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The Disappointing Recovery of Output after 2009

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ABSTRACT: U.S. output expanded only slowly after 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 largely unrelated to the financial crisis and recession. These forces were in play before the recession.

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Why did U.S. output grow so slowly in the post-2009 recovery, especially relative to recovery in unemployment? 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 show changes in the unemployment rate from the troughs of recent recessions. In contrast, the right panel shows that the growth of output after 2009 has fallen far short. Output per person—the solid black line, in logs—fell sharply in the recession and, as of this writing, remains below any reasonable linear trend line extending its pre-recession trajectory.

The dashed red line provides an alternative output path that removes the normal cyclical effects of the deep recession in a simple way, using Okun's Law, as described later. 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 then plateaued.

We argue for taking this dashed red 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 red line. Two components explain nearly all the growth gap: slow growth in total factor productivity growth (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.

We do not focus directly on the collapse of demand that began at the end of 2007 and that 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 figure. But by 2016, the economy had returned to full employment, so the disappointing level of output at that point reflected non-demand 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—hysteresis, in other words. Three channels are the leading candidates for hysteresis: TFP, labor-force participation, and the capital stock. We examine these three channels in detail to understand 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 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 Aaronson and others (2006) forecasted declines in participation as the baby boom retired and the 1960s to 1980s surge of women into the labor force plateaued. And Oliner, Sichel, and Stiroh (2007) and Jorgenson, Ho, and Stiroh (2008) noted before the recession 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 over-predicted output growth even while 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 overoptimistic 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 endogenous. Capital accumulation was, as many have noted, 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 pre-recession trend line.

Under standard growth theory, slower TFP growth and falling participation should *raise* the capital-output ratio, since 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. Gutierrez and 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. Alexander and Eberly (2016) attribute part of the decline in investment to the relocation of capital-intensive manufacturing industries outside the U.S. Importantly, neither of these hypotheses is obviously related to the recession.

Although our account 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 during 2012 through 2014, which we associate in part with the sequester; and the delay in the usual rebound 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 in the recovery. The black line in Figure 1 would have intersected the red line sooner, implying less cumulative loss in output (and employment). But, looking over the entire recovery, the seeds of the disappointing growth in output were sown prior to the recession in the form of a declining 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. Blanchard, Lorenzoni, and 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, used 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, conditions 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 in the unemployment rate; the second measures slow growth, relative to a "normal recovery" forecast made at the trough. As discussed in Section 3, 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 method implies that growth of business output per person in the recovery fell short of its average in the three prior recoveries by 1.8 percentage points (pp) per year, cumulating to a total shortfall over the recovery of 13.5 percent. The TFP shortfall contributed nearly 1 pp per year, or 7 pp of the cumulative output shortfall. The participation shortfall accounted for 0.9 pp per year of the output shortfall, or 6.1 pp of the cumulative shortfall.

The centrality of the decline in TFP growth and the fall of 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 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 over 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 pre-recession 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 slowdown in the broad-based, transformative effects of information technology—a productivity boom that began in the mid-1990s ended in the mid-2000s.

The labor force participation rate. In 2016, the participation rate, at 62.7 percent, was three 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 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 0.6 pp of the overall decline of 1.8 pp from 2010 to 2016. Changes in participation rates within detailed demographic groups account for the remaining 1.2 pp, or nearly two-thirds, of the decline.

There is no consensus about the sources of the persistent unexplained component of participation. We argue that it is not plausibly just a consequence of the increase in unemployment in the 2007-2009 recession. For example, the twin recessions of the early 1980s did not lead to a comparable decline in participation relative to trend. Our review of the evidence supports the less optimistic view that the non-demographic part of the decline represents a continuation of pre-existing trends that have a variety of sources which 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 (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 of the forecast error (0.31 pp per year, of which 0.20 is federal and 0.12 state-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 per year.

Total household consumption—by far the largest component of total spending—contributed 0.26 pp per year to the shortfall in output growth. Durable and non-durable goods behaved almost exactly as forecast during the expansion. Roughly half of the shortfall arose from housing and financial services, consistent with the view that housing and finance were key sectors for understanding 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 pp to the 0.57 pp under-forecast of output. So a small part of the slow measured growth could be due to mismeasurement.

These forecasts suggest little role for some 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 recover. Weak exports exerted a small drag on output growth, mainly during 2011-2013. And business investment was as forecast based on earlier recoveries, 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

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

I.A Focus and Data

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

The slow recovery in output can be examined through the lens of production (output is produced) or expenditure (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 non-profit production, where output is often not measured independently of inputs.

Our measure of output is the geometric average of income and expenditure side measures, as recommended by the recent literature—see the data appendix. 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 refer to this average of gross domestic product and gross domestic income as gross domestic output (GDO) or, where the context is clear, just output. Unless noted otherwise, we scale output by the population eligible for employment, aged 16 and above, denoted *Pop.*

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

I.B Accounting for Growth

Although our growth accounting focuses on the business sector, we 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} :

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

The identities in this section are sometimes in ratios of levels, sometimes in growth rates, depending on which 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 Griliches (1967) which, in turn, expanded and clarified 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 Bosler and others (2016). In per-person terms, we write:

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

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

It is useful to rewrite equation (2) in order 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 that 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):

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

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

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

The terms on the right-hand side of (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.
- $\left(\frac{LabForce_t}{Pop_t}\right)$, the final term, is the labor force participation rate.

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

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

In this expression, output per hour depends on the capital-output ratio, and labor quality, both expressed in labor-augmenting form. It 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 in 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 is stationary. In models with investment-specific technical change—and in the data—that 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 (e.g., 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 2007-2009 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 rate of employment and output.

In this paper, we use two complementary methods for controlling for the depth of the 2007-2009 recession and thus for assessing the speed of the recovery. The first method conditions 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 2009-2016 recovery in 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 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, cycle, and irregular part. Let y_t be the percentage growth rate of a variable at an annual rate, computed using logs (e.g., for GDO, $y_t = 400\ \Delta\log GDO_t$). The decomposition is,

$$y_t = \mu_t + c_t + z_t, \tag{6}$$

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 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 those 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,

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

where U_t is the unemployment rate and β(L) is the distributed lag polynomial with q leads and p lags in the summation. Choice of p and q and other estimation details are discussed 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 long-run mean zero.

Okun's original relationship was the reverse of (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 and/or lags are statistically significant. Also, while 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 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.

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 towards the end of our sample given the severity of the recession and length of the recovery. To address that problem, our estimate of the trend controls for normal cyclical movements implied by Okun's Law.

Substitution of equation (7) into equation (6) yields

$$y_t = \mu_t + \beta(\mathrm{L})\Delta U_t + z_t \tag{8}$$

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

$$\hat{\mu}_t = \kappa(\mathrm{L})\left(y_t - \hat{\beta}(\mathrm{L})\Delta u_t\right) \tag{9}$$

where κ(L) is a filter that passes lower frequencies and attenuates higher frequencies. Because the estimated cyclical part is subtracted prior to smoothing, we will 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 κ(L) helps avoid attributing the recent slow growth mechanically to a declining trend. The online supplement compares the partially linear regression approach to Gordon's (2014) cyclically adjusted state space (unobserved components) method, and discusses computation of the heteroskedasticity- and autocorrelation-robust standard errors.

Estimation. We estimate β(L) by regressing y_t on leads and lags of ΔU_t with $p = q = 2$. For some left-hand 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 κ(L), we use a biweight filter with truncation parameter of 60 quarters. Tukey's biweight filter κ(L) is two-sided with $\kappa_j = d(1-(j/B)^2)^2$ for $|j| \leq B$ and = 0 otherwise, where B is the bandwidth and d is chosen so that $\kappa(1) = 1$. End points 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 multi-decadal swings. If there are sharp breaks this filter will oversmooth, an issue we return to in Section IV.

Additivity. The foregoing method for estimating the trend, cycle, and irregular parts has the useful property that it preserves 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: $\hat{\mu}_t = \hat{\mu}_{1t} + \hat{\mu}_{2t}$ 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 κ(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 dataset omits high-level aggregates to avoid aggregation identities and double-counting—for example GDP is omitted, because its components are included, consumption of goods is omitted because durables and nondurables consumption are included separately, and total employment is omitted because its components are included. The 123 series are transformed to growth rates (for activity variables; see the online supplement for details other series), low frequency trends are extracted as discussed above, and six factors are then estimated by principal components.

These six factors are forecasted through the second quarter of 2016 using a vector autoregression with 4 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 Watson (2016) discuss factor methods and provide empirical results for closely related model and dataset. The online supplement has additional detail, including measures of fit.

With one exception, the simulated forecast 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-boom retirements would depress participation. Here, we use the Divisia-Tørnqvist index developed in Section V to project the effect of evolving demographics. This demographic trend in participation feeds through, with share weights as appropriate, into the trends in employment, hours, and output. We leave the trends in capital, the ratio of business to household employment, and hours per employee unchanged. 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 (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; minus this forecast error measures the growth shortfall of y.

The DFM method, like the Okun method, preserves additivity of 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 cyclicality 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 cyclicality. 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 to 9 add to -2.02, which is the coefficient in line 6 for real business output per capita.

Of the total cyclical variation of 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 (one 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 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 non-business sector (e.g., 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 that worker loses one of those jobs when the unemployment rate rises, then establishment-survey employment falls more than household-survey employment. (After adjusting for coverage, Fernald and Wang (2016) find that hours worked—workers, times hours per worker—has almost the same cyclicality 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 non-technological factors that account for the pro-cyclicality of productivity (see Basu and Fernald, 2001). Investment is pro-cyclical, 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: Trend 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 to 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. The left panel of three columns in the table presents actual average historical growth rates, and contributions to growth rates, at annual rates. The right panel, the remaining four columns, provides the decomposition after cyclically adjusting these variables using the Okun's-law method.

Figure 3, Figure 4, and Figure 5 show (in black) the log levels of the series in Table 3. These figures also plot the cyclically adjusted series, using Okun's Law (red), and the cyclically adjusted trend (blue). The black and red lines in the right panel of Figure 1 and in Figure 3(a) 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 2009-2016 forecast 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 the forecast and the actual. The standard error of the cyclical component (that is, of the common component of the dynamic factor model) is given in the final column.[1]

III.C NIPA Expenditure Components: Trend 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.

Table 5 shows these decompositions using (share-weighted) contributions to growth. The first column of numbers shows the average growth contributions from 2009-2016. 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 second block of columns presents results using the Okun's Law cyclical adjustment, and the right-hand 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 Table 4 and Table 5 are not share-weighted. Plots for all Table 4 and Table 5 variables are given in the online supplement.

III.D Discussion

A key difference between our two methods concerns the counterfactual cyclical path of labor market variables. The Okun method conditions on the unemployment rate path, so 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

[1] 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 fourth column is not the forecast standard error (which incorporates 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.

arbitrarily from its forecast path. The factor forecasts capture two key features of the recovery, in that they under-predict the labor-market recovery and over-predict 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 over the recovery. For clarity, we therefore focus primarily on results using the Okun method.

We begin with the first block 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 non-zero 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 participation rate (row 14).

This comparison of actual growth rates understates the output shortfall, however, since it does not account for how deep the recent recession was relative to the three previous ones on average. The second block 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. The shortfall in business output per person is much larger, at 1.81 percentage points, reflecting the depth of the 2007-9 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 accounting.

Business output. Figure 3, which shows the cumulative parts of the growth of business output per capital, 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 in 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 non-cyclical behavior of output gives equal roles to the high- and low-frequency parts.

Hours per worker. Figure 4 shows the levels of the three statistical parts of weekly hours per worker. Consistent with the coefficient of -0.35 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_t, rose slightly, while the high-frequency irregular part fell slightly. Unlike many other indicators, weekly hours behaved fairly normally in the post-crisis recession.

Labor force participation. Figure 4 shows that the low-frequency trend in participation grew at a declining rate until 1998 and began to shrink thereafter. 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 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 recent anomalous behavior of the labor force.

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 contributes a moderate amount to the shortfall in output. However, as we noted earlier, 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 supplement, we report results for Table 3 estimated using different number 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 increases from -.16 to -.37 when 12 lags are used, but using 12 lags somewhat reduces this coefficient for TFP. Importantly, 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 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 Okun's law and factor model estimates. Table 4 shows that compared to what would have been expected based on the data through 2009, actual GDP growth fell short by 0.57 percentage points, GDO growth by 0.43 percentage points, and business output by 0.35 percentage points. These cyclically-adjusted shortfalls are smaller than their counterparts in Table 3 because the recovery in employment was stronger than expected based on the factor forecasts: The Okun's law method in Table 3 conditions on the unemployment rate path, but the factor model forecast has a shortfall in the CPS employment rate of -0.42, i.e., the factor model predicts a less rapid fall in the unemployment rate. This feature of the factor forecasts—an unexpectedly strong recovery in the labor market and an unexpectedly weak recovery in output—is consistent with the real-time errors of professional forecaster 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 points, 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 (=

2.02×0.42 + 0.27) of the shortfall in business output per capita from the factor model, adjusted for the fact that 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, while 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 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 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 has been an unusual shortfall in capital deepening? We reach two conclusions.

First, in 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 concluding that productivity growth slowed after the early 2000s because of a pause or 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 prior three recoveries, the capital/output ratio would have grown by an improbably large amount. Using the capital/output 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 estimates of trend labor-productivity growth. 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 finally 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 of that decline occurred before the financial crisis, between 2006 and (early) 2008.

The slowdown is also evident in the time-series data on TFP. Figure 5(a) shows that TFP growth picked up in the mid-1990s and slowed prior to 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 slower time variation in the mean of cyclically-adjusted productivity growth. The second provides Bayes posterior inference on whether the decline in the mean occurred before the 2007-2009 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 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 focuses power on small martingale variation in μ_t, and the LFST test (Müller and Watson (2008)), a low-frequency point-optimal test for martingale variation.

All five tests reject the null hypothesis that μ_t is constant using 1956 through 2016 sample, but not using the shorter 1981 through 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 of the tech boom. Notably for our purposes, the test does not find a break during or after the 2007-2009 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 prior to the recession. Details are given in the online supplement.

The results are summarized in Figure 8 and Figure 9. Figure 8 shows the 4-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 distribution of the date of the maximum of the local mean of productivity growth between 1981 and 2016.

Taken together, we interpret Table 6, Figure 8, and Figure 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 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 around 2000 and its value in 2007: this calculation yields a posterior median estimate of 0.72 percentage points using the full sample, and a 67 percent posterior set of (0.32, 1.27). These estimates, which suggest a significant decline prior to the cyclical peak, are also consistent with the decline in the biweight estimate and the Bayes posterior sets 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 trend is apparent around 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 (IPP, which includes software; R&D spending by businesses, universities, and nonprofits; and the production of books, movies, TV shows, and music). IPP investment 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 3.0 percent. Recent research adds additional intangible investments in innovation, training, reorganizations, and the like. Estimates of these additional intangible investments from Corrado and Jäger (2015) also show a slower pace of growth after 2000.

In sum, in U.S. data since the early 1970s, the unusual period for productivity growth was roughly the ten years from 1995 to 2005, when growth was faster than before or since. 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 points to GDP growth during the previous three recessions, but only 0.13 percentage points 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.

Understanding 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. Tobin refined the theory by incorporating adjustment costs.

Capital-demand theory suggests benchmarks that would allow us to diagnose the role of special crisis-recession factors. Line (8) of Table 3 shows that using only population as a benchmark—in effect, treating investment as exogenous—implies a substantial capital/population shortfall in the recent recovery compared to the three earlier recoveries. However, line (17) of the same table and Figure 5(d) shows 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. By 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 beside output. One is the return to capital, a measure that Jorgenson 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 dollar of capital fell in 2009, but rebounded to normal in 2010 and have remained normal since. The behavior of the return to capital supports our finding that investment was behaving normally, given the shortfall in output.

Gutierrez and Philippon (2017) use Tobin's q theory of adjustment cost to provide a benchmark. q, a normalized measure of the value of firms recorded in the stock and bond markets, has risen to high levels in the recovery. So why hasn't investment been stronger? Jorgenson's optimization model implies that firms invest until the marginal revenue product of capital equals its rental price. Gutierrez and Philippon cite evidence such as rising concentration ratios to argue that rising market power has increased the gap between the average and marginal revenue products. Market power rationalizes weak investment with a strong stock market.

Gutierrez and Philippon consider only the relation with adjustment cost—Tobin's q equation—not the investment function. In the investment-q plane, the q equation slopes upward (the "supply" of investment), the demand for investment function slopes down, and their intersection determines investment and the value of q. An increase in market power shifts the q equation to the left, riding up the demand function, with 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 2007-2009, 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 U.S. 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 findings.

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 trend output growth fell. Accordingly, the capital-output ratio should have risen, according to standard growth theory. Because, in fact, it did not rise, there has been a shortfall in the ratio. On the other hand, rising market power would be a source of a decline in the capital/output ratio. It is beyond the scope of our paper to sort out quantitatively which effect dominates for the capital/output ratio. Our empirical evidence that the capital-output ratio is on its previous trend is consistent with the two forces roughly offsetting. 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 from 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 section, we review several hypotheses about the productivity slowdown. We begin with three non-recession explanations then return to the recession story.

1. ***Mismeasurement***. Perhaps the problem of slow growth in both productivity and output is illusory? Plausibly, we miss many of the gains of from tech-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 ten years.

Neither Byrne, Fernald, and Reinsdorf (2016) nor Syverson (2016) find evidence that, on balance, the mismeasurement of tech-related real output growth has in fact worsened since the early 2000s. In addition, the steady shift of economic activity towards 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. Aghion and others (2017) find a modest increase after 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.

2. ***Rising regulation and loss of dynamism.*** A rising regulatory burden could have slowed productivity growth (e.g., Barro, 2016), and differing regulatory barriers do seem to matter across countries (e.g., Fatas, 2016; Cette, Fernald, and Mojon, 2016). Indeed, regulation could be a reason why, by many measures, dynamism in the U.S. economy has declined over time (Decker and others, 2016a, b). Job creation and destruction has slowed; the business startup rate has fallen; and young firms have grown less in recent years. 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 2007-2009 recession. S lack of dynamism could be a symptom of lack of available or exploitable ideas. But some observers assert that its source is regulatory burdens, so we examine the regulatory-productivity link.

In the U.S., 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. Al-Ubaydli and McLaughlin (2015) apply text-analysis methods to the *Code of Federal Regulations* to construct industry-level indices of regulations from 1970 through 2014. Their "RegData" database covers 42 private industries that match industries for which we have BLS productivity data (1987 through 2014). (The appendix describes the data further.) Industries with substantial increases in regulation after 2008 include, most notably, (i) finance, (ii) energy (pipelines, oil and gas extraction, and utilities), (iii) construction, and (iv) transportation (especially trucking, water, and rail).

Table 7 presents selected cuts of the BLS's industry 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 on financial services in industry gross output. Both groups slow sharply after 2004, but the finance-intensive grouping actually improve after 2007, despite increasing finance regulation. Over 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 Goldschlag and 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 level (e.g., land-use restrictions and occupational licensing). But at a first cut, we find no evidence that federal regulation is a first-order issue.

3. ***A pause in the information technology (IT) revolution***. The hypothesis that IT was the culprit is natural. A large 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, Fernald, Oulton, and Srinivasan, 2004). Businesses throughout the economy became more efficient by reorganizing to take advantage of an improved ability to manage information. But, 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 5) grew much slower after 2000 and even slower after 2007. Industries that use tech intensively show a larger slowdown after 2007 relative to the period from 2000 through 2004. But it is fair to say that the slowdown is broad-based. All industries use IT, and increasingly so. If that is the story, we 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 those gains in the data.

This story rings true in a number of ways. First, it is consistent with the large literature on the role of IT in the productivity acceleration in 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 levels effects. The gains might ebb and flow (Syverson, 2013), and it is hard ex ante to know when the transformative gains will cease.

4. ***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 long literature argues that deep recessions, and especially financial crises, might reduce the level or growth rate of TFP; see Fatas, 2000, for an early review, and Adler et al., 2017, for a recent survey. 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 those effects and lead to faster growth in innovation (Yellen, 2016)

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

Overall, there is limited empirical evidence for the United States that historical business-cycle downturns, financially related or otherwise, permanently cut the level or growth rate of productivity. An obvious counter-example is the depressed 1930s which were, by all accounts, an extraordinarily innovative period (Field, 2003, Alexopoulos and Cohen, 2011, and Gordon, 2016). More broadly, Huang, Luo, and 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 growth rates are largely exogenous to the business cycle.

The biggest challenge for explaining recent U.S. data is the timing: Productivity growth slowed prior to the recession. Anzoategui and others (2016) suggest that there might have been a pre-recession shock to exogenous growth followed by the large shock from the recession. Yet as noted above, measured U.S. investments in R&D and other intellectual property slowed markedly after 2000, with a much smaller effect in 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 since the mid-2000s is real, contributed substantially to the disappointing recovery, and–with roots in the temporary IT-spurred productivity boost of the 1990s–may well continue.

V Changes in the Labor market

The trends in labor force participation for men and women were very different in earlier years, with women rising and men falling. As shown in Figure 11, however, both moved together since 2006 and both fell sharply starting in 2008. This decline exerted a large negative force on output growth. Table 3 shows that the contribution of participation to output, after cyclical adjustment, was -0.69 percentage points per year (column e), compared to an increase of 0.15 points per year averaged over the three previous recoveries (column d), for a shortfall of 0.85

points per year (column f). Cumulated over the recovery through 2016, the shortfall was 6.11 percentage points (column i), almost as large as for TFP.

Prior to the crisis, recessions depressed participation, though there were forces on both sides. Higher unemployment discouraged participation since 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 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 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 fell from its peak of 10 percent to normal levels below 5 percent. This episode would be hard to understand if cyclical developments dominated participation towards the end of the recovery.

Many authors ascribe part of the decline in participation to demography, specifically to the rising fraction of the population aged 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-plus 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

$$\Delta L = \sum_i s_i \Delta L_i + \sum_i L_i \Delta s_i \tag{10}$$

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 Divisia and the refinement of measuring shares as equally weighted averages is named after Tørnqvist. The variation in the rates over 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 (10) with annual data from the CPS 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 of the cells in each year are empty. Figure 12 shows the overall 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 aged 16 and older, fell by 1.8 percentage points. Of this, 1.2 points came from the rate effect—the result of lower participation, on average, within demographic groups—and 0.6 points came from compositional change. In other words, forces other than demography accounted for about two-thirds of the overall decline during the recovery, and for about one-half of the decline since the cyclical peak in the fourth quarter of 2007.

The key question is, what explains the large non-demographic decline in the participation rate? Some specifications suggest the cyclical component of the participation rate is larger than in our specification here (e.g. Erceg and Levin (2014) or our longer-lag results reported in the online supplement). Even with a large cyclical coefficient, however, by the middle of 2016, the unemployment rate had had returned to a normal or near-normal range, leaving only a very small normal cyclical component by mid-2016.

If the non-demographic 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 pp increase in the unemployment rate from its 2006 trough to its 2009 peak was comparable to the 5 pp 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. Over the 5 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 that our cyclical estimate is misspecified; but we find no evidence of such an asymmetry.

Aaronson and co-authors (2014) report a variety of results on 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 not much related to conditions in the labor market. Though they do not discuss the post-2009 expansion specifically, 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 non-demographic participation gap as of 2016 lie somewhere other than in the recession. Research has so far been inconclusive about the sources.

Figure 13 shows participation rates for people aged 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 labor-market marginalization of poorer families.

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

The surprising, large, and persistent decline in labor-force participation is a phenomenon that deserves and will receive intensive study. While there is room for disagreement about the extent to which the early-recovery decline in 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 successful explanation will also consider changes in family structure, real wages, taxes, benefits, and the value of time spent outside the labor market.

VI Other Explanations for Slow Output Growth

So far, our discussion has highlighted the non-cyclical 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 five percent imply an economy in a cyclically normal condition, then that rules out explanations based on permanent or highly persistent weak demand. Moreover, explanations based on temporary demand deficiency need to reconcile them 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 supplement, 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 forecast 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 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 forecast 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 in Table 5 indicates that most of the demand components tracked their forecast paths on average. Although exports were unexpectedly weak, so were imports: After share-weighting their contributions to the average shortfall in output growth is negligible, 0.03 and -0.01 pp per year, respectively. Table 5 indicates that the average forecast error in GDP of 0.57 pp is largely attributable to three sources: consumption of services (0.18 pp), 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 unwinding Recovery 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 over the recovery was slightly weaker than predicted—a 0.26 pp contribution to the output shortfall. Much of this weakness is attributable to two service sectors: housing and utilities (0.07 pp) and financial services and insurance (0.07 pp). The forecast error in residential investment averaged -0.08 pp over the full period, but this masks the delayed recovery in the housing sector. Through 2011, the normal cyclical recovery in housing did not materialize, and housing investment growth did not stabilize around the forecast 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 sheds 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 contribution of consumption growth to the shortfall in output growth was only 0.26 pp; rather, consumption growth largely tracked its predicted path over 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).

That growth of consumption and investment largely tracked their historical cyclical patterns suggests that 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 both federal and state and local government purchases. The timing of the forecast errors suggests that the unwinding of the Recovery 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 over this period of state and local government employment, points to 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 in addendum line to 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 poor or missed measurement of real output. Gross domestic income growth averaged 2.34 percent over 2009 through 2016, while GDP grew at 2.06 percent. Table 5 suggests that some of this difference may come from unexpected sources. In particular, half of 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 in the recovery from the 2007-2009 recession than would normally have accompanied the healthy decline in the unemployment rate. It grew less than it would have given its normal relation to an index derived from many macro 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 prior to 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 2017, first quarter, forecasts growth in the next three years, and the next 10, to exceed its average pace over 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 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. While 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.

Data Appendix

Growth and expenditure-side decompositions of output

Our main growth-accounting data for the U.S. business sector are described in detail in Fernald (2014). Those data are available quarterly, in growth rates, from 1947:Q2 on at http://www.frbsf.org/economic-research/economists/jfernald/quarterly_productivity.xls. The version used in this paper were prepared on December 30, 2016.

For the overall economy, output is measured by real gross domestic product (GDP) and the geometric average of GDP and real gross domestic income (GDI) (see Nalewaik (2010), Greenaway-McGrevy (2011), and Aruoba et al (2012)). We refer to the average as gross domestic output (GDO). Business sector output is also GDO using Fernald's measure.

Per-person values are formed using the civilian noninstitutional population 16 years of age and older from the Bureau of Labor Statistics (BLS) Current Population Survey (FRED series CNP16OV). Other BLS-CPS variables include employment (CE16OV), labor force (CLF16OV) and the civilian unemployment rate (UNRATE). Quarterly data were constructed by averaging the monthly data for each quarter.

Expenditure variables (Table 5) are from the Bureau of Economic Analysis NIPA accounts.

Industry level TFP, finance intensity, and regulation data,

BLS multifactor productivity (MFP) data and industry capital data were downloaded from http://www.bls.gov/mfp/mprdload.htm (accessed September 6, 2016). Growth-rate data run 1988-2014. The industry classification system is NAICS. See the online appendix to Fernald (2015) for details on how the data were manipulated and aggregated.

IT intensity is based on factor shares, i.e., payments for IT as a share of income. "IT intensive" is the set of industries with the highest IT shares that constitute 50 percent of the value-added weight (averaged 1987-2014) for the business sector excluding finance and direct IT production. For finance intensity, we aggregated industries from annual BLS I-O tables (accessed February 23, 2017) from http://www.bls.gov/emp/ep_data_input_output_matrix.htm. The finance share was nominal purchases of intermediate financial services as a share of industry gross output. "Finance intensive" is set of business (excluding finance) industries with the highest finance shares constituting roughly half the value-added weight.

Al-Ubaydli and McLaughlin (2015) produced the regulation data, available at regdata.org. The website summarizes the data as "RegData is a database that quantifies the number of individual restrictions in the Code of Federal Regulations and…determines which industries are targeted by those regulatory restrictions." They match regulations to BEA industries, which we then matched with BLS industries. Not all industries have reliable measures of regulation, and those industries are omitted. The included industries cover more than 80 percent of private value added and, when aggregated, have a similar TFP pattern to overall private business.

Labor force participation rates

The data underlying the demographic and family income decompositions for labor force participation are from the 2005-2016 monthly CPS microdata, accessed via IPUMS.

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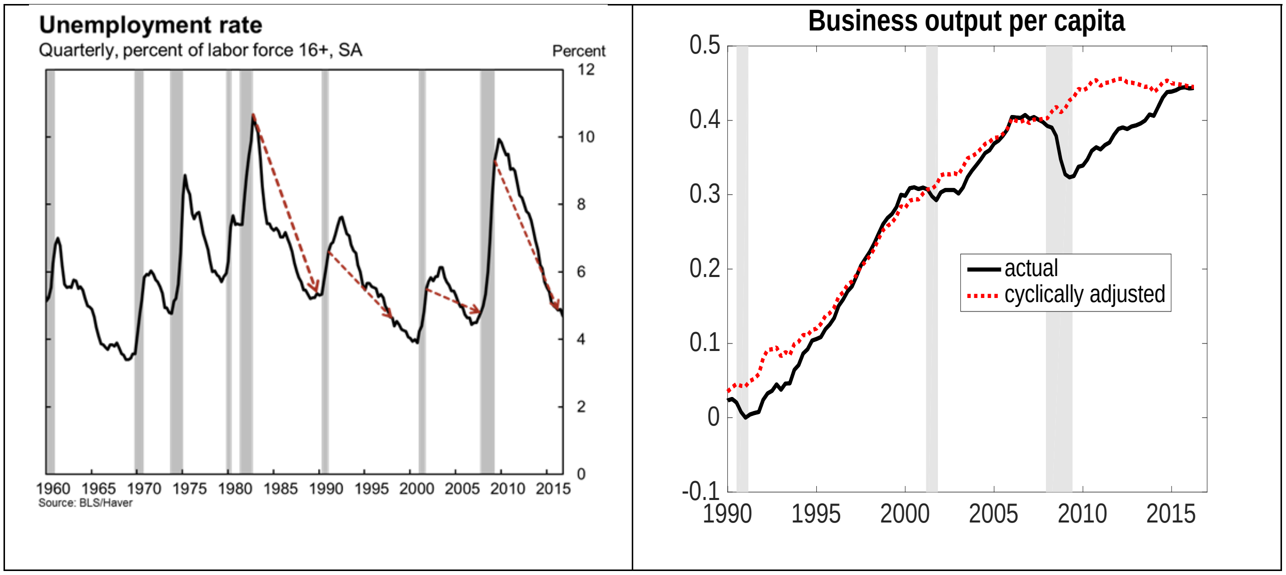
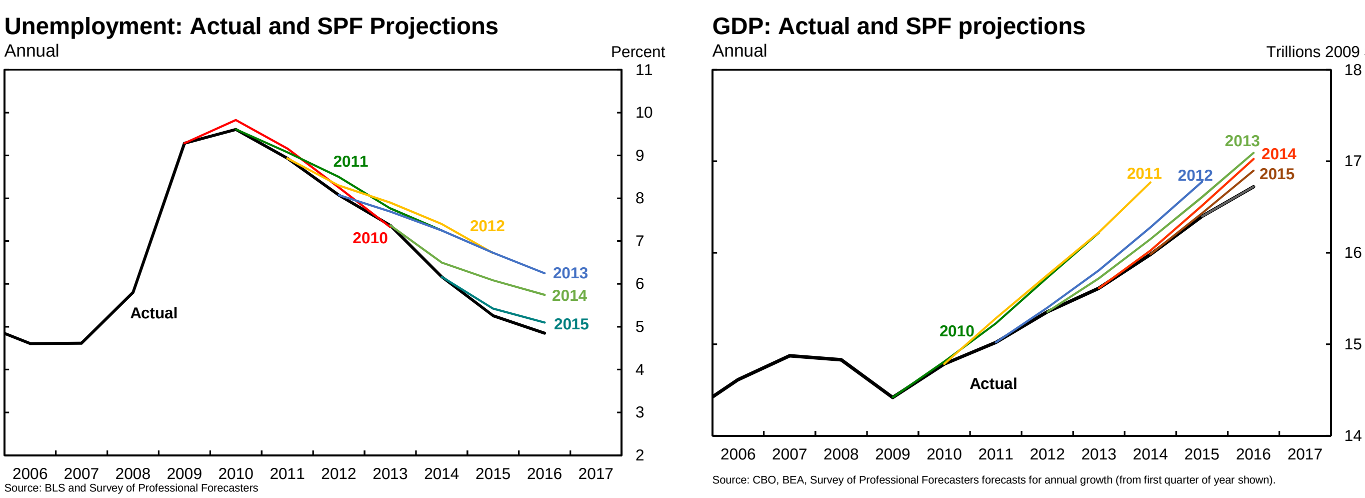
Figure 1: Unemployment and Output



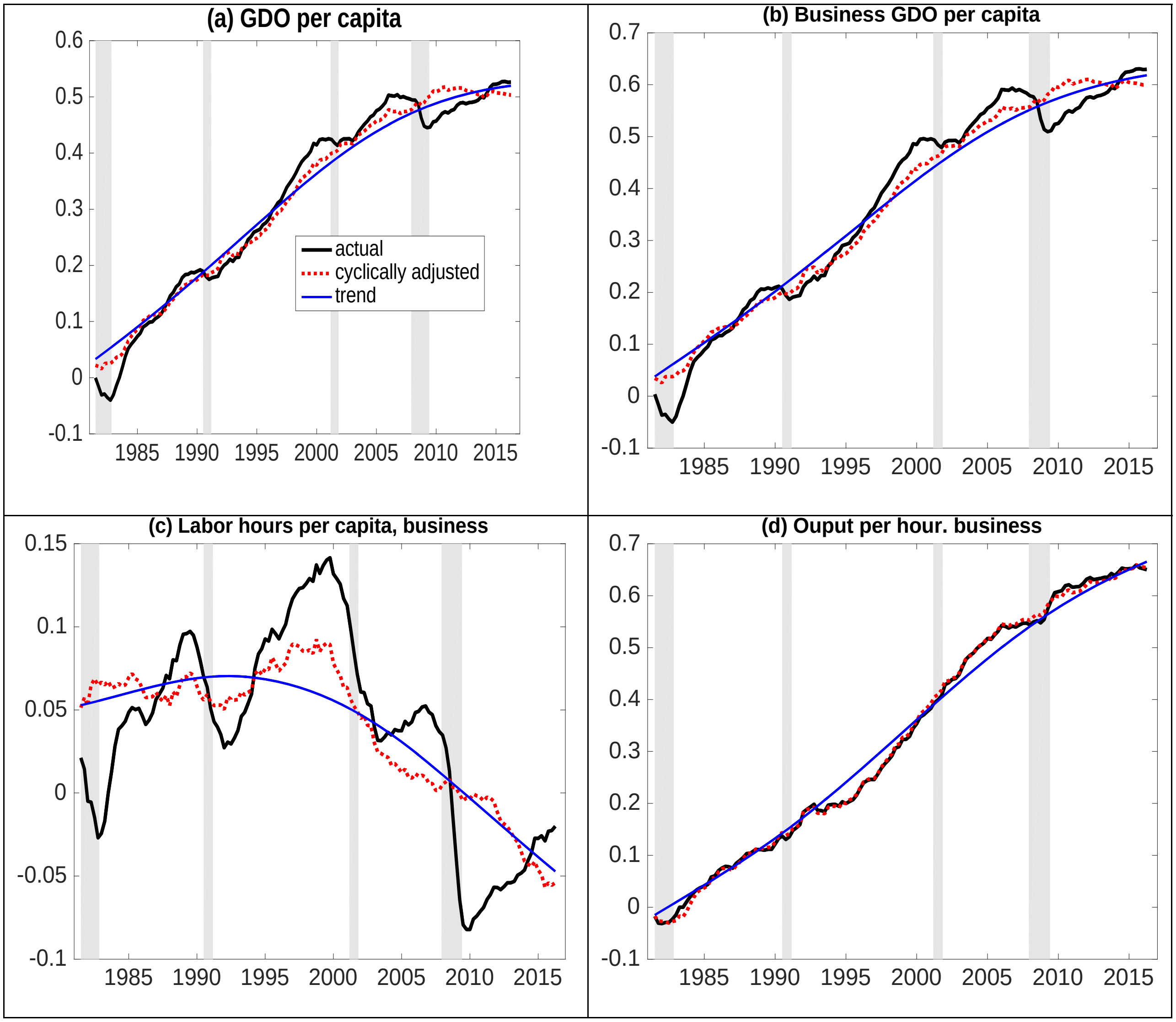
Notes: In the left panel, arrows connect the unemployment rate at the NBER-dated troughs with the rate 28 quarters later (or at the next peak, whichever comes first). In the right panel, the black line is the log of business output per person (normalized to 0 in 1991); the red line cyclically adjusts those data using Okun's Law as described in the text (normalized to equal the black line in 2007Q3).

Figure 2. SPF Forecasts of GDP and the Unemployment Rate, made in 2010 through 2015



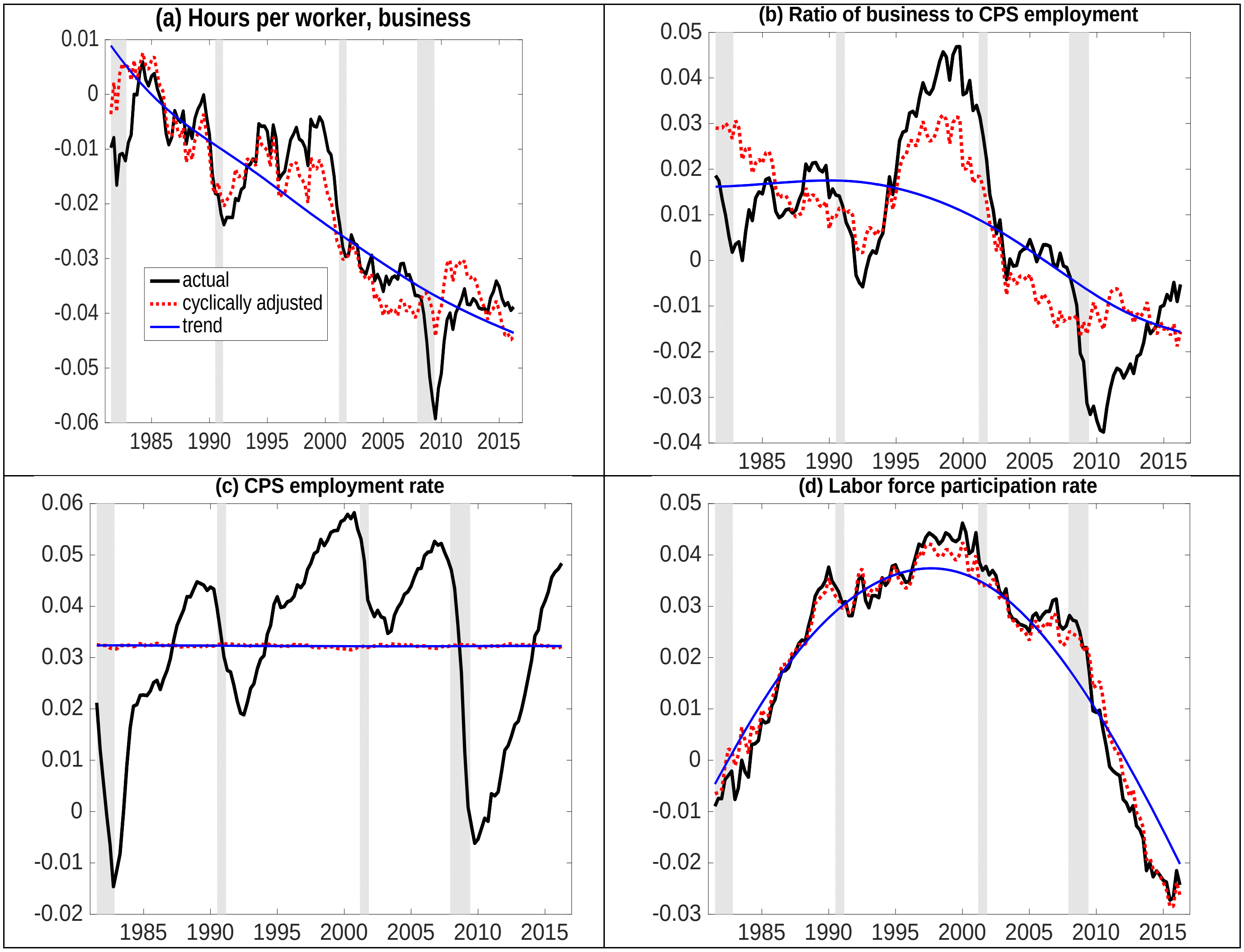
Notes: Median forecasts from the Survey of Professional Forecasters are from the first quarter of year indicated for annual averages of unemployment and GDP growth in that and subsequent years. The GDP figure on the right assumes the previous year's (revised) level is known and then projects using the published forecasts for annual growth rates. For example, the line for 2010 starts at 2009 actual, and uses 2010Q1 forecasts for annual growth in years 2010 on. The GDP figure follows Lansing and Pyle (2015).

Figure 3: Data and Okun's Law Filtered Data: Output and Labor Productivity



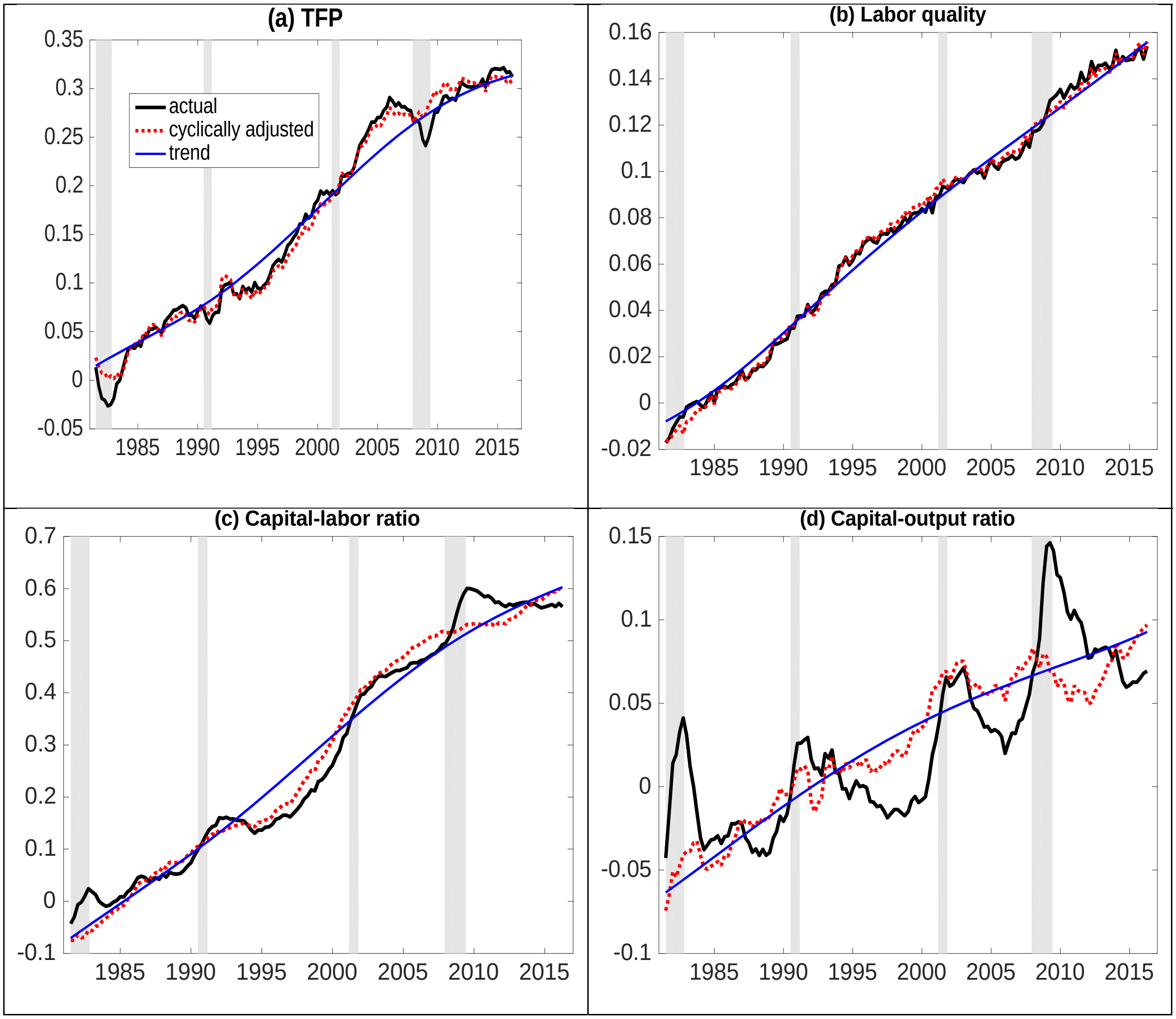
Notes: Plots of cumulated growth rates. Black lines are raw data, red lines are residuals (including constant terms) from Okun's Law regressions. Blue line is biweight filtered trend (bandwidth 60 quarters) fitted to the Okun's Law residuals. Levels are normalized to have the same means over the sample shown.

Figure 4: Data and Okun's Law Filtered data: Labor Market Variables



Notes: See Figure 3.

Figure 5: Data and Okun's Law Filtered Data:
Productivity, Capital Ratios, and Labor quality



Notes: See Figure 3.

Figure 6. Forecasted and Actual Paths from the Factor Model: Selected Variables

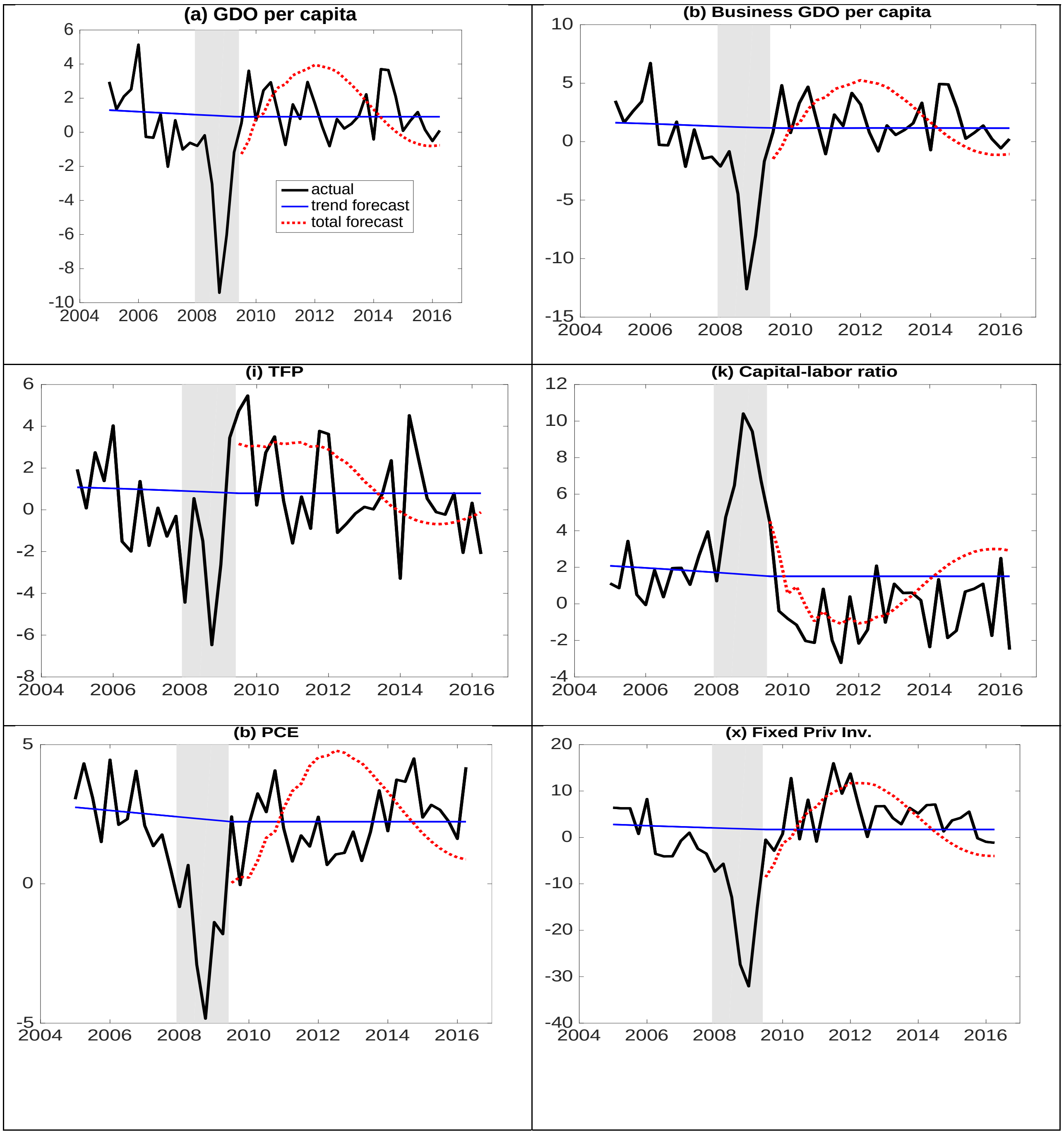
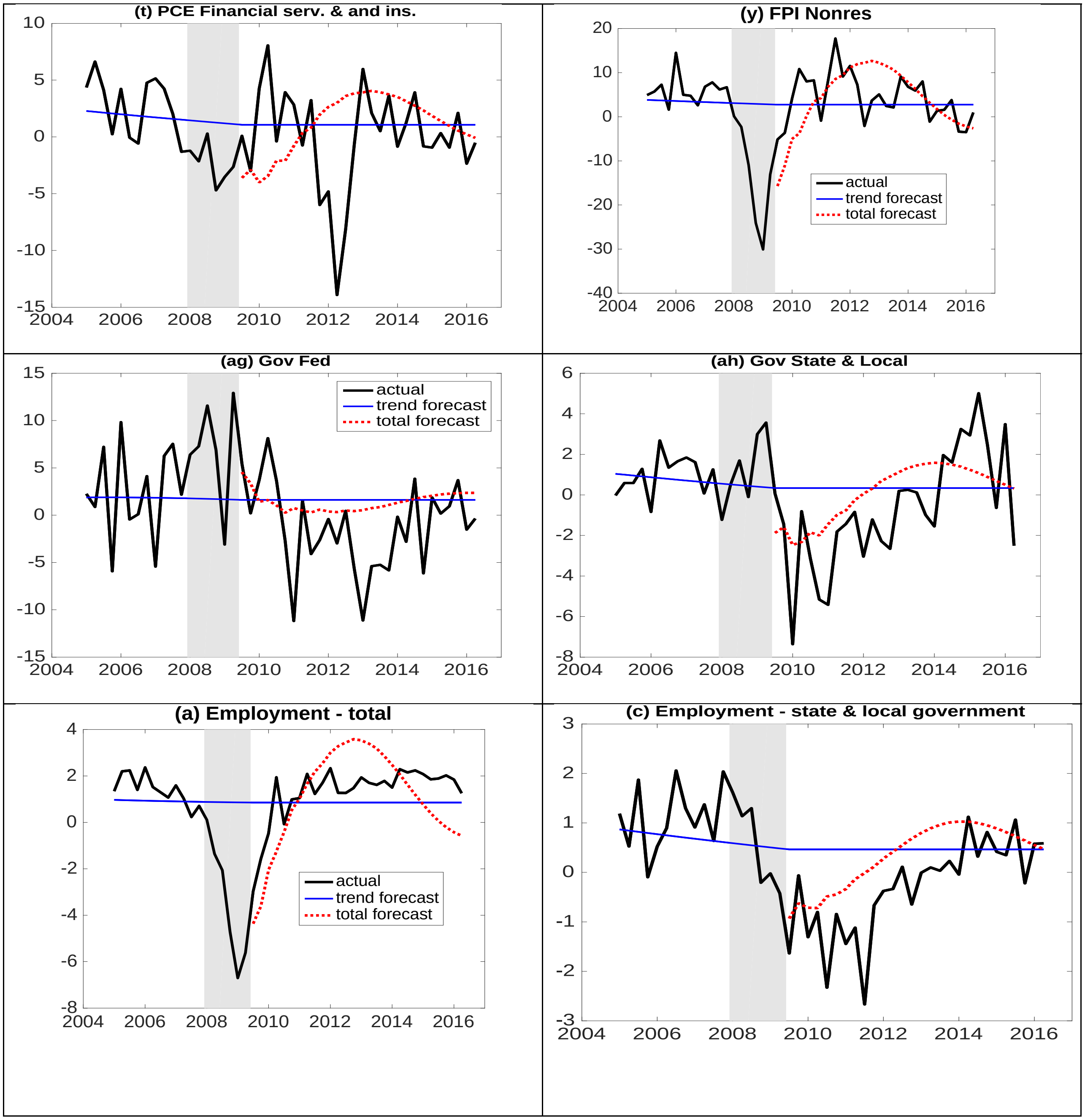
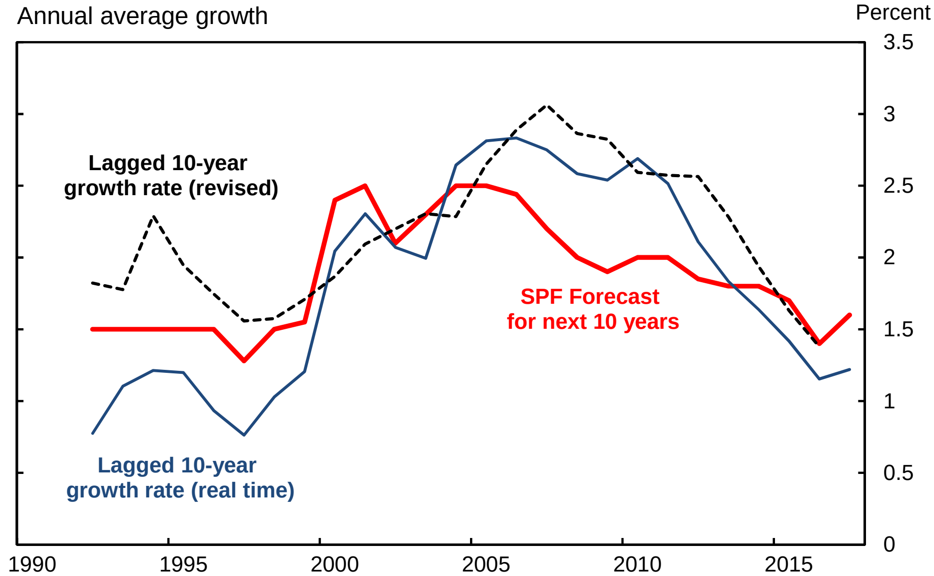


Figure 6, continued



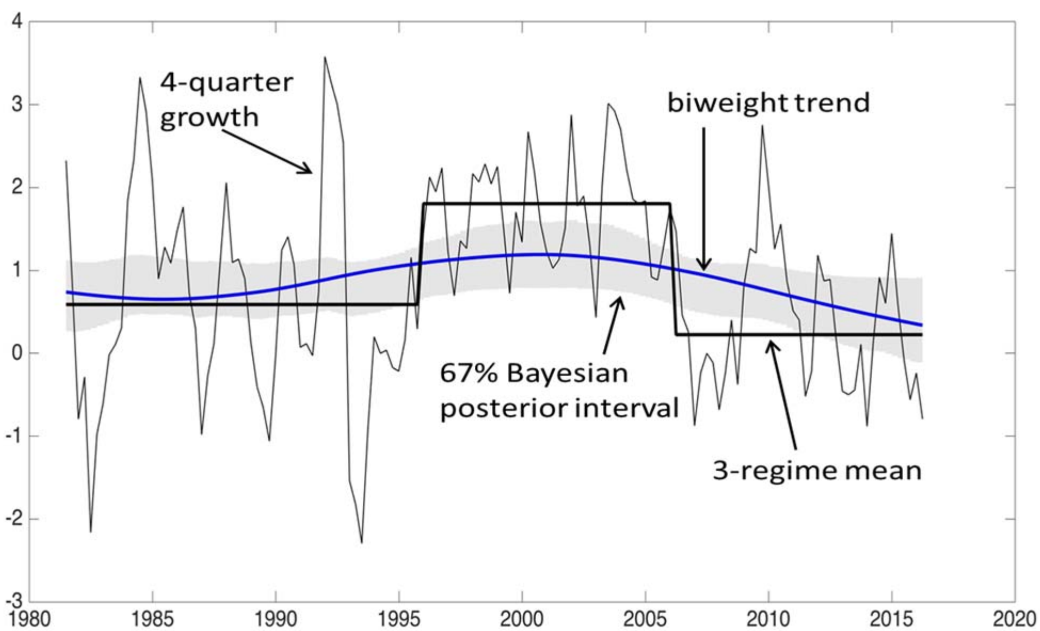
Notes Black line is the actual growth rate of the variable, red line is its forecast based on the six factors, and the blue line is the long-term growth trend.

Figure 7: Real-Time Estimates of Prospective 10-year Growth in Labor Productivity



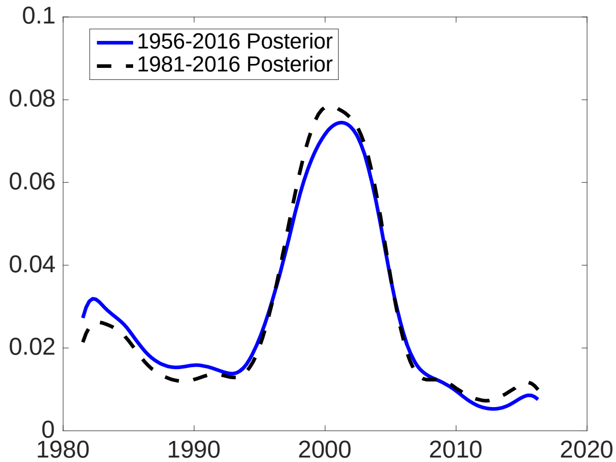
Source: Survey of Professional Forecasters, ALFRED (FRB St. Louis), and BLS. Revised actual data are from Feb. 2, 2017.. Output per hour is for the non-farm business sector. Surveys are from the first quarter of the year, and are the annual average over the next 10 years.

Figure 8: Cyclically-Adjusted TFP Growth and Estimated Low-Frequency Means



Notes: TFP is cyclically adjusted. The thin black line is its four-quarter growth rate. The blue line is the cyclically-adjusted trend using a biweight filter (60-quarter bandwidth). The shaded area is a 67% Bayes posterior set. The dark black line are the means estimated within the three regimes estimated by break tests, with break dates in 1995Q4 and 2006Q1 from Table 6.

Figure 9: Posterior Density of Date of Maximum Trend Growth in TFP, 1981-2016



Notes: TFP growth is cyclically adjusted. Computed using Bayes implementation of the random walk-plus-noise model for productivity growth, as discussed in the text.

Figure 10. Business Earnings as a Ratio to the Value of Capital

Figure 11: Labor-Force Participation Rates by Sex, 2006-2016

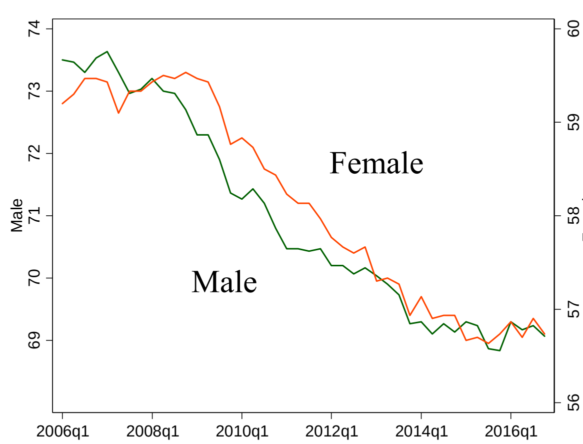


Figure 12. Labor-Force Participation Rate, Actual and Adjusted for Changing Demography, Annual 2006-2016

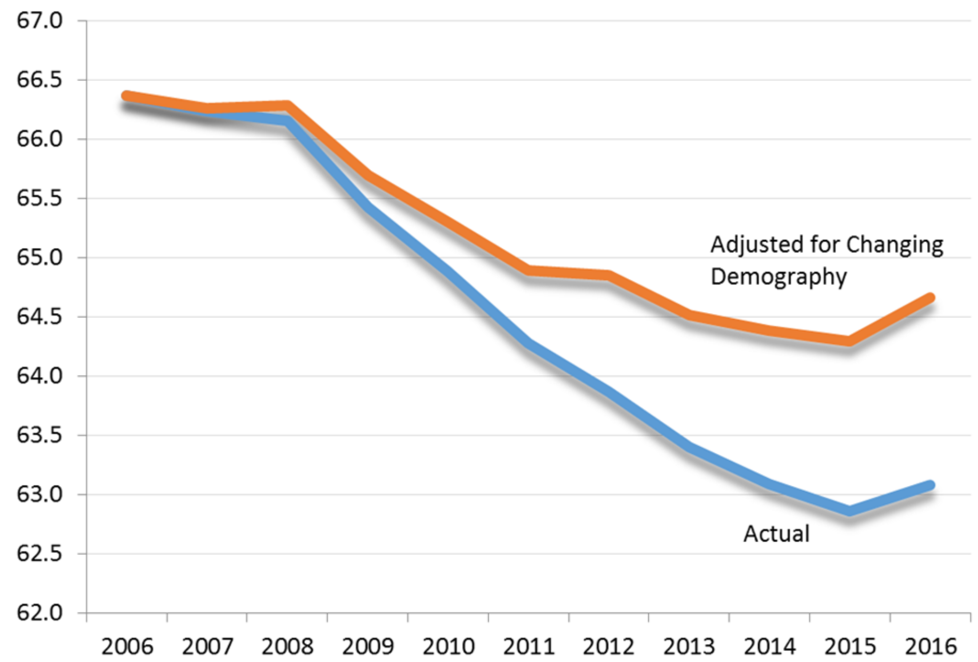


Figure 13. Role of Family Income in Participation Rates

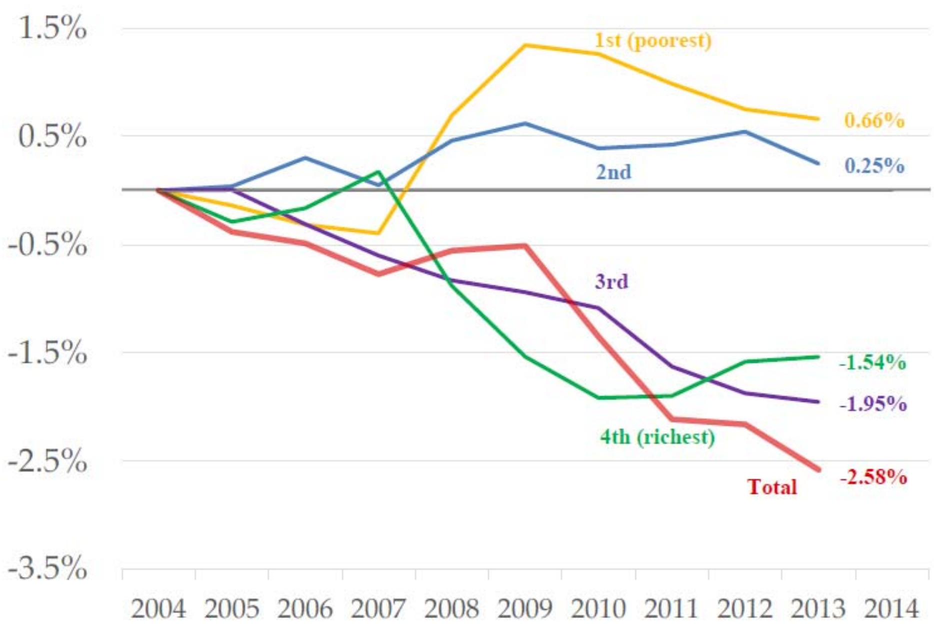


Table 1. Categories of Quarterly Time Series Used to Estimate the Factors

	Category	Number of series
(1)	NIPA	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	9
(11)	Asset Prices, Wealth, Household Balance Sheets	9
(12)	Oil Market Variables	6
	Total	123

Notes: For the full list of series and data transformations see the supplemental data appendix.

Table 2. Cyclicality of Real Output and its Components

	Generalized Okun's law coefficient and std. error	Standard deviations of components			R^2 from regressing on factors
		cycle (c)	trend(μ)	irregular (z)	
(1) GDP	-1.49 (0.18)	1.90	0.58	1.77	0.66
(2) GDO (Average of GDP, GDI)	-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) α*Capital/Pop.	-0.09 (0.06)	0.20	0.19	0.32	0.37
(9) (1-α)*(Lab Qual * Hours/Pop.)	-1.43 (0.14)	1.54	0.26	1.24	0.57
(10) Bus. labor hours per capita	-2.30 (0.19)	2.54	0.36	1.51	0.74
(11) Hours per worker, business	-0.35 (0.1)	0.55	0.04	1.05	0.25
(12) Ratio of bus.empl to CPS empl	-0.71 (0.09)	0.73	0.08	1.20	0.24
(13) CPS 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) Bus. output per hour (labor prod.)	0.28 (0.22)	0.77	0.37	2.23	0.24
(16) TFP / (1 -α)	-0.75 (0.29)	1.88	0.35	3.41	0.39
(17) Capital-Output ratio × α/(1-α)	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

Notes: The Okun's law coefficients are $\beta(1)/4$, so they are measured in quarterly percentage points of growth per percentage point change in the unemployment rate. The standard deviations of the components are for quarterly growth rates reported in percentage points at an annual rate. The R^2 is from the regression of the variable on the factors used in factor model.

Table 3: Shortfall of the Post-Crisis Recovery Relative to Earlier Recoveries: Growth Accounting Decomposition Using Okun's Law Cyclical Adjustment

	Historical values (not cyclically adjusted)			**Cyclically adjusted**					
						Annual shortfall			
	Three previous recovs.	2009Q2-2016Q2	Annual shortfall (a)-(b)	Three previous recovs.	2009Q2-2016Q2	**Cyclically adjusted shortfall (d) - (e)**	*Shortfall in smooth trend*	*Residual shortfall (f) - (g)*	Cumul. shortfall
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
(1) GDP	3.60	2.06	1.54	2.95	0.96	1.99	1.26	0.73	14.94
(2) GDO (Average of GDP, GDI)	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) α*Capital/Pop.	0.79	0.24	0.55	0.77	0.24	0.53	0.40	0.13	3.78
(9) (1-α)*(Lab Qual * Hours/Pop.)	0.83	0.59	0.24	0.30	-0.27	0.57	0.41	0.15	4.04
(10) Bus. labor hours per capita	0.81	0.63	0.18	-0.06	-0.76	0.70	0.55	0.14	5.00
(11) Hours per worker, business	0.07	0.24	-0.17	-0.10	-0.07	-0.03	-0.06	0.03	-0.24
(12) Ratio of bus.empl to CPS empl	0.12	0.37	-0.25	-0.11	0.01	-0.12	0.06	-0.18	-0.83
(13) CPS 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) Bus. output per hour (labor prod.)	2.11	1.09	1.03	2.12	1.01	1.11	0.62	0.49	8.09
(16) TFP / (1 -α)	1.95	1.44	0.51	1.48	0.51	0.96	0.48	0.48	6.98
(17) Capital-Output ratio × α/(1-α)	-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

Notes: Entries are average annual percent changes or percentage point differences. Indented rows sum to next level of aggregation. Post-crisis recovery period is 2009Q2 through 2016Q2 (28 quarters). The three previous recoveries are the averages during the first 28 quarters from the troughs of 1982 and 1991, and the 24 quarters of the expansion after the 2001 trough. Cyclically-adjusted entries in columns (d) and (e) are residuals from Okun's Law regressions.

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

	Forecast	*Actual*	*Shortfall*	*(std. error)*
(1) GDP	2.63	2.06	0.57	(0.07)
(2) GDO (Average of GDP, GDI)	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) α*Capital/Pop.	0.43	0.24	0.19	(0.01)
(9) (1-α)*(Lab Qual * Hours/Pop.)	0.15	0.59	-0.44	(0.05)
(10) Bus. labor hours per capita	-0.08	0.63	-0.72	(0.06)
(11) Hours per worker, business	0.08	0.24	-0.16	(0.03)
(12) Ratio of bus.empl to CPS empl	-0.16	0.37	-0.53	(0.06)
(13) CPS employment rate	0.26	0.68	-0.42	(0.02)
(14) Labor-force participation rate	-0.27	-0.66	0.40	(0.03)
(15) Bus. output per hour (labor prod.)	2.07	1.09	0.98	(0.08)
(16) TFP / (1 -α)	2.15	1.44	0.72	(0.12)
(17) Capital-Output ratio × α/(1-α)	-0.43	-0.69	0.26	(0.03)
(18) Labor quality	0.34	0.33	0.01	(0.04)

Notes: The first two numerical columns are forecasted and actual values of the variable in the first column, where the forecasts are computed using the factor model and the values of the factors through 2009q2. The third column is the shortfall (the negative of the forecast error), and the final column gives the standard error of the shortfall arising solely from sampling error in the estimated model parameters.

Table 5. Expected and Unexpected Contributions to GDP growth: NIPA Demand Components

	Growth Rate, 2009Q2-2016Q2	Average Share	Okun's Law Cyclical Adjustment: Okuns law coefficient (SE)	CA Growth Rate: Three previous recoveries	CA Growth Rate: Post-crisis recovery	Total Shortfall	Trend shortfall	Irregular (z) shortfall	DFM Forecast: Forecast	DFM Forecast: Shortfall	DFM Forecast: SE
Real gross domestic product	2.06	1	-1.49 (0.18)	2.95	0.96	1.99	1.26	0.73	2.63	0.57	0.07
Personal consump. Expend.	1.54	0.68	-0.74 (0.14)	2.00	1.04	0.96	0.70	0.26	1.80	0.26	0.04
Goods	0.78	0.23	-0.44 (0.08)	0.80	0.48	0.32	0.24	0.08	0.86	0.08	0.03
Goods, durable	0.47	0.07	-0.25 (0.06)	0.43	0.28	0.15	0.12	0.03	0.50	0.03	0.03
Motor vehicles & parts	0.11	0.02	-0.09 (0.04)	0.10	0.04	0.06	0.09	-0.03	0.10	-0.01	0.02
Furn. & dur. HH eqpt	0.11	0.02	-0.06 (0.01)	0.08	0.06	0.02	0.02	0.00	0.10	0.00	0.00
Recreat. goods & vehicles	0.20	0.02	-0.06 (0.01)	0.21	0.15	0.06	0.02	0.04	0.24	0.04	0.01
Other durables	0.05	0.01	-0.03 (0.01)	0.05	0.03	0.02	0.00	0.01	0.06	0.01	0.00
Goods, nondurable	0.32	0.15	-0.19 (0.03)	0.38	0.20	0.18	0.13	0.05	0.37	0.05	0.01
Food & beve. off premises	0.06	0.05	-0.03 (0.02)	0.08	0.03	0.04	0.03	0.01	0.08	0.02	0.00
Clothing & footwear	0.06	0.02	-0.05 (0.01)	0.12	0.03	0.09	0.07	0.02	0.08	0.02	0.01
Gasoline & energy	0.00	0.02	-0.03 (0.01)	0.03	-0.02	0.04	0.02	0.02	0.00	0.00	0.01
Other nondurable goods	0.19	0.06	-0.07 (0.01)	0.15	0.15	0.00	0.00	0.00	0.19	0.00	0.01
Services	0.76	0.46	-0.30 (0.08)	1.21	0.57	0.64	0.46	0.18	0.93	0.18	0.02
Housing & utilities	0.13	0.13	-0.06 (0.02)	0.28	0.10	0.18	0.12	0.07	0.20	0.07	0.01
Health care	0.31	0.11	0.00 (0.03)	0.23	0.31	-0.08	-0.07	-0.01	0.31	0.00	0.01
Transportation services	0.04	0.02	-0.08 (0.01)	0.07	0.00	0.07	0.06	0.01	0.03	-0.01	0.00
Recreational services	0.04	0.03	-0.04 (0.01)	0.09	0.02	0.07	0.05	0.03	0.06	0.02	0.00
Food serv. & accomm.	0.11	0.04	-0.06 (0.02)	0.09	0.08	0.01	0.01	0.00	0.11	0.00	0.01
Fin. services & insurance	0.00	0.05	-0.02 (0.04)	0.18	-0.03	0.21	0.16	0.05	0.06	0.07	0.01
Other services	0.10	0.06	-0.06 (0.02)	0.15	0.06	0.09	0.07	0.02	0.11	0.01	0.01
NPISH	0.03	0.02	0.02 (0.01)	0.12	0.05	0.07	0.05	0.02	0.06	0.03	0.01
Gross priv. dom. investment	0.91	0.15	-1.11 (0.14)	0.63	0.03	0.60	0.45	0.15	0.89	-0.02	0.04
Fixed private investment	0.70	0.15	-0.94 (0.07)	0.53	0.09	0.43	0.41	0.03	0.59	-0.11	0.03
Nonresidential	0.50	0.12	-0.69 (0.08)	0.47	0.13	0.34	0.26	0.08	0.48	-0.02	0.02
Structures	-0.01	0.03	-0.19 (0.03)	-0.01	-0.06	0.05	0.02	0.03	0.00	0.01	0.01
Equipment	0.38	0.06	-0.44 (0.05)	0.30	0.09	0.20	0.17	0.03	0.33	-0.05	0.02
Intell. property products	0.14	0.04	-0.06 (0.01)	0.19	0.11	0.07	0.06	0.02	0.15	0.01	0.01
Residential	0.20	0.03	-0.25 (0.05)	0.07	-0.03	0.10	0.15	-0.05	0.12	-0.08	0.02
Structures	0.20	0.03	-0.25 (0.05)	0.07	-0.03	0.10	0.15	-0.05	0.11	-0.08	0.02
Equipment	0.00	0	0.00 (0.00)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Government expenditures	-0.19	0.19	0.10 (0.06)	0.45	-0.11	0.56	0.31	0.25	0.12	0.31	0.03
Federal	-0.09	0.08	0.11 (0.05)	0.18	-0.04	0.22	0.07	0.15	0.11	0.20	0.02
State & local	-0.10	0.12	-0.01 (0.03)	0.26	-0.07	0.34	0.24	0.10	0.02	0.12	0.01
Exports	0.58	0.13	-0.27 (0.08)	0.60	0.36	0.24	0.10	0.14	0.60	0.03	0.04
Imports	-0.76	-0.16	0.54 (0.09)	-0.70	-0.34	-0.36	-0.29	-0.08	-0.77	-0.01	0.03
Addendum:											
Government cons. expend. + transfer payments	0.66		1.22 (0.52)	3.67	1.33	2.34	0.91	1.44	2.86	2.20	0.23

Notes: Indented components add to the final entry at the prior level of indentation.

Table 6: Test Statistics for a Break in the Mean Growth Rate in TFP

	QLR (sup-Wald) test 1 break	2 breaks	3 breaks	Nyblom test	LFST test
A. 1956-2016					
p-value for H_0: $\mu_t = \mu$	0.01	0.06	0.01	0.02	0.03
Estimated break dates	1973Q1	1973Q1 2006Q1	1973Q1 1995Q4 2006Q1		
$\hat{\sigma}_{\Delta\mu}$	0.11			0.11	
90% CI for $\sigma_{\Delta\mu}$	(0.03, 0.36)			(0.02, 0.40)	
B. 1981-2016					
p-value for H_0: $\mu_t = \mu$	0.38	0.14	0.25	0.35	0.31
Estimated break dates	2006Q1	1995Q1 2006Q1	1988Q1 1995Q4 2006Q1		
$\hat{\sigma}_{\Delta\mu}$	0.05			0.05	
90% CI for $\sigma_{\Delta\mu}$	(0.0, 0.15)			(0.0, 0.27)	

Notes: All test are of a constant mean against a non-constant alternative: for the QLR, regime changes; for the Nyblom, against random walk drift; for the LFST, against more general martingale variation. All tests are heteroskedasticity and autocorrelation-robust. The final two rows in each block provide the point estimate of the standard deviation of a random walk drift in the mean, $\sigma_{\Delta\mu}$, and its 90% confidence interval based on inverting the test statistic.

Table 7: Industry Growth by Subperiod

	Pre-1995	1995-2000	2000-2004	2004-2007	2007-2014	Change after 2004 (d-c)	VA Weight
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
(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 (Oil/gas, pipeline, refining, utilities)	3.15	-3.47	5.55	-3.51	3.14	-9.06	5.9
(4) Transportation (ex. 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 producing	8.47	14.46	7.23	6.78	2.49	-0.45	5.7
(7) Business ex. 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 ex. finance and IT prod	0.25	0.23	1.84	-0.10	0.12	-1.93	86.0
(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

Notes: Industry and aggregate growth based on BLS 60-industry MFP data. Entries are percent change per year, except for value-added weight, which is average percentage share from 1988-2014.

Table 8: Panel Regressions of Industry TFP Growth on Regulatory Restrictions

	(1)	(2)	(3)	(4)
$Regulation_{i,t}$	0.032 (0.032)	0.033 (0.033)		
$Regulation_{i,t\text{-}1}$	-0.023 (0.027)	-0.011 (0.026)		
$Regulation_{i,t\text{-}2}$	-0.045 (0.039)	-0.036 (0.035)		
$Regulation_{i,t\text{-}3}$	0.022 (0.023)	0.036 (0.034)		
$\overline{Regulation}_{i,t:t-2}$			-0.018 (0.040)	-0.009 (0.036)
$\overline{Regulation}_{i,t-3:t-5}$				0.060 (0.050)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes
F-statistics for *Regulation* (*p*-value)	0.36 (0.83)	0.44 (0.78)	0.19 (0.67)	0.86 (0.43)

Notes: Data are annual observations of industry TFP growth (the dependent variable) and regulations for the 42 industries for which Regdata has an index of regulation, 1988-2014. Standard errors (in parentheses) are clustered by industry. $\overline{Regulation}_{i,t:t-2}$ denotes the average value of *Regulation* for lags 0-2, and $\overline{Regulation}_{i,t-3:t-5}$ is defined analogously.

Table 9: Changes in Weekly Hours of Time Use, 2007 to 2015, People 15 and Older

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