

Beyond Okun's Macroscope: The Cyclicalities of Margins of Adjustment

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Abstract: We present and implement a growth-accounting decomposition that links traditional discussions of “Okun’s Law” to recent macroeconomic research. This decomposition sheds light on the empirical magnitude of key margins of adjustment used by firms and households. We also investigate how business-cycle comovement of output and unemployment has changed over time. The most notable feature is the evolving cyclical behavior of labor productivity, which shifted from procyclical to countercyclical in the decades prior to 2007 before becoming roughly acyclical since the onset of the Great Recession. Much of the time-series variation in the cyclicalities of productivity reflects variation in the use of the “utilization” margin (e.g., labor hoarding). We also find, in general, that productivity is more procyclical during recessions than in normal times, reflecting greater use of the intensity margin. Finally, we explore the conditional response of the Okun coefficient to particular shocks. Our results provide insight into desirable features of macro models that seek to match central facts about both labor markets and business cycles..

Keywords: Margins of adjustment, growth accounting, output and employment fluctuations, cyclical productivity, Okun’s Law

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1. Introduction

Okun's Law is one of the most celebrated empirical relationships in applied macroeconomics. In its growth rate version, it is a reduced-form relationship that when unemployment rises 1 percentage point, output tends to fall about 2 percent.¹ It serves as a benchmark rule of thumb for macroeconomic forecasting and is widely referenced in textbooks and economic blogs.²

In contrast, it rarely appears in academic macroeconomic literature. One reason is that, since the 1980s, dynamic models of business cycles have typically modeled output and *employment* rather than *unemployment*. However, recent DSGE research has increasingly incorporated models of frictional unemployment, making discussions of Okun's relationship potentially relevant once again.

In this paper, we ask what a modern macroeconomist can learn from Okun's Law? We develop and implement a growth-accounting/ production-theory framework to interpret the comovement of output with unemployment. The margins of adjustment that are captured in this framework—many of which were discussed implicitly or explicitly in Okun's original work—map to a wide range of recent macroeconomic models.³ Okun's Law thus provides an easy way to check whether the underlying dynamics of the economy are changing and is a useful guide for identifying the empirically important margins of adjustment needed for a parsimonious and well-disciplined DSGE model.

We take this framework to the data on the U.S. business economy to document how output, unemployment, and related underlying variables comove over time, using the relatively new quarterly

¹ Okun documented this relationship in studies focused on measuring potential output (Okun 1962, 1965). His original work used data from 1947-1960. He regressed unemployment change on real GNP growth and reported that a 1 percent increase in GNP was associated with a 0.30 percentage point decrease in unemployment. As Plosser and Schwert (1979) point out, the coefficient on the reverse regression—i.e., the expected change in output from a 1 percentage point increase in unemployment—is not the inverse of 0.3, but depends on the R^2 . Using Okun's original estimates, where the R^2 is 0.62, implies that a 1 percentage point increase in unemployment predicts a 2.1 percent decline in output.

² Okun's Law is used as a forecasting guidepost by many central banks and the U.S. Congressional Budget Office. In the aftermath of the Great Recession numerous commentators worried that Okun's Law was broken and might be best laid to rest. In contrast, Ball, Leigh, and Loungani (2012) concluded that it remained a useful and reliable description of the relationship between output and unemployment.

³ Like us, Prachowny (1993) also links Okun's Law to production theory. However, he does not provide a growth-accounting decomposition, nor does he quantify the contribution of various margins in accounting for Okun's Law. Finally, he does not discuss Okun's Law conditional on particular shocks.

growth-accounting dataset from Fernald (2012b). The Fernald data include a model-based empirical measure of factor utilization (i.e., labor effort and the workweek of capital) and technology (i.e. total factor productivity controlling for utilization), which allows us to be more precise in our decompositions.

The empirical estimates highlight the large response of hours worked to a change of unemployment—the response is roughly 2 to 1, much more than in typical DSGE models with unemployment (e.g., Gali, Smets, Wouters 2011 or Christiano *et al*, 2013). The estimates also highlight the importance of procyclical variations in factor utilization, which reduces measured TFP growth about 1 percent for each 1 percentage point increase in unemployment.

Okun (1962) argued that unemployment was a reasonably stable and parsimonious proxy for a range of underlying responses of firms and households. Our growth accounting, in many ways, seeks to illuminate more formally the key margins of adjustment that Okun discussed, such as labor-force participation, hours per worker, and the intensity with which capital and labor are utilized. Operationally, Okun assumed these margins of adjustment comoved systematically and in a stable manner with unemployment over time, then there should also be a stable relationship between unemployment and output.

The question of stability leads us to look at how the output-unemployment relationship has changed over time. An important aspect is the changing cyclicalities of labor productivity, as noted by other authors.⁴ Specifically, in the decades prior to the Great Recession, productivity shifted from procyclical to countercyclical with respect to unemployment. What has not previously been noted, to the best of our knowledge, is that since the mid-2000s, the strong countercyclicality has largely disappeared.

In terms of this changing cyclicalities of productivity, we find several facts of interest. First, the degree of the shift in cyclicalities is much stronger using output measured in terms of real expenditure than in terms of real income. Most macroeconomists use the “standard” expenditure-side data, where the shifting cyclicalities is marked. However, Nalewaik (2010) argues that real gross domestic income

⁴ See, for example, Stiroh (2009), Gali and Gambetti (2009), Barnichon (2010), and Gali and van Rens (2010).

provides a better read on economic developments in recent decades and is better at identifying turning points. This suggests some caution for macroeconomists seeking explanations for the changing cyclicalities of productivity and, more generally, suggests the importance of checking robustness in empirical estimation to using real income rather than just real expenditure. Second, even with income-side data, there is some shift in cyclicalities. Most notably, this shift reflects a sharply reduced role for variations in factor utilization in the 1990s.

We also find that productivity is always more procyclical in recessions than in normal times. This greater procyclicality appears to reflect greater variation in factor utilization around these times. In typical linear macro models, the dynamics of recessions are not different than the dynamics in normal times. The recession effects could reflect either the shocks that cause recessions, or (possibly nonlinear) dynamics during recessions.

Of course, one potential resolution is that the shocks causing recessions might be different than normal shocks, even if the dynamics are similar. Our reduced-form relationships necessarily hold in any reasonable empirical model, but they do not provide insight into whether any particular shock has the average dynamic effects. After all, in a macro model, it would be reasonable to expect the comovement of business-cycle variables to depend on the shocks that hit. To understand whether different shocks lead to a different degree of comovement between output and unemployment, we use empirical measures of various demand and technology shocks. Those shocks allow us to identify adjustments conditional on particular shocks, e.g., technology versus monetary policy shocks. (These results are very preliminary, and are not presented in this version of the paper, though some of the statistical considerations are discussed.)

The remainder of the paper proceeds as follows. Section 2 provides a growth-accounting framework for Okun's Law and presents an empirically tractable decomposition of the Okun's coefficient into aggregate hours and productivity components. Section 3 describes the data. Section 4 describes our unconditional (not-shock-dependent) results, including how responses change over time and during

recessions. Section 5 discusses and (partially) implements the theory behind Okun responses conditioned on particular shocks. Section 6 concludes.

2. Accounting for Okun's Law

Various versions of Okun's Law exist in the literature—sometimes estimated in levels, sometimes in differences; sometimes with unemployment as the dependent variable, sometimes as the independent variable. We take a growth-accounting perspective, which links naturally to the modern macro literature as well as to a large literature on measurement and production theory. From this perspective, it is natural to relate output growth to input growth. Since unemployment changes are closely related to input growth, we focus primarily on a growth-rate relationship between output growth and the change in the unemployment rate. Specifically,

$$\Delta y_t = \alpha + \beta \Delta U_t + \varepsilon_t \quad (1)$$

Lower-case letters are log-levels. Δy_t is the growth rate (log change) in real output and ΔU_t is the change in the rate of unemployment. Underlying this simple reduced form relationship is a more complicated set of relationships that can help us identify the margins of adjustment driving the comovement of output and unemployment. This section discusses underlying relationships in the context of a production-function/growth-accounting structure.

As an identity, output growth equals the sum of growth in hours and labor productivity:

$$\Delta y \equiv \Delta l + (\Delta y - \Delta l) \quad (2)$$

where Δl is the log change in total labor hours. The OLS estimate of β from equation (1) can then be expressed in terms of the linear projections of growth in hours and labor productivity on the change in unemployment:⁵

$$\hat{\beta} = \hat{\beta}^{Hours} + \hat{\beta}^{LP}, \quad (3)$$

⁵ To see this, note that the Okun coefficient is $\beta^y = \text{cov}(dy, dU) / \text{var}(dU)$. Inserting (2) yields $\text{cov}(dl, dU) / \text{var}(du) + \text{cov}(dy - dl, dU) / \text{var}(du) = \beta^{Hours} + \beta^{LP}$.

where the coefficients are from the regressions:

$$\Delta l = \beta^{Hours} \Delta U + \eta_{Hours} \quad (4)$$

$$\Delta y - \Delta l = \beta^{LP} \Delta U + \eta_{LP} \quad (5)$$

The pieces of equations (4) and (5) can be expanded further in terms of theory and identities.

Beginning with β^{Hours} , consider the relationship between labor hours, L , and the unemployment rate, U .

Labor hours depend on the number of workers, N , and hours per worker, $H=L/N$:

$$L = \left(\frac{L}{N} \right) N = H \cdot N \quad (6)$$

Variations in the number of workers naturally affect the unemployment rate through the following relationship:⁶

$$N = \frac{N}{Emp} \frac{Emp}{LabForce} \frac{LabForce}{Pop} Pop \equiv gap \cdot (1-U) \cdot LFPR \cdot Pop. \quad (7)$$

N is the number of workers, Emp is the number of people employed, $LabForce$ is the labor force, and Pop is the overall working-age population.

The first term on the right-hand side, $Gap = \frac{N}{Emp}$ reflects the fact that the number of workers is potentially different from the number of people employed. One person employed might have two or more jobs, and thus count as more than one worker. This term also captures any other gaps between the payroll and household surveys.⁷ The second term is employment as a share of the labor force, which is by definition equal to $(1-U)$. The third is the labor-force participation rate, $LFPR$.

The log of $(1-U)$ is (approximately) $-U$. Hence, combining (6) and (7) and taking log-differences:

$$\Delta l \approx \Delta h + \Delta gap + \Delta lfpr + \Delta pop - \Delta U \quad (8)$$

⁶ Gordon (2011) uses a similar, somewhat expanded, identity.

⁷ In practice, there are also coverage differences between the payroll and household surveys.

Other things equal, a one percentage point increase in the unemployment rate reduces hours worked by one percent. In the data, however, we would expect other factors on the right-hand-side to vary as well. For example, when unemployment rises, we would expect that hours per worker fall, the gap term falls (as workers lose second or third jobs), and labor-force participation might fall (reflecting a shift towards home production or, for other reasons, a reduction in labor force attachment). So in terms of the OLS regression, we expect the coefficient β^{Hours} to exceed unity in absolute value.

Next consider the projection of labor productivity growth on unemployment change, as reflected in β^{LP} . Suppose aggregate output can be approximated by a constant-return production function:

$$Y_t = F(W_t \cdot K, E_t \cdot H \cdot N \cdot LQ, A_t), \quad (8)$$

where A is technology, K is the stock of capital and W is the workweek of capital (the number of hours the capital is actually in operation). Labor input depends on the number of workers, N ; hours per worker, H ; the average “quality” of each hour (including age, experience, and other observables), LQ ; and the effort E per quality-adjusted hour. Note that variation in capital utilization shows up in W and labor hoarding shows up in E .

In growth rates, this production function takes the form:⁸

$$\Delta y = \alpha(\Delta k + \Delta w) + (1 - \alpha)(\Delta l + \Delta e + \Delta lq) + \Delta a. \quad (9)$$

Rearranging equation (9), labor productivity can change because of capital-deepening, $\alpha(\Delta k - \Delta l)$, labor quality, cyclical variations in utilization, $\Delta util$, or technology:

$$\begin{aligned} \Delta y - \Delta l &= \alpha(\Delta k - \Delta l) + (1 - \alpha)\Delta lq + (\alpha\Delta w + (1 - \alpha)\Delta e) + \Delta a \\ &\equiv \alpha(\Delta k - \Delta l) + (1 - \alpha)\Delta lq + \Delta util + \Delta a. \end{aligned} \quad (10)$$

⁸ Suppose the production function takes the translog form, which provides a flexible second-order approximation to any function. Then the factor shares/output elasticities α and $1 - \alpha$ are time-varying and are properly taken as the average of shares in periods t and $t-1$. In the Cobb-Douglas case, the shares are constant over time. Basu and Fernald (2001) discuss the more general case in which an aggregate constant-returns production function may not exist and how, in practice, the effects are likely to show up as procyclical movements in the cyclicalities of the aggregate Solow residual (measured TFP, the empirical counterpart of a).

At times, we will refer to the standard measure of total factor productivity growth, defined as

$\Delta tfp = \Delta y - \alpha \Delta k - (1 - \alpha)(\Delta l + \Delta lq)$. From (10), we can write this as $\Delta tfp = \Delta util + \Delta a$. We will also refer to the empirical counterpart to Δa as “utilization-adjusted TFP” (as a reminder that it is technology only under the conditions that there is a constant returns aggregate production function).

We can use expression (10) to understand why the sign of the reduced-form β^{LP} in equation (5) is theoretically ambiguous. Simply put, the ambiguity of the sign of β^{LP} comes from the fact that the components of equation (10) have different cyclical properties. The first two terms in (10) tend to push β^{LP} to be positive. For example, in recessions unemployment rises and hours worked fall. Then, since capital is relatively smooth, capital deepening tends to rise. This capital-deepening effect, which reflects the diminishing returns to labor alone, pushes labor productivity up, or to be countercyclical. The labor quality term has a similar effect. Since firms typically up-skill in recessions, disproportionately laying off lower-skilled workers, labor quality tends to rise, pushing β^{LP} to be positive.

On the other hand, declining utilization pushes measured productivity down during downturns. When unemployment is high, firms hoard labor and reduce the workweek of capital (e.g., going from two shifts a day to one).⁹ This moves β^{LP} to be negative.

Finally, the effects of utilization-adjusted TFP growth, Δa , on β^{LP} are theoretically ambiguous but, empirically, appear to be positive. In traditional real-business-cycle-type models, positive technology shocks not only raise labor productivity but would typically be expected to reduce unemployment. This procyclical productivity pushes β^{LP} to be negative. In models with nominal or real rigidities, however, labor productivity and unemployment may be positively correlated conditional on a technology shock (β^{LP} pushed positive). Gali (1999), Francis and Ramey (2005), Basu, Fernald, and Kimball, 2006) and others argue that this is the empirically relevant case.

⁹ Basu and Fernald (2001) discuss the importance of procyclical fluctuations in utilization margins in productivity measurement.

This decomposition provides a map of important variables that might affect the observed comovements of output and unemployment. It also helps us understand the implications of particular empirical values of the Okun coefficient β from equation (1).

To see this consider a simple example in which the Okun coefficient is the negative of labor's share in income. This would occur if unemployment changes were unaccompanied by systematic changes in hours per worker, the employment-worker gap, labor-force participation, or population (immigration would be the channel for population to change). It would also require that unemployment and technology be unrelated systematically as would be the case with a demand shock. In this simple case, $\Delta l = -\Delta U$ and $\beta^{Hours} = -1$. If at the same time, capital, labor quality, and utilization do not change systematically with unemployment, then, from (10), $\Delta y - \Delta l = \alpha(-\Delta l) = \alpha\Delta U$. Hence, $\beta^{LP} = +\alpha$. In this example, the Okun coefficient is the negative of labor's share in income or $\beta = -(1 - \alpha)$. This result is intuitive in terms of the production function (9). A one percentage point increase in unemployment reduces labor hours by one percent, while leaving all other inputs and technology unaffected. So output falls by labor's share.

But, as is well known, and we confirm in our empirical results, in almost all cases the magnitude of Okun's coefficient is substantially larger than labor's share. The decomposition shows that this larger coefficient necessarily reflects the systematic cyclicalities of other margins of adjustment, as reflected in (8) and (10). And the components of these equations point us to where to look for potential answers. It could be on the labor side, driven by changes in hours per worker, or the fact that workers lose second or third jobs. It could also be on the productivity side, if utilization of capital and labor falls when unemployment rises. The actual drivers are ultimately an empirical question but as demonstrated in this decomposition, the structure underlying Okun's simple reduced form relationship provide a useful framework for organizing the empirical analysis.

3. Data

We use detailed growth-accounting data for the U.S. business sector from Fernald (2012b). The data run from 1947:2 through 2012:4. The unemployment rate corresponds to the overall economy, but most of the economy's cyclicalities arises from the business sector. An appendix describes the data and the relationship between the business and overall economies in greater detail.

We use both expenditure-side and income-side measures of output. Nalewaik (2010) raises the question of whether GDP or gross domestic income (GDI) provides a more accurate reading on economic activity, especially around turning points. Specifically, the “standard” measure of GDP and business-sector output from the Bureau of Economic Analysis (BEA) is from the expenditure side. Nalewaik (2010) argues that GDI may better capture the business cycle variations in output growth and that it correlates more strongly with other business cycle variables, before and after data revisions. Nevertheless, Greenaway-McGrevy (2011) and Aruoba *et al* (2012) suggest that both GDP and GDI provide independent information, and recommend taking a weighted average of the two.

The standard measure of business output in the NIPAs and in the BLS productivity releases comes from the expenditure side. In particular, it is GDP less non-business output. Fernald constructs a corresponding income-side measure as GDI less non-business output. Our benchmark measures of business-sector output, labor productivity, and TFP use an equally weighted average. However, in several places, we discuss where the distinction matters.

An important aspect of the Fernald dataset is its empirical measure of factor utilization, which is a quarterly version of the Basu, Fernald, and Kimball (BFK, 2006) measure. BFK wrote down a dynamic cost-minimizing model of the firm where labor and capital are quasi-fixed. If the firm wants more input in the short run, it can adjust an observable intensity margin of hours per worker; or unobserved margins of labor effort and the workweek of capital. The first-order conditions imply that the firm uses all margins simultaneously. Hence, the observable hours per worker can proxy for the unobservable utilization margins; BFK estimate the parameters relating them. BFK and Fernald implement this

measure using detrended industry hours per worker, with different parameters across industries. Hence, variations in utilization are not perfectly correlated with aggregate hours per worker.

4. Okun's Law in Practice

4.1 Okun's Law Decomposed

Table 1 below shows the simple Okun coefficient relating output growth to changes in unemployment as well as the full decomposition of Okun's coefficient based on our growth-accounting derivation. The estimates are based on the full sample of business-sector data which goes from 1948:Q1 through 2012:Q4. Each entry is the slope coefficient from a regression of the four-quarter growth rate of the variable shown on the four-quarter change in the unemployment rate. (Quarter-to-quarter changes yield qualitatively similar results, but the four-quarter change allows some of the adjustment that might not be instantaneous.) Specifically, for any variable X , it shows β^X from the following regression:

$$\Delta_4 \ln X_t = c_J + \beta^X \Delta_4 U_t + \varepsilon_{J,t}.$$

Row (1) of the table shows the Okun coefficient for β^Y . The first column shows that output (the average of income and expenditure measures) falls 2.33 percent when unemployment rises 1 percentage point. The second and third columns show that the decline is slightly larger with real income than with real expenditure. Although this difference is relatively modest, we show below that estimates with the two output measures have strikingly different patterns in recent decades.

The next two rows decompose the Okun coefficient for β^Y into the part attributable to hours versus labor productivity, consistent with equation (3) above. Row (2) shows that most of the Okun coefficient is "explained" by the decline in hours, which falls more than 2 percent when the unemployment rate rises by a percentage point. Accordingly, row (3) shows that much less of the Okun coefficient is explained by labor productivity. The response of labor productivity is roughly an order of magnitude smaller than the response of output.

Consistent with the literature on the cyclicalities of productivity, row (3) shows that over the full sample, productivity is modestly procyclical, i.e., the coefficient is negative. (Note that we define cyclicalities with respect to labor as reflected in the unemployment rate. Hence, procyclical productivity growth means that in a boom, labor productivity rises when unemployment falls—so they covary negatively.) With income-side data, as well as with the average of the expenditure and income sides, the coefficient is significantly negative.

The next two sections of Table 1 further decompose hours and labor productivity into their respective component parts. Looking first at the contribution of hours growth, rows (2a) and (2b) show that about 80 percent (1.69 percentage points) of that decline in total hours reflects a decline in the number of workers, and about 20 percent reflects a decline in hours per worker. This means that most of the adjustments to total hours take place at the extensive, rather than the intensive, margin. Nevertheless, both margins matter quantitatively.

The final section (rows (3a)-(3c)) shows the growth-accounting decomposition of labor-productivity growth. As expected, capital deepening and labor quality are countercyclical and contribute positively to labor productivity. Hence, they contribute positively to the Okun coefficient in row (1). In contrast, row (3c) shows that measured TFP growth is strongly procyclical, especially with the income measure. Row (3c.1) shows that this procyclicality mainly reflects the procyclicality of factor utilization. Indeed, after controlling for utilization, row (3c.2) shows that TFP is actually countercyclical with respect to unemployment. This countercyclicalities is particularly strong with the product-side measure. These findings are in line with the literature cited earlier that finds that technology improvements are contractionary with respect to inputs.

In sum, the empirical estimates of Okun's coefficient and the underlying drivers highlight the large response of hours worked to a change of unemployment—the response is roughly 2 to 1. This is much more than in typical DSGE models with unemployment (e.g., Gali, Smets, Wouters, 2011, or Christiano *et al.*, (2013), which generally assume that the number of people employed moves close to one-

to-one with unemployment. Although part of this reflects our focus on the more-cyclically sensitive business sector, analysis of unpublished BLS data on the total economy, from Glaser (2013), shows that a 1 percentage point increase in the unemployment rate is associated with a fall of 1.4 percent in total economy employment and 1.8 percent in total economy hours. This suggests that our results accurately reflect the fact that other margins, such as changes in number of multiple-job holders, are also quantitatively important. As such, DSGE models that ignore these margins miss quantitatively important aspects of the economy's adjustment to shocks.

Finally, these estimates highlight the importance of variations in factor utilization (labor effort and capital's workweek), which reduces measured TFP growth about 1 percent for each percentage point increase in unemployment. The utilization margin is also crucial to understanding why TFP is strongly procyclical and labor productivity weakly so. In addition, the importance of the utilization margin is consistent with many papers that find that measured TFP growth has an important endogenous element.

4.2 Okun's Law over Time

We now consider how the output-unemployment relationship has changed over time. Figure 1 plots 40-quarter rolling estimates of the Okun coefficient β^y for real income and real expenditure. The dotted lines show the full-sample Okun coefficients, for expenditure and income data, from Table 1. The first thing to note is that there is considerable variation over time in the Okun coefficients on both the expenditure and income side. Casual observation suggests that some of the largest deviations occur around recessions, a possibility we test more formally later in the paper.

Another point to note in Figure 1 is the striking divergence between the income and expenditure measures beginning in the early 1990s. Note the two series also diverged briefly in the second half of the 1970s. The crosses on each series represent periods when the differences in the two coefficients are statistically significant. Looking first at the expenditure series, the magnitude of the Okun coefficient has declined over time and has been smaller in the last two decades than it was in the previous three decades. This pattern is not present in the income data where the coefficient has been more stable.

Nalewaik (2010) argues that over the past few decades, the income side is more correlated with other measures of activity (say, ISM surveys); and is more closely related to what forecasters are saying. More pointedly, he argues that the product side has gotten worse. If this is true, the magnitude of the Okun coefficient on the expenditure side should fall, since the covariance with unemployment should fall. Nalewaik's claim is thus consistent with our results.

As we did for the average Okun coefficient, we next consider how underlying variables have contributed to variations in Okun's coefficient over time. We begin by looking at the contribution of hours and its two components: employment and hours per worker. These are shown in Figure 2. As in Figure 1, the plots reflect coefficients computed from 40-quarter rolling regressions. The results show the changes over time in the contribution of employment, hours per worker, and total hours (the sum of those two areas) to the Okun coefficient. For comparison, the solid black line shows the Okun coefficient itself, using the average of real income and real expenditure.

The results in Figure 2 clearly show that total hours have become more responsive to unemployment over time. The coefficient on hours, and on employment in particular, became far more negative during the Great Moderation period than it had been previously in our sample. This contrasts with the slight decline in the magnitude of the Okun coefficient itself. The more-negative coefficient on hours is not an artifact of focusing on the business sector; the appendix shows that the same pattern holds for the overall economy. Although we don't focus here on the reason for the change in the unemployment-hours relationship, the fact that it has changed has direct implications for the cyclicity of productivity.

This is clear in Figure 3 which plots labor productivity for the income and expenditure data. As the figure highlights, labor productivity turned countercyclical in the 1990s and through the mid-2000s, especially using the expenditure data. Importantly, the evidence for the changing cyclicity of productivity has mainly focused on the expenditure data and the fact that the income side data are so different suggests that caution on this issue may be warranted. Still, even the income-side data show

some shift towards countercyclicality. However, in samples ending during or after the onset of the Great Recession in 2007, labor productivity has reverted to being largely acyclical or even procyclical (with income-side data).

Figure 4 shows why the labor productivity/unemployment relationship changed over time, using the same decomposition as in the bottom of Table 1. For this decomposition, and henceforth in the paper, we measure output as the geometric average of real expenditure and real income. A number of aspects of Figure 4 are worth noting. First, as expected, the greater responsiveness of hours to unemployment implies that the endogenous response of capital deepening turned countercyclical. Second, and more importantly, a key driver of the changing cyclicity of labor productivity growth is utilization. In the pre- and post-Great Moderation periods, the Okun coefficient on utilization was consistently around -1. In contrast, during the 1990s especially, the correlation between changes in utilization and unemployment was close to zero. The absence of a relationship between utilization and unemployment during this period meant the other variables, which are all countercyclical, pushed labor productivity itself to be countercyclical during this period.

The remaining variables had much smaller impacts on labor productivity over time. The coefficient on utilization-adjusted TFP is fairly stable over the sample. And with the exception of an increase in the coefficient on labor quality during the Great Moderation, it has made a small and relatively constant contribution over time. (The increase in the labor-quality coefficient in the 1990s presumably reflects that the strength of the labor market, when unemployment was falling, pulled lower-skilled workers into the labor force.)

In sum, the decompositions of Okun's coefficient over time point to greater responsiveness of total hours—mostly employment—to changes in unemployment, and a largely offsetting change in the cyclicity of productivity. The productivity changes, in turn, reflect especially the response of utilization.

4.3 Okun's Law during Recessions

Our final reduced-form exercise considers whether recessions are different than normal times. Some of the variation in the Okun coefficient over time (Figure 1) lines up with recessions. And the importance of the utilization margin in the changing cyclicity of productivity hints that firms may be making different adjustments in recessions than when the economy is functioning normally.

We examine this hypothesis using the following reduced-form specification:

$$\Delta x_t = \alpha^X + \alpha_R^X R + \beta^X \Delta U_t + \beta_R^X (\Delta U_t \cdot R) + \eta_t \quad (11)$$

Since there is clearly time variation in these relationships we estimate this equation on a constrained sample from 1972:Q1 through 2012:Q4. This sample gives us three deep recessions, in the 1970s, the 1980s, and the Great Recession. The results of our estimation are provided in Table 2.

The results show that recessions are, indeed, different. Specifically, in recessions, both the slope and the constant term differ. Looking down the table what turns out to vary in recessions is productivity. Labor productivity (row 3) moves from being countercyclical with respect to labor in normal times ($\beta^{LP} > 0$) to being procyclical in recessions ($\beta^{LP} + \beta_R^{LP} < 0$). The lower constant term in recessions, α_R^{LP} is also a measure of greater procyclicality, since it is negative in recessions. Further decomposing the effect we find that the change in labor productivity is primarily driven by utilization (row 3c.1). This suggests that recessions are times when firms reduce effort or capital's workweek more than we would predict based on changes in the unemployment rate alone.

Overall, the analysis of recessions highlights an interesting challenge for macro models. In the context of such models, the recession effects reflect either the shocks that cause recessions, or (possibly nonlinear) dynamics during recessions.

5. Conditional Okun Coefficients: Statistical Considerations

Although the components of Okun's Law might have changed over time, it is nevertheless striking how stable Okun's Law appears over time in Figure 1. Other research has also documented the

stability of Okun's law over time (see, e. g. Ball, Leigh and Loungani, 2012). Theoretically, there is every reason to expect otherwise. We might expect a shock affecting output by a given amount will affect employment, hours and utilization differently depending whether its source is an improvement in technology, a monetary policy intervention, a government spending shock or an oil price spike, to mention a few. Variations in the responses to different shocks might also help us understand which shocks and macroeconomic mechanisms are most important. Moreover, to the extent that these differences characterize the business cycle, we should expect improvements in our forecasting ability. Given these considerations, it is somewhat puzzling that Okun's Law is rather stable historically in light of these natural sources of variation. These are the main threads of the discussion in this section. We begin by reviewing statistical methods to investigate the cyclical properties of the relationship between output and unemployment as a function of the type of shock and conditional on past information.

Using the same notation adopted earlier, we are interested in characterizing the following two objects:

$$R(y_t, h, v) = E \left\{ \frac{E(\Delta_h y_{t+h} | v_{jt} = v_j, X_t, X_{t-1}, \dots) - E(\Delta_h y_{t+h} | v_{jt} = 0, X_t, X_{t-1}, \dots)}{E(\Delta_h y_{t+h} | v_{jt} = 0, X_t, X_{t-1}, \dots)} \right\}$$

and

$$R(U_t, h, v) = E \left\{ \frac{E(\Delta_h U_{t+h} | v_{jt} = v_j, X_t, X_{t-1}, \dots) - E(\Delta_h U_{t+h} | v_{jt} = 0, X_t, X_{t-1}, \dots)}{E(\Delta_h U_{t+h} | v_{jt} = 0, X_t, X_{t-1}, \dots)} \right\},$$

for $h=1, \dots, H$. Recall that y_t denotes log output (we will discuss momentarily how this is measured) so that 100 times $\Delta_h y_{t+h} = y_{t+h} - y_t$ denotes the percentage point change in output from time t to $t+h$; $v_{jt} = v_j$ denotes an identified intervention of type $j \in \{1, 2, \dots, J\}$ and size v_j at time t ; and X_t denotes a vector of variables that include output and the unemployment rate U_t among other controls. These two expressions measure the change in the outcome variable from time t to time $t+h$ as a result of an intervention at time t through v_{jt} , conditional on the information in X_t and its past. The natural

interpretation is as the cumulated impulse response of the outcome variable (whether output or unemployment) to a shock v_j .

Using $R(y_t, h, v_j)$ and $R(U_t, h, v_j)$ we can characterize the evolution of the Okun coefficient in response to the shock v as:

$$O(h, v_j) = \frac{R(y_t, h, v_j)}{R(U_t, h, v_j)}. \quad (12)$$

$R(y_t, h, v_j)$ and $R(U_t, h, v_j)$ can be calculated in a variety of different ways. Ultimately, however, it all hinges on achieving proper identification. As we will discuss momentarily, we examine several types of shock from the literature. That is, we have observable estimates of \hat{v}_{jt} for $j \in \{1, \dots, J\}$.

Suppose X_t , the vector of controls (which also includes the outcome variables), is covariance-stationary and therefore admits the Wold representation:

$$X_t = \Phi_0 V_t + \Phi_1 V_{t-1} + \Phi_2 V_{t-2} + \dots, \quad (13)$$

where V_t is the vector of structural shocks with elements v_{jt} and $j \in \{1, \dots, J\}$. In that case, the equation for, say, output, will be:

$$\begin{aligned} \Delta y_t = & \phi_{y1}^0 v_{1t} + \dots + \phi_{yj}^0 v_{jt} + \dots + \phi_{yJ}^0 v_{Jt} + \\ & + \phi_{y1}^1 v_{1t-1} + \dots + \phi_{yj}^1 v_{jt-1} + \phi_{yJ}^1 v_{Jt-1} + \dots \end{aligned} \quad (14)$$

Since $\Delta_h y_{t+h} = \Delta y_{t+h} + \Delta y_{t+h-1} + \dots + \Delta y_{t+1}$, then it is clear that

$$R(y_t, h, v_j) = \phi_{yj}^0 + \dots + \phi_{yj}^h$$

and

$$O(h, v_j) = \frac{\phi_{yj}^0 + \dots + \phi_{yj}^h}{\phi_{Uj}^0 + \dots + \phi_{Uj}^h}.$$

If estimates \hat{v}_{jt} are available, and these can be shown to be orthogonal to the remaining elements in V_t (some of which we may not have available data for), then estimates $\hat{R}(\cdot)$ and $\hat{O}(\cdot)$ can be obtained from the direct regression:

$$\Delta y_t = \alpha + \phi_{yj}^0 \hat{v}_{jt} + \phi_{yj}^1 \hat{v}_{jt-1} + \dots + \phi_{yj}^H \hat{v}_{jt-H} + e_{yt} \quad (15)$$

and a similar regression for ΔU_t . Estimates $\hat{\phi}_{yj}^h$ will be consistent for ϕ_{yj}^h even though the regression omits the regressors other than the j^{th} and denoted $\hat{v}_{-j,t-h}$. Econometric justification can be found, e.g. in Lewis and Reinsel (1985) and Chang and Sakata (2007).

Similar specifications of this type of regression in economics include Ramey and Shapiro (1998) and Basu and Fernald (2006). In these studies it is common to include lags of the dependent variable in equation (15) so that the effect of the shocks v_{jt} is propagated through the internal univariate dynamics implied by the added lags of the outcome variable. As an example, suppose we replace equation (15) with an abbreviated version:

$$\Delta y_t = \alpha + \rho \Delta y_{t-1} + \phi_{yj}^0 \hat{v}_{jt} + \phi_{yj}^1 \hat{v}_{jt-1} + e_{yt}.$$

The effect of a unit shock to \hat{v}_{jt} over time is then given by: $\phi_{yj}^0, \rho \phi_{yj}^0 + \phi_{yj}^1, \dots, \rho^h \phi_{yj}^0 + \rho^{h-1} \phi_{yj}^1, \dots$

In general, if the process (13) has been generated by an autoregressive process, then expression (15) would be naturally specified to include the lags of the elements in X_t along with the estimated residuals \hat{v}_{jt} and its lags. As long as the \hat{v}_{jt} are properly identified, it does not affect the consistency of an expression such as (15) although inclusion of the lagged values of X_t would improve accuracy (ignoring for now that we often do not have an easy way to control for first stage estimation uncertainty in the \hat{v}_{jt}).

An alternative estimation strategy is to extend the instrumental variable approach used in the estimate of Okun's law in equation (1) using Jordà's (2005) local projection approach. Specifically, consider estimating $O(\cdot)$ in expression (12) directly using the sequence of regressions:

$$\Delta_h y_{t+h} = \alpha_h + \beta_h \Delta_h U_{t+h} + \sum_{i=1}^p \Gamma_i^h X_{t-i} + e_{t+h}, \quad (16)$$

for $h = 0, 1, \dots, H$. It is easy to see that, under linearity:

$$E \left\{ \begin{array}{l} E(\Delta_h y_{t+h} \mid \Delta_h U_{t+h} = u, X_t, \dots) \\ -E(\Delta_h y_{t+h} \mid \Delta_h U_{t+h} = 0, X_t, \dots) \end{array} \right\} = E(\hat{\beta}_h) = O(h, u)$$

Since fluctuations in $\Delta_h U_{t+h}$ are a function of a variety of shocks, an estimate of β_h would be a reduced-form average summary $O(h, u) = E_j(O(h, v_j))$. In order to obtain a measure of $O(h, v_j)$ for each v_j , it is natural to estimate (16) using instrumental variables for $\Delta_h U_{t+h}$ based on \hat{v}_{jt} to obtain estimates $\hat{\beta}_h^j$ for each of the j shocks considered. These provide an alternative way of estimating $O(h, v_j)$ in which the regressors X_{t-i} act as controls and instruments at the same time so as to orthogonalize the \hat{v}_{jt} against observables. The next section explores the approaches encapsulated by equations (15) and (16).

5.1 Conditional Okun's Coefficients: A First [Very Preliminary] Pass

This section serves as a bridge between the traditional specification of Okun's law in expression (1) and the corresponding results reported in Table 1, and the dynamic version introduced in (16) and the corresponding results reported in the next section. As a first pass, the objective is to determine whether Okun's coefficient is sensitive to the source of fluctuations in the unemployment rate and output. Do the margins by which the economy adjusts vary depending on whether the economy is hit by a technology improvement or a monetary policy intervention?

The empirical strategy is straightforward. We estimate expression (1) using instrumental variables based on three alternative series of shocks that have been extensively analyzed in the literature.

Conceptually, instrumenting involves relating the components that are "explained" by each of the

shocks—whatever the dynamics of how the economy actually adjusts to them. The results in this section serve as a platform to interpret the dynamic results reported in the next section.

The Fernald (2012b) dataset includes a measure of technology, which is a residual of TFP growth after controlling for utilization. . These have been labeled Δa_t in expression (10). Basu, Fernald, and Kimball (2006) discuss how the economy responds to such a shock.. For example, the economy’s ability to produce more output with the same inputs in an environment of sticky prices may lead to a temporary reduction in inputs and higher unemployment before productivity gains take hold. After that, output grows and unemployment declines. Typical RBC models would give a very different response. (Francis and Ramey (2005) point out that even with flexible prices, models with habit persistence, investment adjustment, and/or low capital-labor substitutability can potentially lead to a decline in equilibrium inputs, since aggregate demand rises less than productivity following a rise in technology.)

In a series of articles, Hamilton (e.g., 2011 and 2003), Hamilton and Herrera (2004), and numerous others investigate the role of oil prices in macroeconomic fluctuations. The margins through which output responds to fluctuations in oil prices remains a matter of intense debate. For example, an open questions is the role that monetary policy can play in dampening or magnifying the effect of an increase in oil prices. Another is whether oil prices decreases have a symmetric effect on economic performance. Our second candidate shock series is therefore based on a series that updates Hamilton (2003), which measures oil shocks as increases in the price of oil above its peak level in the preceding 12 quarters.

Our final candidate shock series help us explore how the economy adjusts to economic policy. Theoretically, we think of monetary policy as following different channels than our earlier two shocks. An extensive empirical macroeconomics literature (see, e. g. the review by Christiano, Eichenbaum and Evans, CEE, 1999) documents that monetary policy tends to generate a hump shaped response in output and employment/unemployment although less is known about other margins of adjustment such as hours and utilization. Therefore, our third candidate shock series is residuals from the CEE VAR. .

The first step in the empirical analysis is to determine whether these shock series are orthogonal to one another. If they are not, we may suspect that, for example, fluctuations in output and unemployment due to an oil price increase may be confound the response of the monetary authority to such an increase in oil prices. A simple way to check for orthogonality is to regress each shock on eight lags of itself and another shock and eight of its lags, one at a time. Then one can evaluate the joint significance of the regressors associated with each candidate shock. The results of this exercise are reported in Table 3. By and large, the null holds pretty well, though there are several instances of p-values above 5 percent but below 10 percent. Henceforth, we proceed under the assumption that these shocks are orthogonal to one another.

Next, Table 4 displays estimates of the Okun coefficients instrumented with the technology (utilization-adjusted TFP) and monetary shocks, using the same breakdown as Table 1. Broadly speaking, separating the source of the shock through instrumental variable estimation has surprisingly little impact on the estimate of Okun's coefficient. Whereas in Table 1 we found a benchmark unconditional (OLS) estimate of -2.33, the conditional responses are between -2.41 and -2.51 in Table 4—a narrow interval.

Even looking at differences across shocks at a more granular level in the margins used to adjust to each type of shock, there are relatively few differences for employment, hours, and even TFP. For TFP, the breakdown between utilization and utilization-adjusted TFP does look very different for a shock to technology versus a shock to demand (money or oil). In particular, the component of unemployment that is explained by technology shocks is highly positively correlated with technology shocks; the component explained by monetary or oil shocks is (as expected) insignificantly correlated. However, the response of utilization is much larger, and negative, with technology shocks.

The evidence in the literature that technology improvements raise unemployment on impact, but eventually reduce unemployment, may be able to generate this pattern. In particular, that response

generates a strong incentive to hoard labor in the near term, since firms will want those workers in the future.

Still, the results are surprising in light of a large extant literature in macroeconomics that emphasizes differences across model paradigms in the manner economies adjust to shocks. There is considerable stability in the margins of adjustment spelled out by Okun's law regardless of the source of the shock. These results help explain why Okun's coefficient appears fairly stable in our results and elsewhere in the literature (see Ball et al. 2012). The next section resolves the conundrum of a stable Okun coefficient in the context of macro models where shocks have very different effects. In particular, it provides a dynamic version of these estimates as characterized by expression (16).

5.2 Conditional Okun Coefficients: Impulse Responses

[To be added]

6. Conclusion

In this paper, we examine whether the celebrated reduced form relationship known as Okun's Law, relating changes in output to changes in unemployment, holds relevant lessons for modern macroeconomic theory. From the perspective of production theory, Okun's Law fundamentally relates output growth to input growth, with unemployment changes serving as a proxy for growth in labor and other inputs. In this way, Okun's Law acts like a microscope, focusing our attention on comovement of the key business cycle variables of output and unemployment as a way to summarize more complicated and difficult to observe underlying relationships.

Looking beyond the macroscopic view, we then derive and implement a growth-accounting framework that links Okun's Law to recent macroeconomic research. This decomposition sheds light on the empirical magnitude of key margins of adjustment used by firms and households that underlie the observed comovement of output and unemployment. This light, in turn, can guide macroeconomic researchers who need to model fundamental relationships parsimoniously. That is, accounting for Okun's relationship provides insight into features of models that are essential to match the data.

In this regard, we highlight two key lessons for macroeconomists. First, the responsiveness of hours to changes in unemployment is much larger than typically allowed in DSGE models. We find that hours worked falls about 2 percent when unemployment rises a percentage point. The typical DSGE model assumes a relationship that is rarely much larger than 1-to-1. This finding suggests that incorporating additional margins of adjustment into DSGE models may be important for matching fluctuations in the economy.

Second, we find that the factor-utilization margin is particularly important in recessions—leading productivity to be more procyclical in recessions than other times. Moreover, this margin plays a quantitatively important role in explaining the cyclicity of labor productivity. Specifically, a reduced response of utilization to unemployment fluctuations is important in explaining why labor productivity shifted from procyclical to countercyclical around the time of the Great Moderation. These results tie into a large previous literature that emphasizes the importance of unobserved variations in factor intensity in explaining productivity movements (see Basu and Fernald, 2001, for discussion and references), as well as the many DSGE models that find that a utilization margin helps to propagate shocks.

Our analysis also has implications for forecasters and policymakers, who often use Okun’s law as a convenient rule of thumb. We find that Okun’s Law responds differently to different shocks.¹⁰ The most striking example is for the case of technology shocks, which directly change output without any change in inputs. Hence, over any short period, there’s no reason to expect Okun’s Law to hold. We also find that the persistence of shocks matters for the short-run movements in Okun’s Law. For example, Fernald (2012a) finds that utilization returned relatively quickly to trend after the Great Recession—much more quickly than the return of unemployment to its natural rate; indeed, as of mid-2013, this process is still ongoing. More generally, the relationship between unemployment and intensive margins (utilization and hours per worker) may well differ from its unconditional average if the source or persistence of shocks differs from average.

¹⁰ At least, that’s what we expect to find!

The fact that variations in Okun's Law relate directly to the source and persistence of shocks suggests that policymakers may not want to rely on it as a short-run tool for calibrating forecasts. That said, in the preliminary finding reported here we also show that the fitted values to technology and monetary shocks yields similar "average" Okun coefficients, implying that although the path of adjustment might differ, averaging across that path yields surprisingly similar results.

Appendix A: Fernald (2012b) Quarterly Growth-Accounting Data

These data are available at http://www.frbsf.org/economics/economists/jferald/quarterly_tfp.xls. They include quarterly growth-accounting measures for the business-sector, including output, hours worked, labor quality (or composition), capital input, and total factor productivity from 1947:Q2 on. In addition, they include a measure of factor utilization that follows Basu, Fernald, and Kimball (2006). They are typically updated one to two months after the end of the quarter (for example, data through 2011:Q4 were posted on February 2, 2012, following the release of BLS Productivity and Cost data for the fourth quarter). Once aggregated to an annual frequency, they are fairly close to the annual BLS multifactor productivity estimates, although there are some differences in coverage and implementation.¹¹ The data are described in greater detail in Fernald (2012b).

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

- (i) Business output: We use income and expenditure side measures of real output. The expenditure side, which corresponds to GDP is reported in NIPA tables 1.3.5 and 1.3.6 (gross value added by sector). Nominal business income (the business counterpart of GDI is GDI less nominal non-business output from table 1.3.5. Real GDI and business income uses the expenditure-side deflators.
- (ii) Hours: From the quarterly BLS productivity and cost release.
- (iii) Capital input: Weighted growth in 13 types of disaggregated quarterly capital. Weights are estimated factor payments (which, in turn, use estimated user costs). The quarterly national income and product accounts (produced by the Bureau of Economic Analysis, BEA) provide quarterly investment data for 6 types of non-residential equipment and software; and for 5 types of non-residential structures. I use these data to create perpetual-inventory series on (end of previous quarter, i.e., beginning of current quarter) capital stocks by different type of asset. In addition, I use quarterly NIPA data on inventory stocks and interpolate/extrapolate the annual BLS estimates of land input. Note that the data also allow me to calculate sub-aggregates, such as equipment and software capital, or structures capital.
- (iv) Factor shares: Interpolated and, where necessary, extrapolated from the annual data on factor shares, α and $(1 - \alpha)$, from the BLS multifactor productivity database.
- (v) Labor composition: Interpolated and extrapolated from annual measures in the BLS multifactor productivity data.

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

- (vi) Hours-per-worker (H^i / N^i) by industry from the monthly employment report of the BLS. These are used to estimate a series on industry utilization $\Delta \ln U_i = \beta_i \Delta \ln(H^i / N^i)$, where β_i is a coefficient estimated by Basu, Fernald, and Kimball (BFK, 2006).

¹¹ To name six minor differences: (i) BLS covers *private* business, Fernald covers total business. (ii) BLS uses expenditure-side measures of output, whereas Fernald combines income and expenditure-side measures of output. (iii) BLS assumes hyperbolic (rather than geometric) depreciation for capital. (iv) BLS uses the more disaggregated investment data available at an annual frequency. (v) Fernald does not include rental residential capital. (vi) There are slightly different methodologies for estimating labor quality. Some of these differences reflect what can be done quarterly versus annually. For a review of the methodology and history of the BLS measures, see Dean and Harper (2001).

Fernald then calculates an aggregate utilization adjustment as $\Delta \ln U = \sum_i w_i \Delta \ln U_i$, where w_i is the industry weight from BFK (taken as the average value over the full sample).

The resulting utilization-adjusted series differs conceptually from the BFK purified technology series along several dimensions. BFK use detailed industry data to construct estimates of industry technology change that control for variable factor utilization and deviations from constant returns and perfect competition. They then aggregate these residuals to estimate aggregate technology change. Thus, they do not assume the existence of a constant-returns aggregate production function. The industry data needed to undertake the BFK estimates are available only annually, not quarterly. As a result, the quarterly series estimated here does not control for deviations from constant returns and perfect competition.¹²

For this paper, we modify the TFP and utilization-adjusted TFP measures in two ways relative to the figures in the downloadable spreadsheet. First, we create separate income- and output-side labor- and total-factor productivity measures, rather than simply using the geometric average in Fernald (2012b). Second, the Fernald dataset uses two measures of labor “quality” to adjust for the composition of the workforce by age, education, and other observable demographics. The first measure is interpolated from the annual estimates available from the BLS and is available for the entire sample. The second is a true quarterly measure from the Current Population Survey, which implements the quarterly composition adjustment from Aaronson and Sullivan (2001). Although theoretically preferable, this second measure is available only since 1979. Especially when we look at time variation in coefficients, it is important to have a consistent measure. Hence, we adjust TFP and utilization-adjusted TFP to use the consistent, interpolated BLS measure.

Appendix B: Demand-Side Shocks

Following the literature on procyclical productivity and production-function estimation, we use identified shocks that are orthogonal to technology shocks in the production function. Specifically, we follow Basu, Fernald, and Kimball (2006) and use an updated version of the Hall-Ramey oil-price instrument. Our second demand shock is a “monetary shocks” from an identified VAR.

Monetary Shocks. We use quarterly VAR monetary innovations, following Christiano, Eichenbaum, and Evans (1999) and Burnside (1996). Following Burnside (1996), we measure monetary policy as innovations to the 3-month Treasury bill rate, since the fed funds market did not exist until the mid-1950s (from 1954:1 through 2003:1, the quarterly average 3-month T-bill rate has a correlation with the fed funds rate of over 0.99). More specifically, we measure monetary shocks as the innovations to the 3-month T-bill rate from a VAR with GDP, the GDP deflator, an index of commodity prices, the 3-month T-bill rate, and M1. (We thank Charles Evans for providing RATS code that estimated the VAR and innovations).

Petroleum prices. We base our oil instrument on the “composite” refiner acquisition price (RAP) for crude oil, a series produced by the Department of Energy. The composite price is refiners’ average purchase price of crude oil, i.e., the appropriate weighted average of the domestic and foreign prices per barrel. This series is available quarterly only since 1974; Basu, Fernald, and Kimball (2006) discuss how to estimate this series for earlier periods.

¹² The output data also differ, both in vintage and data source, from the annual data used by BFK.

Hamilton (2003) recommends focusing on oil price increases above the peak level over the preceding 3 years. First, Hamilton and others find a nonlinearity: oil price increases are more contractionary than oil price declines are expansionary. Second, he argues that oil price increases have a larger effect if they follow stable prices than if they simply reverse an earlier decline. Thus, we measure the quarterly oil price ‘shock’ as the difference between the log of the quarterly real oil price and the maximum oil price in the preceding 12 quarters. (In all cases, we measure the quarterly oil price using the last month of the quarter.)

Appendix C: Relating Business and Non-Business Sectors to the Total Economy

Unemployment is for the total economy, whereas our growth-accounting data are for the business sector. The business sector accounts for about $\frac{3}{4}$ of GDP (from the national accounts) and employment (from the Bureau of Labor Statistics via Glaser 2013). The non-business sector is mainly government services, nonprofits, and household workers.

The Tornquist approximation to chained GDP implies the following:

$$dy^{Total} = w_{Business} \cdot dy^{Bus} + (1 - w_{Business}) \cdot dy^{Non-Bus}$$

The logic of the growth-accounting decompositions from the text implies:

$$\beta^{Total} = w_{Business} \cdot \beta^{Bus} + (1 - w_{Business}) \cdot \beta^{Non-Bus}$$

where β^J is from $dy^J = c + \beta^J dU$.

Figure A.1, below, shows these estimates. Total economy is the average of real GDP and real GDI (where real GDI is nominal GDI deflated with the GDP deflator). Non-business output is from NIPA Table 1.3.3 (accessed July 1, 2013). Figure A.2 shows the corresponding responses for hours.

Clearly, the cyclical output for the overall economy comes almost entirely from the business sector. Indeed, the non-business sector displays little cyclical output with respect to unemployment, apart from a brief period in the early 1970s.

Figure A.1. Okun Coefficients by Sector

Okun Coefficients by Sector

40-quarter rolling window

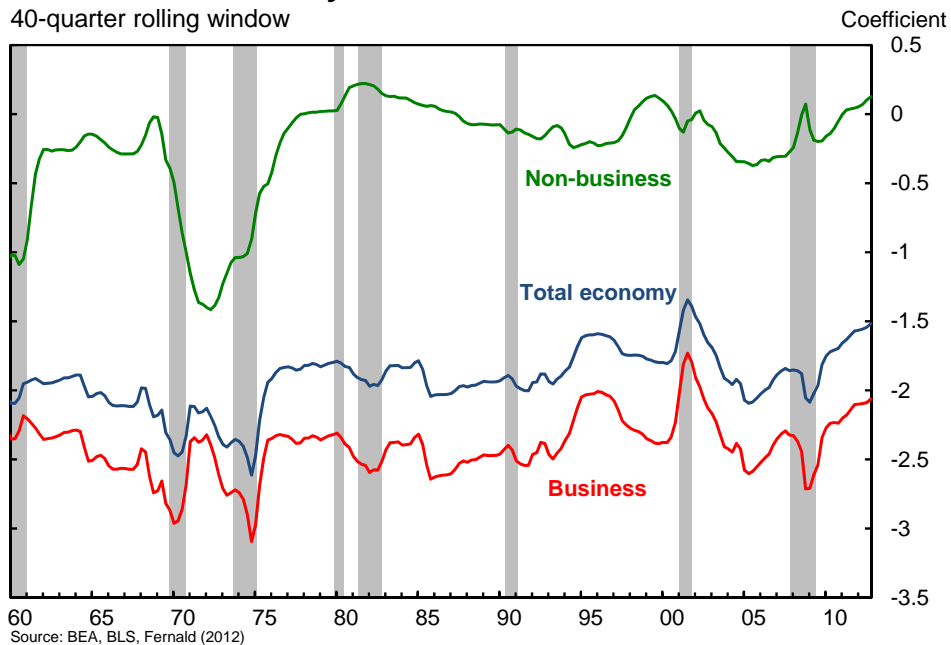
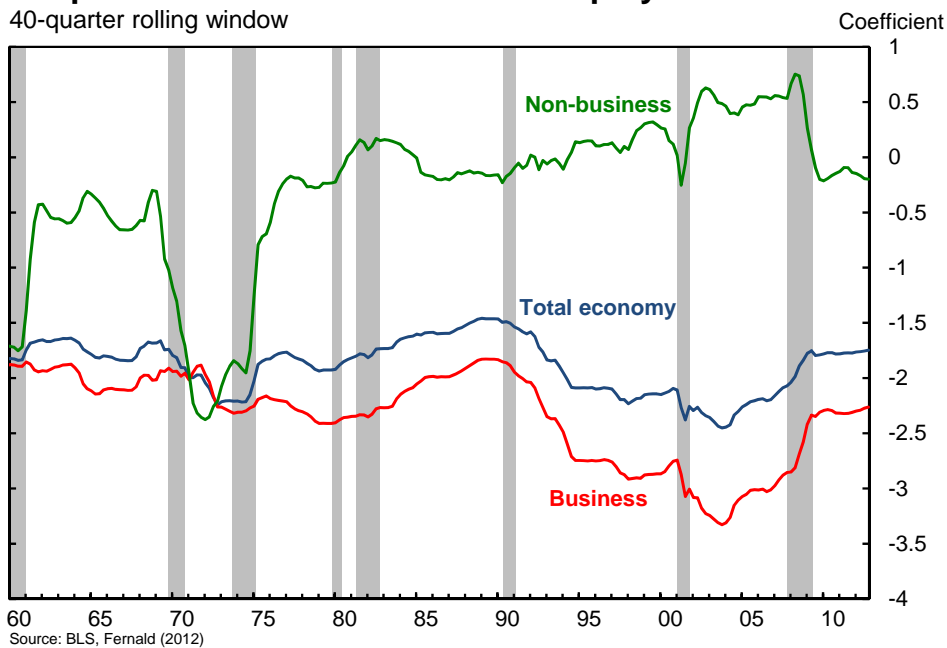


Figure A.2. Response of Hous by Sector

Response of Hours Worked to Unemployment

40-quarter rolling window



Note: Total economy output is average of real GDP and real GDI. Business-sector output, similarly, is average of expenditure and income side data.

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Table 1: Okun's Coefficient Decomposed

		Business Sector		
<u>Variables:</u>		<u>Average</u>	<u>Real Expenditure</u>	<u>Real Income</u>
(1)	Output	-2.33*** (0.10)	-2.24*** (0.10)	-2.42*** (0.10)
(2)	Hours	-2.10*** (0.06)		
(3)	Labor productivity	-0.23* (0.10)	-0.14 (0.10)	-0.31** (0.10)
<u>Contributions to hours growth:</u>				
(2a)	Employees	-1.69*** (0.06)		
(2b)	Hours per employee	-0.41*** (0.03)		
<u>Contributions to labor-productivity growth:</u>				
(3a)	Capital deepening ($\alpha^*(dk-dhours)$)	0.63*** (0.02)		
(3b)	Labor quality ($((1-\alpha)*dLQ)$)	0.07*** (0.01)		
(3c)	TFP	-0.92*** (0.10)	-0.84*** (0.11)	-1.01*** (0.10)
(3c.1)	Utilization	-1.15*** (0.11)		
(3c.2)	Utilization-adjusted TFP	0.23** (0.08)	0.32*** (0.08)	0.14 (0.08)
Sample: 1948Q1:2012Q4				
Source: Authors' calculations				

Notes: For each variable X , the entries shown are the slope coefficients from estimating $\Delta_4 x_t = c + \beta^X \Delta_4 U_t$, where $\Delta_4 x_t$ is the four-quarter growth rate of X and $\Delta_4 U_t$ is the four-quarter percentage-point change in unemployment. The first column of entries measures output as the average of real business expenditure and income; the second and third columns show entries that are affected by the choice of output measure.

Table 2: Okun Decomposition -- Normal Times Versus Recessions

<u>Variables:</u>		α	α^*R	β	β^*R
(1)	Output	3.49*** (0.13)	-1.61*** (0.41)	-1.93*** (0.14)	-0.40 (0.25)
(2)	Hours	1.21*** (0.08)	-0.33 (0.34)	-2.35*** (0.09)	0.29 (0.22)
(3)	Labor productivity	2.27*** (0.12)	-1.28* (0.52)	0.42** (0.13)	-0.69* (0.29)
<u>Contributions to hours growth:</u>					
(2a)	Employees	1.30*** (0.09)	0.44 (0.29)	-2.02*** (0.11)	0.13 (0.19)
(2b)	Hours per employee	-0.09 (0.05)	-0.77*** (0.14)	-0.33*** (0.05)	0.15 (0.11)
<u>Contributions to labor-productivity growth:</u>					
(3a)	Capital deepening ($\alpha^*(dk-dhours)$)	0.70*** (0.04)	0.53*** (0.11)	0.65*** (0.03)	-0.13* (0.06)
(3b)	Labor quality ($(1-\alpha)*dLQ$)	0.23*** (0.02)	0.14* (0.06)	0.11*** (0.03)	-0.06 (0.04)
(3c)	TFP	1.35*** (0.12)	-1.94*** (0.48)	-0.34* (0.14)	-0.50 (0.28)
(3c.1)	Utilization	0.40** (0.14)	-1.02** (0.38)	-0.57*** (0.15)	-0.69** (0.22)
(3c.2)	Utilization-adjusted TFP	0.95*** (0.14)	-0.92* (0.38)	0.23 (0.13)	0.19 (0.25)
Sample: 1971Q1:2012Q4					
Source: Authors' calculations					

Notes: For each business-sector variable X , the entries shown are the coefficients from estimating $\Delta_4 x_t = \alpha + \alpha_R R + \beta \Delta_4 U_t + \beta_R (\Delta_4 U_t \cdot R) + \eta_t$, where R is a dummy for NBER recessions. Output is measured as the average of real expenditure and real income.

Table 3: Exogeneity Tests

Dep. Variable	Regressors		
	Technology	OIL	Monetary
Technology	-	0.09*	0.42
OIL	0.19	-	0.51
Monetary	0.06*	0.09*	-

Notes: p-values of the joint null that the regressor and eight lags are jointly significant. */** used to highlight p-values below 0.10/0.05 respectively.

Table 4: Instrumental Variable Regressions

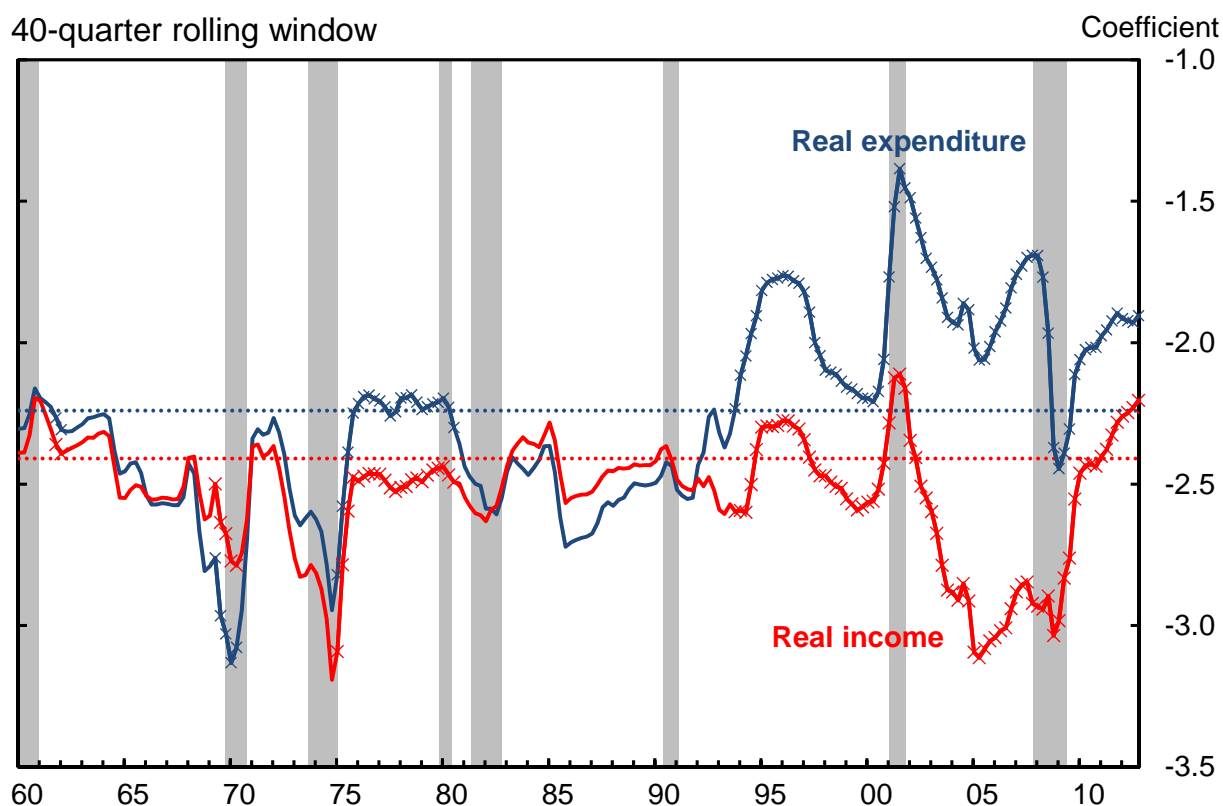
<u>Variables:</u>		<u>Baseline OLS</u>	<u>IV: Monetary</u>	<u>IV: Oil</u>	<u>IV: Technology</u>
(1)	Output	-2.33*** (0.10)	-2.42*** (0.23)	-2.42*** (0.18)	-2.51*** (0.22)
(2)	Hours	-2.10*** (0.06)	-2.29*** (0.17)	-2.12*** (0.08)	-2.11*** (0.13)
(3)	Labor productivity	-0.23* (0.10)	-0.27 (0.26)	-0.31 (0.17)	-0.40 (0.26)
<u>Contributions to hours growth:</u>					
(2a)	Employees	-1.69*** (0.06)	-2.01*** (0.17)	-1.65*** (0.09)	-1.68*** (0.12)
(2b)	Hours per employee	-0.41*** (0.03)	-0.27** (0.09)	-0.46*** (0.05)	-0.43*** (0.06)
<u>Contributions to labor-productivity growth:</u>					
(3a)	Capital deepening ($\alpha^*(dk-dhours)$)	0.63*** (0.02)	0.80*** (0.07)	0.68*** (0.03)	0.69*** (0.05)
(3b)	Labor quality $((1-\alpha)*dLQ)$	0.07*** (0.01)	0.17*** (0.04)	0.10** (0.03)	0.03 (0.03)
(3c)	TFP	-0.92*** (0.10)	-1.11*** (0.24)	-1.08*** (0.20)	-1.12*** (0.24)
(3c.1)	Utilization	-1.15*** (0.11)	-0.66** (0.25)	-0.84*** (0.19)	-2.07*** (0.28)
(3c.2)	Utilization-adjusted TFP	0.23** (0.08)	-0.44 (0.26)	-0.25 (0.18)	0.95*** (0.22)
Sample: 1948Q1:2012Q4					
Source: Authors' calculations					

Notes: Regressions are the same as in Table 1, except that they are estimate via instrumental variables, using current and 8 lags of the four-quarter changes in the shocks as instruments. Conceptually, this regression relates the components of each variable, including unemployment changes, that are explained by the instruments. The instruments, in turn, are monetary innovations from an SVAR, oil-price increases (above their peak of the previous 12 quarters), and utilization-adjusted TFP (see data appendix).

Figure 1: Okun's Coefficient over Time: Real-Income and Real-Expenditure

Okun's coefficient over time

40-quarter rolling window



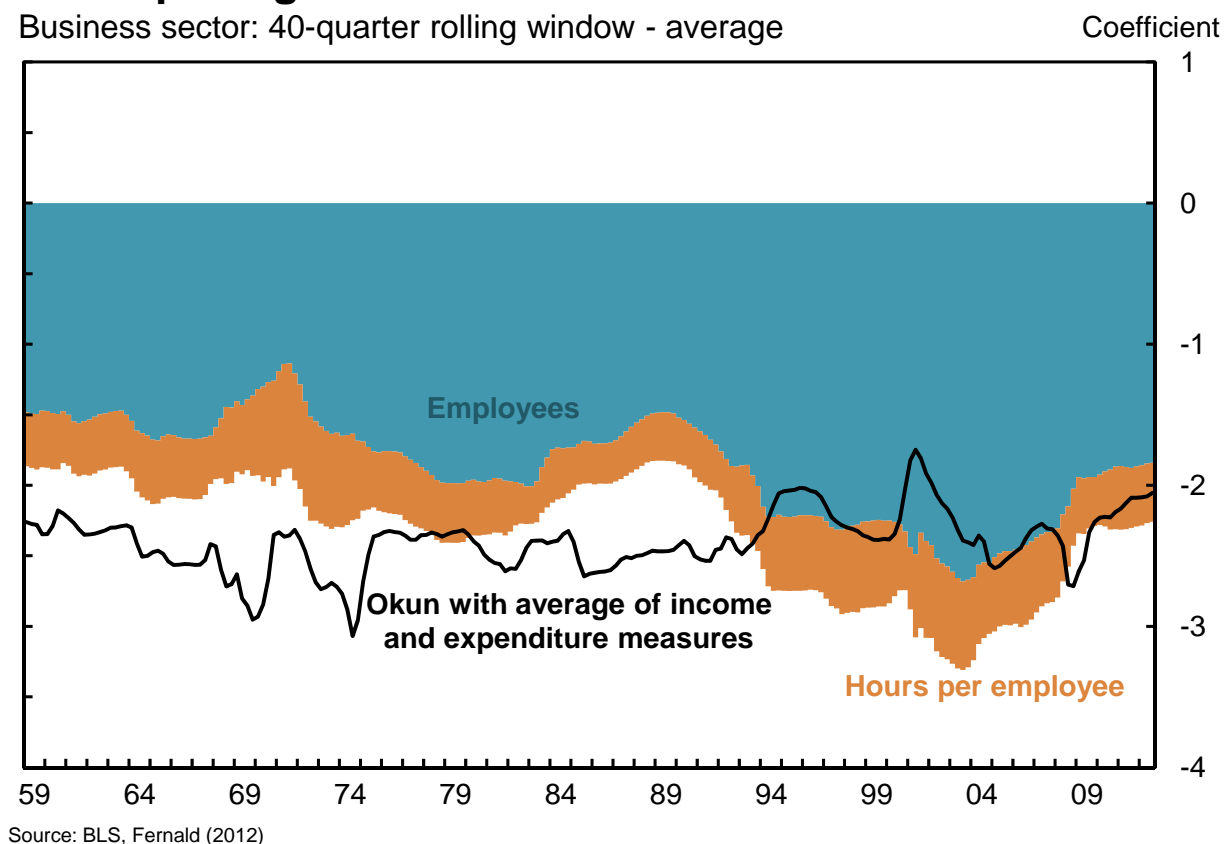
Source: BLS, Fernald (2012)

Notes: The figure plots the slope coefficient from $\Delta_4 y_t = c + \beta^y \Delta_4 U_t$, estimated over the 40-quarters ending in the quarter shown. Cross-hatches show observations where the coefficient is significantly different when output is measured from the income versus expenditure sides.

Figure 2: The Contribution of Hours Growth to Okun's Coefficient over Time

Decomposing Okun's coefficient - hours

Business sector: 40-quarter rolling window - average

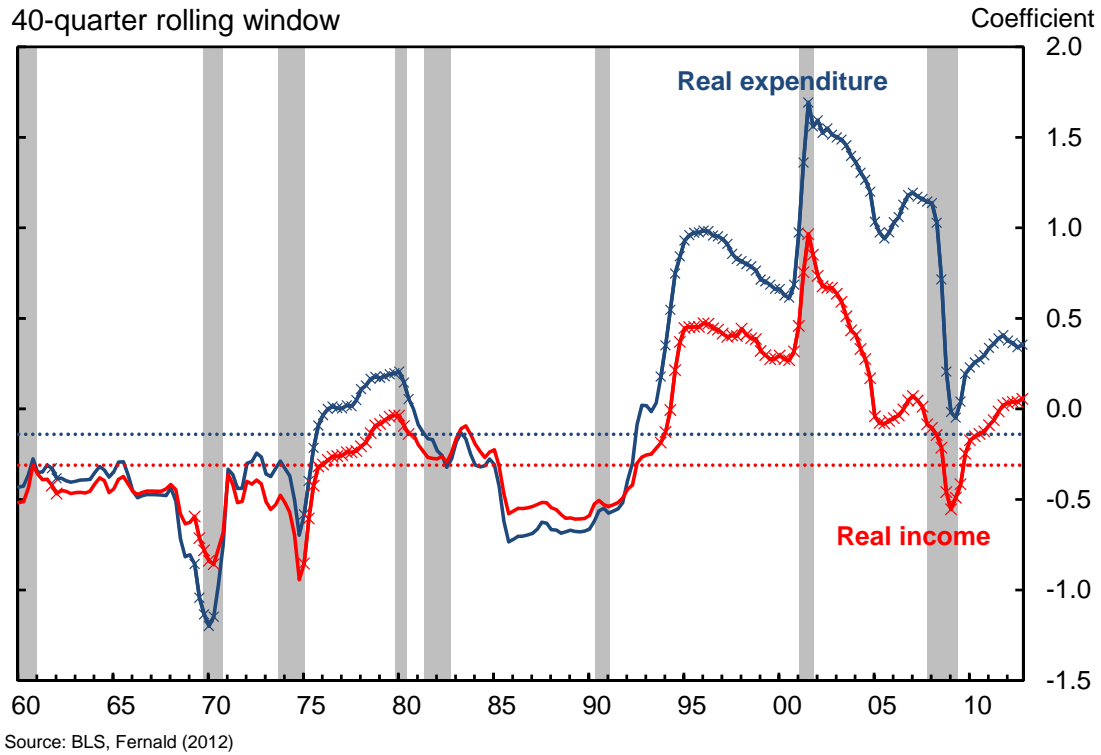


Source: BLS, Fernald (2012)

Notes: For each variable X , the width of each area shows the slope coefficients from $\Delta_4 x_t = c + \beta^X \Delta_4 U_t$, estimated over the 40-quarters ending in the quarter shown. The sum of the areas for employees and hours per employee equals the coefficient for total hours worked. For comparison, the Okun coefficient shows the value of β^Y .

Figure 3: The Contribution of Labor Productivity to Okun's Coefficient over Time

Labor Productivity: Okun's coefficient over time



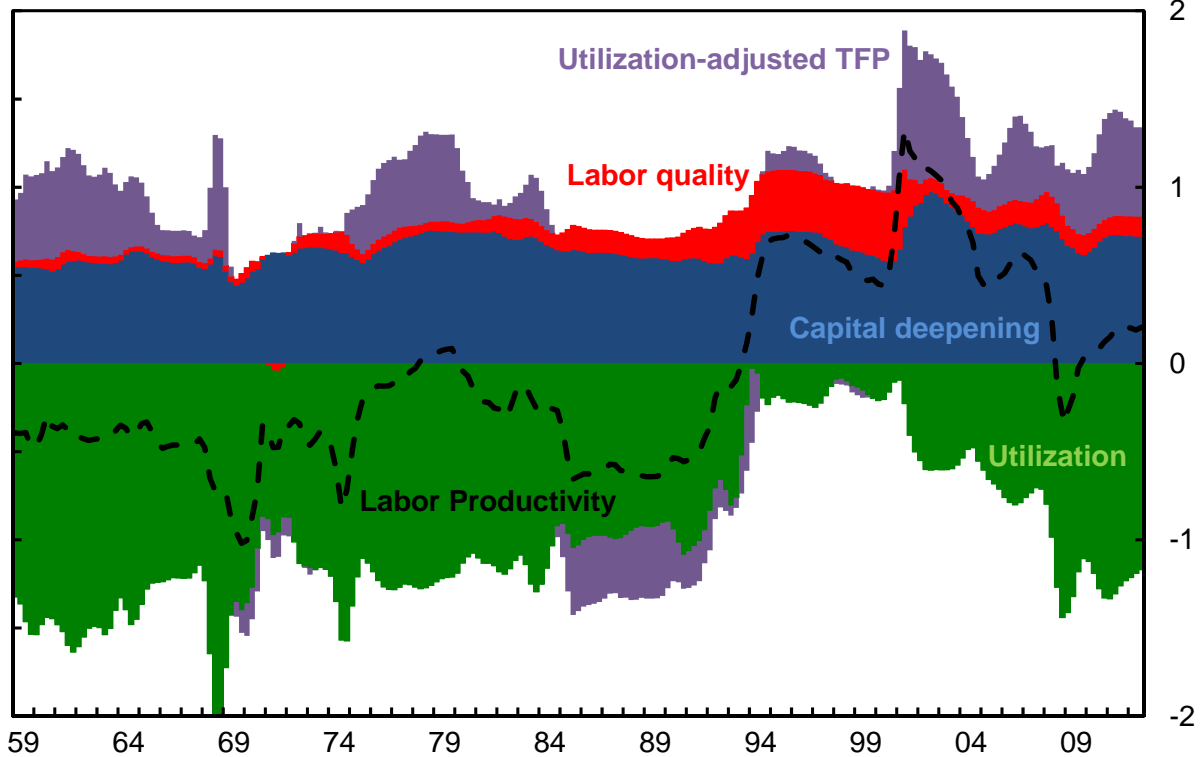
Notes: The figure plots the slope coefficients β^x from $\Delta_4 y_t - \Delta_4 l_t = c + \beta^{LP} \Delta_4 U_t$, estimated over the 40-quarters ending in the quarter shown. Cross-hatches show observations where the coefficient is significantly different when output is measured from the income versus expenditure sides.

Figure 4: Contributions to Labor Productivity Growth over Time

Decomposing Okun's Coefficient - Labor Productivity

Business sector: 40-quarter rolling window - average

Coefficient



Source: BLS, Fernald (2012). Output is the average of the income and expenditure measures.

Notes: For each variable X , the width of each area shows the slope coefficients from $\Delta_4 x_t = c + \beta^X \Delta_4 U_t$, estimated over the 40-quarters ending in the quarter shown. The width of the positive areas, less the width of the negative areas, equals the coefficient on labor productivity, shown with the dashed line.