Okun's law, I consider a vector autoregressive model that includes GDP, unemployment, investment, output, and productivity (see my table 1 for a precise definition of the data):

$$X_t = A(L)X_{t-1} + u_t,$$

where u_t is normally distributed multivariate white noise with covariance matrix Σ , and $A(L)$ is a polynomial of order $p = 5$ in the lag operator L .

The model parameters are estimated over the sample 1984:Q1–2009:Q4. I then compute the conditional expectation of each series for 2010:Q1–2016:Q4 based on estimated parameters and the observed unemployment path, including the period 2010–16. My figure 1 reports the median of the conditional expectation of GDP with confidence bands and the unconditional forecast for 2010:Q1–2016:Q4. Unemployment and its unconditional forecast are also reported.

Table 1. Data and Transformations for Vector Autoregressive (VAR) and Factor Models

<i>Variable</i>	<i>Notes on measurement</i>	<i>Transformation in VAR model</i>	<i>Transformation in factor model</i>
Unemployment rate	Seasonally adjusted, percent	Levels	Levels
Real GDP	Seasonally adjusted at an annual rate, 2012 = 100	$4 \times \log$	Levels
Real private nonresidential fixed investment	Seasonally adjusted at an annual rate, 2012 = 100	$4 \times \log$	Levels
Business sector output	2012 = 100	$4 \times \log$	Levels
Business sector hours	2012 = 100	$4 \times \log$	Levels
Business sector labor productivity	2012 = 100	$4 \times \log$	Levels
Capital input	2012 = 100	$4 \times \log$	Levels
Business sector TFP	2012 = 100	$4 \times \log$	Levels

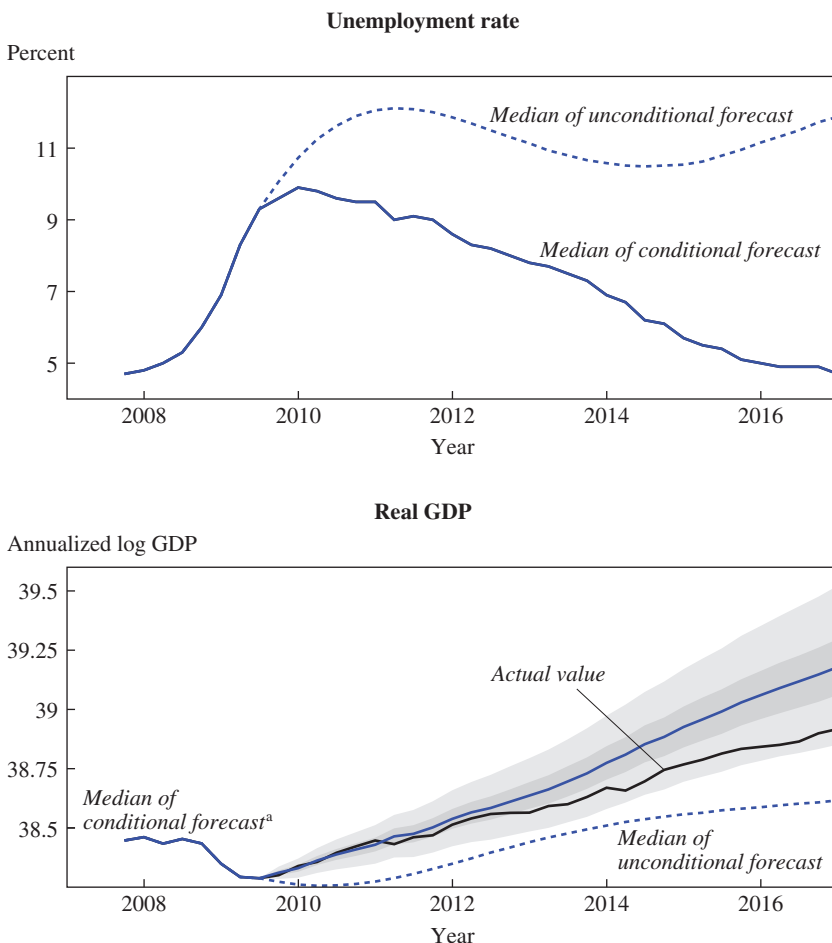
My figure 1 shows that realized GDP in the sample for 2010–16 is lower than what one would have expected, given the dynamics of unemployment. This has an ambiguous interpretation. One can interpret it as being in line with the authors’ findings—that is, as indicating that there are factors other than the cycle dragging down output—or, alternatively, it can be interpreted as showing that the characteristics of the last cyclical recovery, as captured by the correlation with unemployment, have been different than in the past. Indeed, the unconditional forecast for unemployment is much higher than the realized path.

The second interpretation points to an unstable Okun’s law. If this is the case, the notion of a typical cycle based on Okun’s law is hard to interpret. Given the unusually sharp recovery of unemployment since 2010, the authors’ method forces the cycle to recover fast, thereby attributing the cause of the shortfall with respect to past recoveries to the trend and the noise.

To shed some light on this point, I introduce a different statistical method to obtain a cycle-trend decomposition that is more similar in spirit to that of the second technique of decycling proposed by the authors. As is the case for their factor model, the cycle is extracted exploiting multivariate dynamics rather than a bivariate relation and should therefore be more robust. I am considering here a factor model in levels that allows me to extract trend and cycle in one step rather than relying on factor extraction on detrended data.

The model assumes that each series can be decomposed into a stochastic random walk trend and an orthogonal stochastic cycle. Trends and cycles

Figure 1. Conditional Forecast of GDP Given Unemployment, 2007:Q3–2016:Q4



Sources: U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis; author's calculations.

a. The dark shaded area is the 68 percent confidence interval, and the light shaded area is the 90 percent confidence interval.

can be further decomposed into a component that is common to all series and a series-specific idiosyncratic component. The latter can be interpreted as a stationary noise component.²

2. The model is identified thus: (i) $\delta_1 = 1$, $\tau_1 = 0$, $\tau_2 = 1$, and the covariance matrices of the errors of the unobserved components (common and idiosyncratic trends and cycles) are diagonal; and (ii) the cyclical components are constrained to be stationary. The model is estimated using a Bayesian approach.

Let $y_{i,t}$ be the element of a vector y_t including the key variables (see my table 1):

$$\begin{aligned} y_{i,t} &= C_{i,t} + T_{i,t}, \\ C_{i,t} &= \delta_i \psi_t^c + \psi_{i,t}, \\ T_{i,t} &= \tau_i \mu_t^c + \mu_{i,t}, \end{aligned}$$

where $y_t = [y_{1,t}, \dots, y_{n,t}]'$ is a vector of n time series; $i = 1, \dots, n$ and $t = 1, \dots, m$; $T_{i,t}$ is a nonstationary trend; the common trend is a driftless random walk, while the idiosyncratic trends are random walks with drift

$$\begin{aligned} \mu_t^c &= \mu_{t-1}^c + u_t^c & u_t^c &\sim \mathcal{N}(0, \sigma^2) \\ \mu_{i,t} &= \gamma_i + \mu_{i,t-1} + u_{i,t} & u_{i,t} &\sim \mathcal{N}(0, \tilde{\sigma}_i^2); \end{aligned}$$

ψ_t^c and $\psi_{i,t}$ are mutually orthogonal autoregressive moving average processes, which implies that $C_{i,t}$ is a stationary cycle; and trends and cycles are mutually orthogonal.

Notice that I am forcing the cycle to be stationary. The trend, unlike in the authors' decomposition, is stochastic, and therefore reflects the effect of persistent shocks. As is the case for the authors' decomposition, it only captures low-frequency movements.

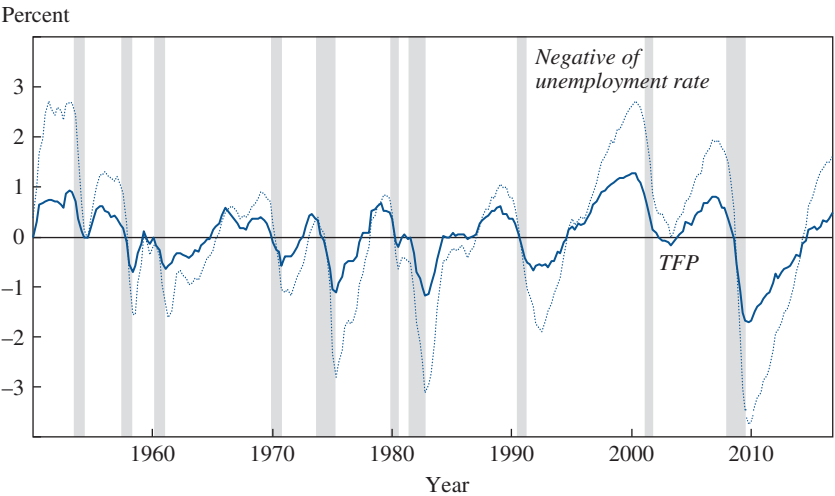
My figure 2 plots the cycle of TFP against the cycle of unemployment (multiplied by -1).

The two series are highly correlated. Notice that in the post-2009 sample, there is a sharper recovery of cyclical unemployment than of cyclical TFP. This suggests that the authors' decomposition captures some cyclical TFP dynamics in the noise component, with the consequence of attributing too much weight to the cyclically adjusted contribution of TFP in growth accounting. Indeed, this would explain why the noise component of TFP explains such a large part of output and productivity variation.

My figure 3 plots together the cyclical components of GDP, TFP, and investment (which is plotted on the right axis). The figure shows a high degree of correlation between the cycles of these series, including in the last recovery. Again, this implies that the authors' method attributes part of the last recovery's dynamics of GDP and investment to the noise component. Interestingly, the slow recovery of TFP is correlated with that of investment, implying some contamination of demand factors in TFP dynamics.

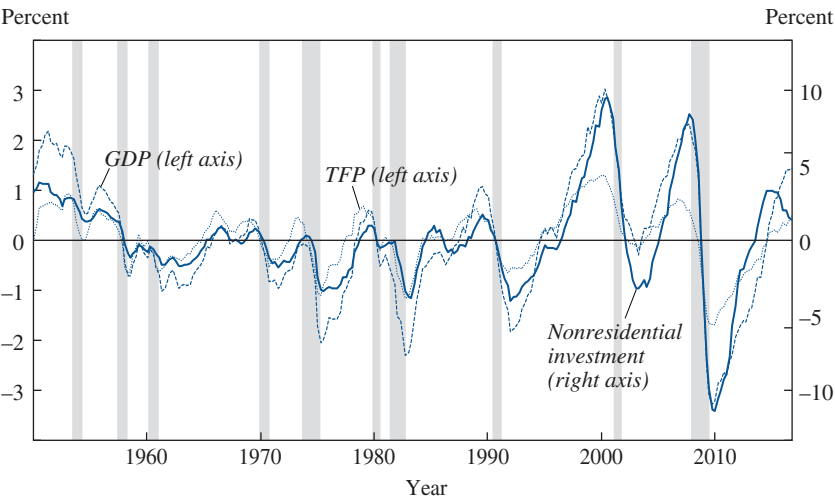
The cycle of TFP, investment, and output seems to be more persistent than that of unemployment in general. Another way to see this point is to

Figure 2. Cycles in TFP and the Unemployment Rate, 1950–2016

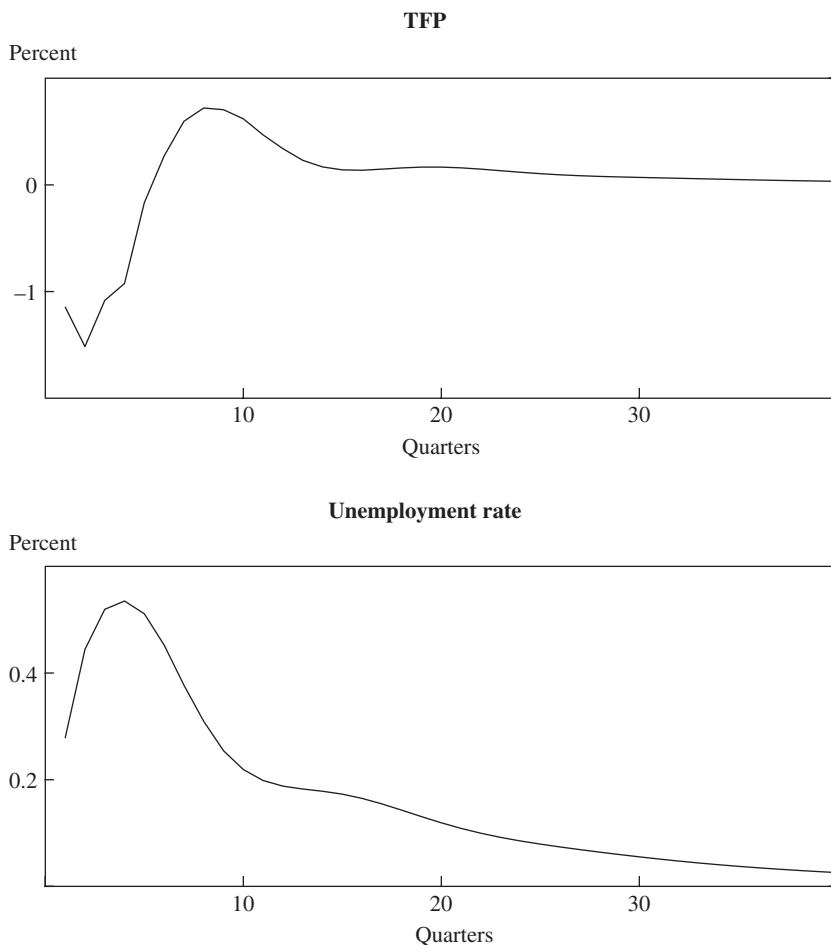


Sources: U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis.

Figure 3. Cycles in GDP, TFP, and Nonresidential Investment, 1950–2016



Sources: U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis.

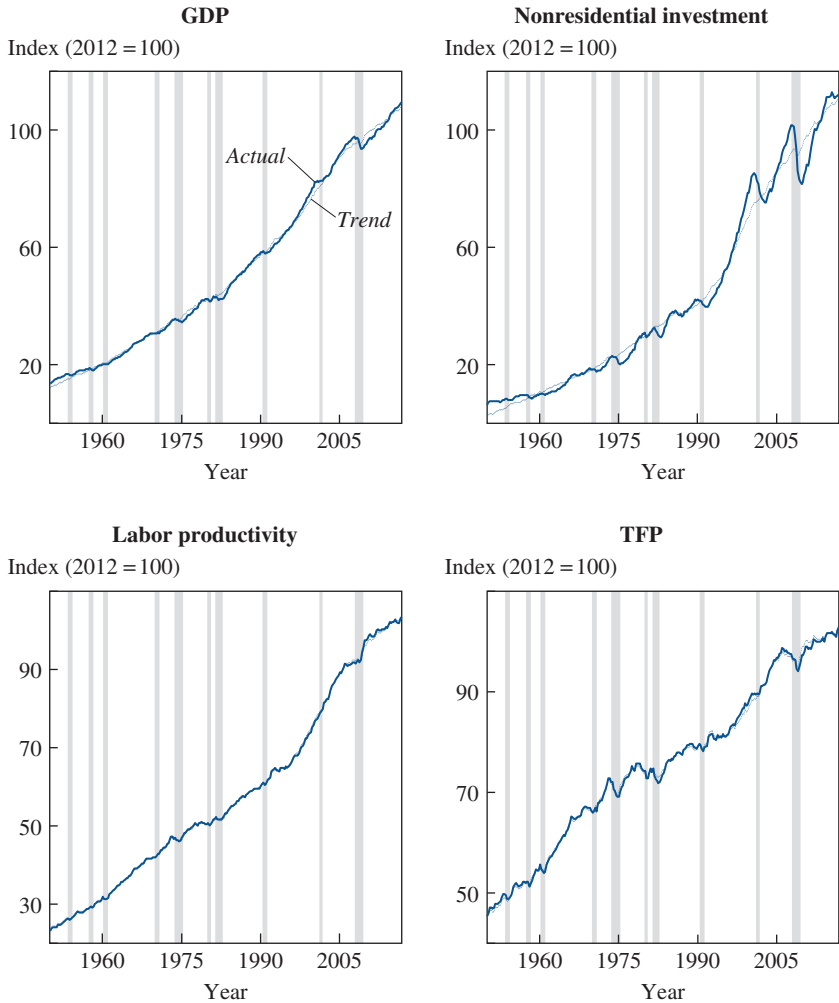
Figure 4. Cumulative Response of TFP and Unemployment to Demand Shocks

Sources: U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis; author's calculations.

perform a simple exercise on the basis of the vector autoregressive model introduced above. My figure 4 shows the impulse response functions of a demand shock identified as being the long-run neutral shock on TFP.

The figure shows that the effect of a demand shock is more persistent for TFP than for unemployment, which dies out after only 20 quarters. This again supports my conjecture that a part of the dynamics identified as noise by the authors is likely to capture an endogenous component of TFP that is generated by persistent, cyclical shocks.

Figure 5. Trends in GDP, Nonresidential Investment, Labor Productivity, and TFP, 1950–2016



Sources: U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis.

TRENDS Let us now turn to the trends. My figure 5 shows the trends in GDP, investment, labor productivity, and TFP, as estimated by the unobserved component model described above against the associated observed series.

The trend in TFP clearly shows a downward change in slope in about 2005, and the same seems to be true for GDP, which grew above trend before the crisis. Labor productivity has almost no cycle.

Although the trend from my methodology is different from that of the authors by construction, these results convey a similar message because they identify a change in trend before the crisis. However, as we have seen, the details of the decompositions differ. The decomposition I have proposed points to explanations based on changes in the characteristics of the cyclical recovery for TFP, investment, and output.

CONCLUSIONS Different ways of filtering the data come to the same conclusions: The trends in TFP, output, and productivity slowed down before the crisis. The slow recovery must be at least partly attributable to this fact.

However, I have identified persistent fluctuations in TFP that can possibly be driven by demand factors and that are underestimated by the authors' methodology. Cyclical TFP is highly correlated with cyclical investment, and this fact needs further investigation.

GENERAL DISCUSSION Jonathan Pingle noted that the paper highlights a lack of a consensus about the secular trends that were putting downward pressure on labor force participation before the financial crisis. He saw the paper as a contribution to the literature on those trends, as well as estimating ongoing declines in the aggregate trend, building on the work of Stephanie Aaronson and colleagues dating back to 2006.¹ In addition, he believed the paper overlaps with the related earlier microeconomics literature, including that on declining job opportunities for older men, David Autor's work on disability, and other work preceding the financial crisis consistent with secular declines in labor force participation.²

However, Pingle believed some humility was needed regarding the degree of expected cyclicity. The composition of those out of the labor force is very different today than historically; levels of education are higher, many are in better health immediately following retirement, and for many life expectancy is longer. We do not really know how they might respond to future cyclical improvements in labor market conditions.

On this point, N. Gregory Mankiw suggested there might be some interactions between demographic forces and unemployment. During the 1982 recession, for example, the baby boomers were in prime working age, and

1. Stephanie Aaronson, Bruce Fallick, Andrew Figura, Jonathan Pingle, and William L. Wascher, "The Recent Decline in Labor Force Participation and Its Implications for Potential Labor Supply," *Brookings Papers on Economic Activity*, Spring 2006: 69–154.

2. David Autor's related work can be found at <https://economics.mit.edu/faculty/dautor/papers/disability>.

were not likely to leave the labor force permanently in response to the recession, and the unemployment rate rose substantially as a response. But in the recent recession, most baby boomers were in their 50s or older, and they may have been less reluctant to leave the labor force permanently this time around.

George Perry thought the paper was both correct and useful in its analysis of the detailed time trends in labor force participation, and in the nature of those trends. But he disagreed strongly with the paper's uncritical acceptance of the slow growth in output and productivity as measured in the official data. Over the past decade, technical advances have led to goods and services that never existed before. Such changes should ideally be reflected in increased real output and productivity. Technically, however, we have no good way to deflate for goods and services that are truly new, rather than simply easier to produce. While this measurement issue is always present, Perry noted that recent technical advances have occurred very rapidly, and have changed people's everyday lives and consumption habits in a big way. If price deflators could properly account for such things, there might well be no productivity slowdown in the official measures, and those measures might better reflect the changes being experienced by consumers. Should we worry about this? Perry reasoned that since we cannot construct more realistic price deflators for output in this period when so much is changing rapidly in the marketplace, we should just accept that real output is especially difficult to measure in this period, and that it is likely rising faster than the official data show. At a minimum, given the greater uncertainty about its growth in recent years, we should not be obsessed with the slow growth in the official productivity data. Policy discussions should not center on the so-called "productivity disaster" or cures to the "productivity problem." The technical changes that are emerging in this century may well represent a speedup in productivity growth that we just do not capture in present GDP accounts.

Narayana Kocherlakota thought it would be interesting to compare a fourth-quarter 2007 forecast with a mid-2009 forecast. If those were roughly the same, that might be compelling evidence that not much actually happened between 2007 and 2009 to change our understanding of where output is today. Otherwise, something must have happened between 2007 and 2009 to update the forecast.

Kocherlakota also thought that the paper underscored the need for better models of productivity. The paper leaves the reader with the uncomfortable conclusion that output is low relative to what many thought it would be 10 years ago because productivity was lower than expected. More work

needs to be done to try to understand what is actually driving productivity, he concluded.

John Haltiwanger noted that there has clearly been a decline in indicators of dynamism in the United States. There is clear evidence that high-productivity firms are less likely to grow than they used to, and low-productivity firms are less likely to contract and exit. Furthermore, there has also been a rise in within-industry productivity dispersion. Both of these patterns are what one would expect from models where there are rising frictions and distortions, he noted, and so while the frictions and distortions have not been exactly identified yet, clearly there is evidence that something is going on. If nothing else, the contribution of reallocation to productivity growth has declined over the same period. The position that the present paper takes is that this is the return-to-normal hypothesis. Supposing the authors are correct, he asked how they would account for the decline in dynamism and within-industry productivity dispersion.

Jason Furman thought the idea that regulatory changes had a dramatic impact on the growth rate was at best unproven, and stated that the present paper made him even less convinced of this link. He noted that several components of the World Bank's ease of doing business index have improved since 2009, while several others have fallen. Among those that improved from 2009 to 2017 were ease of getting credit, ease of paying taxes, ease of trading across borders, and ease of starting a business. Two that declined were dealing with construction permits and getting electricity. So if regulation is to blame for the slow recovery of output after 2009, these trends in the index do not support that view. Additionally, Furman noted that one would have to push the timing of the productivity slowdown back a lot to think that that is what caused the slow recovery of output.

Janice Eberly noted that the paper's framework and variables—particularly those related to productivity—make the claim that investment behaved more or less normally during the recovery. However, for a broader range of variables related to capital formation—such as profitability and market values—investment does not seem to have behaved normally. The investment literature has shown slow investment relative to profits, business savings, and market values during the recovery from the recession. If the authors argue that investment behaved normally, this should be squared with other determinants of investment, especially those that are more forward looking.

Steven Davis made three comments. The first was with regard to the quality of the evidence presented in the paper on regulation and its effects. The

authors rely heavily on the RegData database.³ The creators of RegData, as he understood it, use an algorithm to comb the *Code of Federal Regulations* for regulatory restrictions, which then tries to assign the restrictions to single industries. Davis saw this approach as problematic, because many federal regulations cut across multiple industries. Examples include regulations of the workplace, environmental regulations, and regulations governing federal contract awards and procurement contracts. Furthermore, the Internal Revenue Service has its own set of pervasive regulations. He suggested there may be many data that are not picked up by RegData, either because it ignores the federal tax code (which by some estimates is roughly 40 percent of the size of the *Code of Federal Regulations*) or because it is not well suited to deal with regulations that cut across industries.

Second, Davis believes that many regulations are likely to have their most important effect on employment, not productivity. This is particularly true of regulations that govern the employment relationship—which have the effect of increasing firms' fixed costs per worker—or that increase the litigation risks associated with hiring and firing. Those types of regulations are likely to squeeze the least-skilled, riskiest workers out of the labor force. So the effect of regulations in many cases would show up in employment and the labor force, not productivity.

Third, as he understood it, the authors adjusted labor quality in terms of observable characteristics when characterizing the evolution of productivity. But Davis conjectured that unobservable aspects of labor quality move in the same direction, and probably with similar intensity, as observed characteristics for selection into employment. If this conjecture is correct, then the authors have actually understated the slowdown in productivity growth during the period when rates of employment and labor force participation fell. He was unsure as to the magnitude of this effect, but thought it would be useful to quantify.

Martin Baily thought that this paper's basic result—which is that GDP growth is slower today than expected because of slow productivity growth, and because of a decline in labor force participation—is entirely right. However, he judged that the paper gave short shrift to the business cycle and to the slow recovery of aggregate demand. After the business cycle trough in the second quarter of 2009, it took nearly 2½ years for business sector output to return to its previous peak level. The mid-1970s recession, in

3. Omar Al-Ubaydli and Patrick A. McLaughlin, "RegData: A Numerical Database on Industry-Specific Regulations for All United States Industries and Federal Regulations, 1997–2012," *Regulation & Governance* 11, no. 1 (2015): 109–23.

contrast, took only 1 year to recover, and the early 1980s recession took only ½ year. No productivity increase is required for output to return to its previous peak, and there was an excess supply of workers at the time. It follows that unusually persistent demand weakness is the correct explanation for the slow recovery in the period immediately following the recession trough. The slow recovery of demand is also why forecasters were inaccurate during that period. He thought the paper gave an unbalanced view of the business cycle, tipping too much toward the supply-side explanation and not enough toward the demand side.

Baily thought investment played an important role in understanding what happened during the recent recovery. Clearly, residential investment was sustaining the recovery and economic growth through 2007; but once residential investment collapsed, shopping centers, office buildings, and the like to some extent went down, too, which made it difficult for the recovery to resume. Even with monetary and fiscal policy being as aggressive as they could be, the recovery was still very slow.

Following up on Baily's comments, William Brainard thought the authors' use of the average rate of decline in unemployment to infer that the recent recovery was comparable to earlier recoveries was misleading. Although the average rate of decline over 28 quarters was roughly the same as the recovery beginning in 1980, unemployment fell at a much slower rate during the earlier months of recovery. As a result, the total unemployed worker-months (relative to labor force) was significantly higher. He calculated, assuming 5 percent as the natural rate of unemployment, that the total was 30 percent greater than in the 1980 recovery, even though the total decline was roughly the same. This may help explain why long-term unemployment and part-time unemployment are currently above what one would expect on the basis of historical experience—another indication that this recovery is not comparable to earlier experience.

Michael Kiley suggested that the authors might be understating the role of aggregate demand in the slowdown of productivity, as the timing of the slowdown could arguably be due to demand to a more significant extent than the discussion acknowledges. The authors date the slowing of the endogenous component of productivity to the mid-2000s, the same period as do Diego Anzoategui, Diego Comin, Mark Gertler, and Joseba Martinez.⁴ Kiley noted that the recovery in the early 2000s was also weak. It required extraordi-

4. Diego Anzoategui, Diego Comin, Mark Gertler, and Joseba Martinez, "Endogenous Technology Adoption and R&D as Sources of Business Cycle Persistence," Working Paper no. 22005 (Cambridge, Mass.: National Bureau of Economic Research, 2016).

nary monetary support and was relatively slow by historical standards; as such, demand may have played a role in the slowing of productivity for some time. According to this argument, the United States has had a cyclical demand problem for a long time and has lacked a high-pressure labor market, and such pressures could contribute to some revival in productivity growth.

Richard Cooper recalled the Brookings Panel in late 2009 or early 2010 debating whether the recovery was V-shaped or L-shaped. According to Baily and Brainard, it was neither, but actually something in between. Cooper thought about three particular drags on the recovery. The first was housing that collapsed; as Baily mentioned, housing is normally part of early recoveries. The second was that the recession began with a financial crisis; as a result, banks were unusually reluctant to lend as they were repairing their balance sheets. And the third factor was that oil prices behaved properly during the recession itself; the price of oil dropped to \$40 a barrel, but because of developments in the oil supply, the price rose above \$100 a barrel in 2011. He asked the authors where these concrete factors that were slowing the recovery show up in their data.

Eric Swanson argued that the authors were too quick to dismiss regulation and reduced financial intermediation as possible causes of the productivity slowdown. The paper makes the case that these factors could not have been responsible because the slowdown occurred before the regulations took effect, but Swanson cited a recent paper by Wenxin Du, Alexander Tepper, and Adrien Verdelhan on covered interest parity (CIP) that tells a different story.⁵ Du, Tepper, and Verdelhan show that CIP broke down in 2007 and has never recovered, leading to persistent apparent arbitrage opportunities in the foreign exchange markets. Based on the timing of the CIP breakdown, one might think that financial regulations such as Basel III and Dodd–Frank could not be responsible, since they came into effect in 2010 or later. But Du, Tepper, and Verdelhan argue very convincingly that financial regulations are to blame, even if they were not the initial cause. The financial crisis threw CIP into disarray in 2007, and just as the effects of the financial crisis were subsiding, the new regulations took effect and prevented CIP spreads from ever recovering to their precrisis levels. One could make essentially the same argument for the productivity slowdown—that the financial crisis was the initial cause in 2007, and then just as the effects of the financial crisis were dying out, the new regulations

5. Wenxin Du, Alexander Tepper, and Adrien Verdelhan, “Deviations from Covered Interest Rate Parity,” Working Paper no. 23170 (Cambridge, Mass.: National Bureau of Economic Research, 2017).

took effect and prevented financial intermediation from recovering. Swanson argued that financial intermediation is plausibly an important intermediate input into production, and an enabler of firm dynamism and productivity growth, and the evidence in the foreign exchange market is that financial intermediation is not as efficient as it was during the crisis.

Athanasios Orphanides agreed with Barro about the importance of global comparisons. One could ask: What if the same methodology were applied to the G-7 countries or the euro area, where the recovery from the recent financial crisis was as bad or in some cases worse than in the United States? He surmised that one would not be able to draw the conclusion that this is a return to normalcy because, in most of these other countries, there was no evidence of an increase in productivity before the 1990s. And that led to a second question: Could some common global factor explain these things? One possibility is that perhaps not all recessions are the same—some may be associated with credit events that involve deleveraging, which are worse than normal. If all recessions are not the same, then the authors might be putting more emphasis on productivity than if these other factors were taken into account. Laurence Ball fully endorsed the view that cross-country comparisons are needed, and he went so far as to suggest the authors' arguments might not survive, because a global phenomenon was being explained using things that seem like factors specific to the United States.

Robert Gordon wondered why the authors seemed to be ignoring the effects of population growth, which by some estimates account for 20 percent of the slowdown in GDP growth. This, in turn, raises the policy issue of immigration—especially legal immigration—to the forefront. He also pointed out that slow productivity can be a cause of low investment—this can happen when there is a decline in the impact of innovation on productivity growth that diminishes the range of profitable opportunities for investment. He thought that this paper handled the issue of investment nicely, by saying that in a steady state with a fixed capital–output ratio, slower productivity growth would feed into slower growth in the capital stock. The implication is that the decline in labor force participation also reduces growth in the capital stock, because fewer machines are needed if there are fewer workers. However, he thought the authors were too casual in treating the decline in labor force participation entirely as a trend. He thought there was more of a cyclical component than the authors let on. He concluded that the revival of participation among prime-age workers in the last year and a half suggests that there is more to come.

Kathryn Dominguez found the paper to be both compelling and depressing. Echoing Orphanides, she urged the authors to think more about the

international dimension. Her own research with Matthew Shapiro finds that the timing of large forecast revisions during the recovery coincided with the euro crisis, the slowdown in China, and a number of other factors coming from abroad.⁶ She thought the authors tried to get at the international dimension in their discussion of exports, but that they gave it short shrift.

Gerald Cohen was not convinced of the paper's argument that the weakness in capital spending is an argument about cyclicalities or slower productivity. He agreed that capital spending is endogenous, but noted that the recent recovery has been the slowest recovery in capital deepening since 1948, or at least as long as capital deepening has specifically been measured. In the 1995–2006 period, there was a slowdown in labor force participation, and yet substantial capital deepening. It did not seem right, then, to assume that firms would not have predicted a slowdown in output during that period, because there was definitely something going on. As Eberly noted, there are many plausible arguments related to profits or the capital–labor ratio that would suggest capital deepening should be stronger.

Robert Hall responded first by stating that the paper does not attempt to be a grab bag of different explanations for demand and supply factors that relate to the slow growth of output. Rather, it takes a more disciplined view of how to think about demand, especially in its first approach, where the unemployment rate is taken as a central index of demand. He explained that there is a strong macroeconomic tradition in the United States holding that changes in aggregate demand translate directly into changes in unemployment. Hall agreed with Brainard's point about unemployment, but countered that the overall path of unemployment for the recent recession was similar to other recessions. This is a fact that Hall thought was important, even though Brainard pointed out that the curvature was different. Unemployment is a single index following the footsteps of a branch of macroeconomics—including, in particular, a modern theory of unemployment—which endorses such an approach.

The most important message of the paper, he maintained, was that one should not say anything about the business cycle by looking at output. Rather, the business cycle should be measured mainly by unemployment, and supplemented by other measures of tightness or slackness. This is not to say that the authors were completely devoted to the U-3 measure of unemployment, but they do insist on the point that there are many short- and

6. Kathryn M. E. Dominguez and Matthew D. Shapiro, "Forecasting the Recovery from the Great Recession: Is This Time Different?" *American Economic Review* 103, no. 3 (2013): 147–52.

long-term trends that influence output, so much so that one should not consider output a cyclical variable.

There were many comments on labor force participation. In writing the present paper, Hall was careful to do a detailed examination of the paper by Christopher Erceg and Andrew Levin, which stands out in the literature as finding a large cyclical effect of labor force participation.⁷ Erceg and Levin rely exclusively on a cross-sectional analysis. Without going into detail, Hall stated that he believed their approach to be wrong, citing as evidence the fall 2014 *Brookings Paper* by Aaronson and colleagues, which followed up quite a few years after their spring 2006 paper, and well after the recession began.⁸ The forecasts Aaronson and colleagues made in 2006 were spot on, which suggests that their framework—which has a relatively small cyclical effect—was correct. No other papers besides the one by Erceg and Levin suggest a large cyclical effect, he concluded.

James Stock stated that many of the features of previous recessions are indeed comparable to the recent recession. With the caveat that labor force demographics were different between recessions, making cyclical adjustments based on the historical evidence seemed a reasonable way to take into account the depth of the recent recession, allowing for comparisons on an apples-to-apples basis with previous ones. He also thought it was helpful to point out that the forecasts reported on in the paper basically do a good job when it comes to the unemployment rate. Later in the recovery there may have been some pessimism on the part of the forecasters, but at the beginning of the recovery they were doing quite well. All this is to say that the recovery in the unemployment rate was part of all the forecasters' models.

Aside from unemployment, other forecasts were massively wrong, particularly in output growth. Stock's sense was that, to a large extent, what happened was not that there were demand shortfalls, but that the forecasters got the intercept wrong in their models, and they had not taken into account the fact that the Congressional Budget Office and others had marked down

7. Christopher J. Erceg and Andrew T. Levin, "Labor Force Participation and Monetary Policy in the Wake of the Great Recession," *Journal of Money, Credit and Banking* 46, suppl. 2 (2014): 3–49.

8. Stephanie Aaronson, Tomaz Cajner, Bruce Fallick, Felix Galbis-Reig, Christopher Smith, and William Wascher, "Labor Force Participation: Recent Developments and Future Prospects," *Brookings Papers on Economic Activity*, Fall 2014: 197–255; Stephanie Aaronson, Bruce Fallick, Andrew Figura, Jonathan Pingle, and William Wascher, "The Recent Decline in the Labor Force Participation Rate and Its Implications for Potential Labor Supply," *Brookings Papers on Economic Activity*, Spring 2006: 69–134.

the growth rate of the labor force participation rate so much. Nobody, at that point, was fully aware of the decline in productivity growth. Figure 7 in the paper shows that, as of 2009, the Survey of Professional Forecasters' forecast of productivity growth was slightly below 2 percent, which Stock believed was basically what was going on.

John Fernald stated that clearly there was a lot going on during the recent recession. As he understood it, investment started to go off track in about 2000, which, like the slowdown in productivity, predated the recession. The U.S. labor market seems to have recovered. But digging into productivity, the slowdown appears to be broad-based across industries, showing up especially after about 2004. One could quibble about missing narrow segments of activity that are not properly measured in GDP, but that does not explain why business sector activity, broadly, slowed. Productivity since 2004 or 2010 has not been all that different than what it had been for most of the period since 1973. That was an exceptional period for productivity growth (according to econometric evidence). Other than that, productivity growth has been only about 0.5 percent a year.