Output and Unemployment Dynamics

Mary C. Daly        John G. Fernald        Óscar Jordà        Fernanda Nechio

Federal Reserve Bank of San Francisco

March 30, 2015

Abstract

The strong and systematic comovement of unemployment and output is a defining feature of business cycles. We derive and implement a new growth-accounting decomposition of this "Okun relationship" that quantifies key margins of adjustment used by households and firms. The relationship has been surprisingly stable over time and over the business cycle—despite considerable changes in underlying economic relationships. When we condition on different shocks, we can explain the patterns we find. Specifically, though the time path of output and unemployment varies considerably depending on the shock, the eventual implications for unconditional comovement turns out to be fairly similar. Regardless of the shock, hours worked typically falls about two percent when the unemployment rate rises by a percentage point—more than typically allowed by the structure of recent macro models. A technology shock leads to a larger decline in hours than a demand shock, but the output-unemployment relationship is nevertheless stable because technology shocks induce positive and offsetting comovement of labor productivity and unemployment. Finally, the shift from procyclical to countercyclical labor productivity reflects two factors during the Great Moderation period: first, technology shocks appear relatively more important; second, factor utilization is less closely associated with unemployment fluctuations, consistent with increasing flexibility of the economy.

JEL classification codes: E23, E24, E32, J20

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

*We thank Valerie Ramey and participants at the SED 2013, 2013 NBER Summer Institute, the 2014 European Economic Association meetings, and several academic institutions for helpful comments on this paper. We also thank Bart Hobijn, Ron Smith, and seminar participants at the Bank of England for helpful comments on an earlier and much different draft. Last but not least, we thank Daniel Molitor and Kuni Natsuki for excellent research assistance. This paper was previously circulated under the title “Okun’s Macroscope and the Changing Cyclicality of Underlying Margins of Adjustment.” The views expressed in this paper are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of San Francisco or the Federal Reserve System. E-mails: mary.daly@sf.frb.org; john.fernald@sf.frb.org; oscar.jorda@sf.frb.org; fernanda.nechio@sf.frb.org. Corresponding author: John Fernald, email: john.fernald@sf.frb.org.
1 Introduction

The strong and systematic relationship between output and unemployment is a defining feature of business cycles. In 1962, Arthur Okun summarized this relationship with a regression that related change in the unemployment rate to changes in real output growth. The relationship, often termed Okun’s Law, appears in forecasting models used by central banks, governments, and the private sector. Empirically, a one-percentage point increase in the unemployment rate is associated with about a 2 percent decline in output, and the $R^2$ of this relationship is above 0.7.

Despite its robustness as an empirical stylized fact, Okun’s Law rarely appears in modern macro studies. In this paper, we present a new growth-accounting decomposition of the Okun relationship that maps it to the language of modern macroeconomics. Specifically, the terms in the decomposition reflect margins of adjustment by firms and workers in the economy—margins which naturally appear in structural models. We implement this decomposition with a relatively recent growth-accounting dataset, both unconditionally and in response to identified shocks.

The results suggest several lessons for macro modelers. First, the magnitude of Okun’s Law primarily reflects the strong association of changes in unemployment with changes in hours worked. A close relationship is not surprising, of course, but the response of hours is almost twice as large as allowed for in many dynamic stochastic general equilibrium (DSGE) models with unemployment (e.g., Gali, Smets, Wouters 2011 or Christiano, Eichenbaum, and Trabandt, 2013). The reason is that one needs multiple margins of labor adjustment to fit the data, not just the direct channel that more unemployment means fewer people employed. Empirically, extensive margins include labor force participation and multiple-job holding, along with the intensive margin of hours per worker.

Second, the overall output-unemployment relationship has remained remarkably stable over time. This stability, which is also discussed by Ball, Leigh and Loungani (2013) and Daly et al., (2014), is surprising in light of evidence that underlying relationships have changed. For example, Gali and Gambetti (2009) and Barnichon (2010) highlight that productivity has shifted from procyclical to countercyclical. They point to increased flexibility of the labor market and an increased relative importance of technology shocks.

Third, we find that the overall stability of the Okun relationship is, indeed, consistent with substantial changes in the underlying relationships. Labor productivity shifted from being procyclical

---

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 Multiple-job holding is extensive from the point of view of firms, but intensive (hours per person) from the point of view of households.
to being countercyclical during the Great Moderation period. In a growth-accounting sense, this shift reflects primarily a reduced association of factor utilization with changes in the unemployment rate. Despite this shift in the cyclicality of productivity, the overall Okun relationship has been stable because of an offsetting increase in the magnitude of the employment decline associated with an increase in the unemployment rate. This larger decline in employment reflects especially an increased importance of the participation margin after the early 1980s. We also confirm that these changing patterns are consistent with data from both the household and establishment surveys. Thus, we find no support for recent claims by Hagedorn and Manovski (2011) that the shift in the cyclicality of productivity reflects an increase in cyclical measurement error in surveys of firms.

Fourth, when we look at responses conditional on different shocks, we can explain the patterns we see in the data. As expected, different shocks imply different dynamic paths for the economy. More surprisingly, demand shocks and technology shocks turn out to imply relatively similar unconditional relationships between output and unemployment. Thus, changes in the mix of shocks over time are consistent with a relatively stable unconditional relationship between output and unemployment.

However, the contributors of this stable output-unemployment relationship change. Specifically, technology shocks lead labor productivity to rise when unemployment rises (i.e., to be countercyclical), while leading to more of a decline in hours worked for a given unemployment change. Thus, as proposed by Gali and Gambetti (2009) and Barnichon (2010), the data are consistent with an increasing relative importance of technology shocks during the Great Moderation period.

We also find evidence that increasing flexibility of the economy contribute to the changing cyclicality of productivity by reducing the association of factor utilization with unemployment changes. This flexibility may also contribute to the greater responsiveness of hours worked to unemployment changes. But the flexibility must go beyond simply a greater propensity to fire workers (which would affect both employment and unemployment one-for-one). Rather, it appears to reflect the increased importance of the participation margin.

2 Margins of adjustment, growth accounting and Okun’s Law

We now develop growth accounting that relates changes in unemployment and changes in output. This approach to Okun’s Law imposes limited structure that is consistent with the supply-side of many macroeconomic models. Thus, it allows us to discuss Okun’s Law in terms of the language of modern macro theory. The objects in the growth accounting, such as changes in hours worked, are equilibrium objects which reflect the choices of households and firms about how to adjust to the shocks that hit the economy. From this perspective, Okun’s Law provides a convenient summary of
many different supply-side margins of adjustment in terms of a single coefficient. The accounting then allows us to discuss the contribution of different margins.

The theoretical underpinning of Okun’s Law in this section comes from production theory. It is straightforward to map changes in the unemployment rate to changes in the inputs used by firms—relatively directly in the case of labor, and indirectly for other inputs. Standard growth accounting then implies a relationship between changes in inputs and changes in output. For this reason, we consider the following specification of Okun’s Law, which relates the growth rate (log change) in real output, $\Delta y$, and the change in the rate of unemployment, $\Delta U$:

$$\Delta y = \mu + \beta \Delta U + \varepsilon. \tag{1}$$

Lower-case letters denote log-levels, and $\Delta$ denotes the time difference operator. This is one of the classical specifications of Okun’s law.

The coefficient $\beta$ directly captures the unconditional (reduced form) comovement of output and unemployment. To map this simple reduced form to underlying economic relationships and margins of adjustment, we decompose $\Delta y$ using production-theory. First, note that output growth can be written as the sum of growth in total hours, $\Delta l$, and labor productivity, $(\Delta y - \Delta l)$:

$$\Delta y \equiv \Delta l + (\Delta y - \Delta l). \tag{2}$$

The OLS estimate of $\beta$ from (1) equals the sum of the coefficients from the linear projections of growth in hours and labor productivity on unemployment changes. That is,

$$\hat{\beta} = \hat{\beta}^{\text{Hours}} + \hat{\beta}^{\text{LP}}, \tag{3}$$

where the coefficients are from the regressions:

$$\Delta l = \beta^{\text{Hours}} \Delta U + \eta^{\text{Hours}} \tag{4}$$

$$\Delta y - \Delta l = \beta^{\text{LP}} \Delta U + \eta^{\text{LP}} \tag{5}$$

Equations (4) and (5) can be expanded further in terms of theory and identities. To begin, labor hours $L = H \cdot N$, where $N$ is the number of workers and $H$ is hours per worker, $L/N$. Hence,

$$\Delta l \equiv \Delta n + \Delta h. \tag{6}$$

---

3 Prachowny (1993) also links Okun’s Law to production theory but not through a growth-accounting decomposition.

4 To see this, note that the Okun coefficient is $\text{cov}(\Delta y, \Delta U)/\text{var}(\Delta U) = \text{cov}(\Delta l, \Delta U)/\text{var}(\Delta U) + \text{cov}(\Delta y - \Delta l, \Delta U)/\text{var}(\Delta U) = \hat{\beta}^{\text{Hours}} + \hat{\beta}^{\text{LP}}$. 

4
Following the logic of the decomposition in (3), we can thus write $\hat{\beta}^{\text{Hours}} = \hat{\beta}^N + \hat{\beta}^h$.

Next, we decompose labor productivity based on an aggregate production function. Following Basu, Fernald and Kimball (BFK, 2006), we allow a broad range of inputs:

$$Y = F (W \times K, L \times Q \times E, A).$$

Output $Y$ depends on capital services, labor services, and technology. Capital services, in turn, depends on the the stock of capital, $K$, and the workweek of capital (the number of hours the capital is actually in operation), $W$. Effective labor services depends on hours $L$; the average “quality” of each hour, $Q$, which captures age, experience, and other observables; and effort $E$ per quality-adjusted hour. Note that capital utilization shows up in $W$ and labor hoarding in $E$. $A$ is technology.

We now take log differences and impose the usual growth-accounting assumptions that the representative firm produces with constant returns, faces perfect competition, and takes factor prices as given. Under these circumstances, cost-minimization implies that output elasticities are equal to factor shares. We denote capital’s share by $\alpha$ and labor’s share by $(1 - \alpha)$. In the Cobb-Douglas case, the factor shares are constant. In the more general case, the shares—and the output elasticities—change over time. (In our data, the shares are time-varying.)

With these assumptions, the production function takes the form (in growth rates):

$$\Delta y = \alpha (\Delta k + \Delta k) + (1 - \alpha) (\Delta l + \Delta e + \Delta q) + \Delta a,$$

where, again, we use lower case to indicate the logs of the variables and $\Delta$ to denote first differences.

We define the standard measure of total factor productivity (TFP) growth, $\Delta z$, as output growth less share-weighted input growth. That is:

$$\Delta z = \Delta y - \alpha \Delta k - (1 - \alpha) (\Delta l + \Delta q).$$

Defining the contribution of factor utilization (the workweek of capital and labor effort) to growth as $\Delta v \equiv \alpha \Delta w + (1 - \alpha) \Delta e$, we can then use expression (7) to write $\Delta z = \Delta v + \Delta a$. In words, TFP growth reflects variations in factor utilization and in technology. We will refer to the empirical counterpart of $\Delta a$ as “utilization-adjusted TFP.” $\Delta a$ is technology for the case of perfect competition.

---

5 An example of a more general functional form is the translog, which is a flexible second-order approximation to any function. With this functional form, growth rates are written as log-changes and the shares are averages in periods $t$ and $t - 1$; these are the conventions followed in our data. Elsby, Hobijn and Sahin (2013) discuss the declining labor share over the past two decades. That said, constant versus time-varying shares has little impact on the later analysis. Basu and Fernald (2001) discuss the more general case in which an aggregate constant-returns production function may not exist. Failures of these maintained assumptions can add additional non-technology terms to the empirical measure of utilization-adjusted TFP.
and an aggregate production function.\footnote{Consistent with our assumptions, BFK find that utilization is the most important non-technological factor affecting measured TFP over the business cycle.}

Expression (7) can now be rearranged as follows:

\[ \Delta y - \Delta l = \alpha (\Delta k - \Delta l) + (1 - \alpha) \Delta q + (\alpha \Delta w + (1 - \alpha) \Delta e) + \Delta a \]

\[ \equiv \alpha (\Delta k - \Delta l) + (1 - \alpha) \Delta q + \Delta v + \Delta a. \] (8)

Therefore, labor productivity, \((\Delta y - \Delta l)\), can change because of capital-deepening, given by \(\alpha (\Delta k + \Delta l)\), labor quality, given by \((1 - \alpha) \Delta q\), factor utilization, \(\Delta v\), or technology, \(\Delta a\).

We can now expand \(\Delta y\) in expression (1) with expressions (2), (6), and (8). Doing so maps the Okun coefficient \(\beta\) to margins of adjustment. Specifically,

\[ \Delta y = \frac{\Delta n + \Delta h + \alpha (\Delta k - \Delta l) + (1 - \alpha) \Delta q + \Delta v + \Delta a}{\Delta l} \] (9)

\(\Delta y\) in expression (1) can now be decomposed using expression (9) to measure the relative contribution of each margin of adjustment. As discussed in the context of equation (3), the OLS estimate \(\hat{\beta}\) in expression (1) is the sum of the projection coefficients of each term in expression (9) on \(\Delta U\). This is the main decomposition we work with in the sections that follow.

Of course, (9) focuses on margins of adjustment from the point of view of firms. To better understand the labor adjustments, it is useful to further decompose the number of workers. Several household margins of adjustment potentially matter for the link. Specifically, firm employment is the product of three intuitive terms: \footnote{[Note: I merged the LFPR and population, both of which can change and which we can still discuss in the empirical section. It felt like too much in the weeds to talk about population changing here. But maybe it’s useful to have LFPR separately.]} 

\[ N = \left( \frac{Emp}{LabForce} \right) LabForce \left( \frac{N}{Emp} \right) = (1 - U) LabForce \left( \frac{N}{Emp} \right). \] (10)

\(N\) is the number of workers from the point of view of firms; \(Emp\) is the number of people employed from the point of view of households; and \(LabForce\) is the labor force. \(\frac{N}{Emp}\) is a gap between the number of workers as viewed by firms and the number of people in the economy who are employed. Conceptually, the two can differ because one person may work multiple jobs. The first term is employment as a share of the labor force, which is by definition equal to \((1 - U)\).

Suppose the unemployment rate rises by 1 percentage point but nothing else on the right-hand side of (10) changes. That is, the labor force and the worker-employment gap are constant. Many macro models assume this is the empirically relevant case by having only a direct employment margin.
Then, taking logs and differentiating, \(dn = d \log(1 - U) = -dU/(1 - U)\). Since the unemployment rate is a small number, the coefficient on the unemployment rate should be close to, though slightly larger than, one in magnitude.

If nothing else on the right-hand-side of (7) changes, then \(\Delta l \approx -\Delta U\) and (from (7)) output should change by about \(-(1 - \alpha)\Delta U\). In that case, \(\hat{\beta}^\text{Hours}\) would be roughly \(-1\), and \(\hat{\beta}^\text{LP}\) would be roughly \(\alpha\).

As shown in the next section, actual empirical magnitudes are far different. \(\beta\) is about three times larger in magnitude, \(\hat{\beta}^\text{Hours}\) is about two times larger, and \(\hat{\beta}^\text{LP}\) is negative (procyclical) rather than positive (countercyclical). The reason is that other margins adjust. In terms of labor, when the unemployment rate rises, multiple job holders tend to lose second or third jobs, and the labor-force participation rate falls. Hours per worker also tends to fall, pushing the coefficient on total hours even further above unity in absolute value.

Now consider labor productivity in expression (9). When the unemployment rate rises, capital deepening tends to respond countercyclically, as noted, since capital is relatively smooth; and labor quality also responds countercyclically since, empirically, low-skilled workers disproportionately lose jobs. These factors push \(\hat{\beta}^\text{LP}\) to be positive.

On the other hand, declining utilization in recessions pushes measured productivity down. When unemployment is high, firms hoard labor and reduce the workweek of capital (e.g., going from two shifts a day to one). This tends to affect the Okun coefficient \(\beta\) negatively.

Finally, the effects of utilization-adjusted TFP growth, \(\Delta a\), are theoretically ambiguous but are often estimated to be positive. In traditional real-business-cycle-type models, positive technology shocks not only raise TFP and labor productivity but would typically be expected to reduce unemployment. Procyclical productivity would contribute negatively to the Okun coefficient. However, in models with nominal rigidities—and some models with real rigidities—labor productivity and unemployment may be positively correlated conditional on a technology shock. Galí (1999), Francis and Ramey (2005), BFK and others argue that this is the empirically relevant case.

In sum, numerous studies since Okun (1962) have shown that the magnitude of Okun’s coefficient is substantially larger than the labor share. The decompositions in (9) and (10) show that this larger coefficient reflects the systematic cyclicality of other margins of adjustment. We quantify these margins in the next section.

### 3 Margins of adjustment: stylized facts

We now implement the decompositions based on the margins of adjustment introduced above. Section 3.1 describes our data. Section 3.2 reports the broad contributions of each margin, based on equation
(9), to the overall Okun coefficient linking changes in output and unemployment. Sections 3.3 and 3.4 investigate the stability of these relations over time and over the business cycle. Finally, Section 3.5 uses equation (10) to understand which household margins are important.

The key lessons from this section are, first, that the magnitude of the Okun coefficient comes mainly from the strong response of hours worked rather than from labor productivity. The hours response is roughly twice as large as allowed for in typical DSGE models with unemployment, because most models do not have enough margins of adjustment. Second, household data show the empirical importance of a participation margin as well as an intensive margin. Overall, the Okun coefficient is stable over time—surprising, given changes in the economy over time, including a shift in the cyclicality of labor productivity (from procyclical to countercyclical).

Although the growth accounting that underlies the analysis imposes some economic structure, the results reflect unconditional comovement. The equilibrium choices made by firms and households may depend on the shocks that hit the economy. So, in Section 4, we discuss how the responses of the various margins depend on the type of shock. Nevertheless, it turns out that many of the reduced-form lessons from this section remain informative. In particular, it turns out that, empirically, different shocks imply relatively similar unconditional comovement in the data.

3.1 Data

Okun (1962) took a “leap from the unemployment rate to potential output rather than [taking] a series of steps involving several underlying factors,” because he was limited by the data. We overcome these data limitations with relatively new, detailed, and carefully constructed quarterly growth-accounting data for the U.S. business sector from Fernald (2014a). Our dataset, which runs from 1947Q2 through 2014Q1, has each piece of (9). The dataset seeks to be as consistent as possible with production theory.

The appendix discusses the dataset in greater detail, but we highlight a few points here. First, output is the geometric average of the expenditure and income sides of the national accounts. Hence, labor productivity in our data is slightly different from that reported by the Bureau of Labor Statistics (BLS), which uses the expenditure side only. In principle, these two measures should be the same but in practice they are not. Nalewaik (2010) argues that income-side data may provide a more accurate read on economic activity around turning points. Greenaway-McGrevy (2011) and Aruoba, Diebold, Nalewaik, Schofheide and Song (2012) recommend taking a weighted average of the two. For most issues we discuss, the distinction does not matter.

Second, in addition to standard growth-accounting terms, the Fernald (2014a) dataset has an empirical measure of factor utilization. Utilization here is a quarterly implementation of what Basu, Fernald, and Kimball (BFK, 2006) measured annually. 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, observable hours per worker can proxy for unobservable utilization margins and BFK estimate the parameters relating them. BFK and Fernald (2014) implement this measure using detrended hours per worker at a detailed industry level, with different parameters across industries. Because of the industry dimension, variations in measured utilization are not perfectly correlated with aggregate hours per worker.\textsuperscript{8}

Third, as noted, the data covers the business sector. From the point of view of firms, little is lost by focusing on the business sector, since that is the cyclical portion of the economy, as well as the portion where the usual firm-level assumptions apply. The hours data come from the BLS productivity and cost release, which in turn decomposes hours into employment and hours per worker. These employment and hours data are based primarily on surveys of establishments.

But the unemployment rate, of course, corresponds to the overall civilian economy. In addition, focusing solely on establishment-survey data would limit our ability to discuss household margins of adjustment. For this reason, we also look at household-survey data, which allows us to examine extensive and intensive margins from the household perspective. We mainly use measures of persons at work and hours at work, which adjust the headline civilian employment figures for vacations and leaves of absence. The BLS website only has these data back to 1976. But Cocinba and Prescott (2012) have used hardcopies of pre-1976 BLS publications to extend the data back to 1948. We use their raw data on non-seasonally-adjusted persons at work and hours at work in the civilian economy.\textsuperscript{9}

When comparing the household and establishment surveys, it is important to be consistent in coverage, i.e., business versus total economy. To do so, we use unpublished BLS data on employment and hours in the non-business civilian sector. By adding non-business hours and employment to the establishment-based business measures, we obtain an establishment-based total civilian economy measure comparable to the household coverage. Conversely, by subtracting the non-business data from the household measures, we obtain an estimated "household business" measure.

As we show, the establishment and household surveys are broadly consistent with one another. This conclusion contrasts with claims by Hagedorn and Manovski (2011), who appear to find sizeable differences in cyclicality across the two surveys. If true, that would be a major concern for productivity analysts. However, it turns out that their claims come from comparing the more cyclical

\textsuperscript{8}The differences in parameters across industries does not per se contradict the assumption of an aggregate production function. As in Hulten (1978), the aggregate growth-accounting terms still have their expected interpretation as long as all producers are competitive and face the same factor prices.

\textsuperscript{9}We focus on four-quarter changes, so there is no need to seasonally-adjust the data. Indeed, for four-quarter changes, non-seasonally-adjusted data are preferable but usually not available.
business-sector data from the establishment survey with the somewhat less-cyclical total economy data from the household survey. Using data with comparable coverage of the economy, their puzzling finding goes away. Hence, the changes we identify appear robust across datasets. Nevertheless, the two sources yield different insights into the margins of adjustment as viewed by households and by firms.

3.2 A static decomposition

We now project the different margins of adjustment in equation (9) on to the unemployment rate over the entire sample. We find that Okun’s Law primarily reflects the very large response of hours worked to a change in the unemployment rate. A close relationship between unemployment and hours worked is not surprising, but the magnitude of the relationship is larger than typically allowed by the structure of many DSGE models. The magnitude reflects a sizeable intensive margin of hours per worker, as well as a sizeable extensive margin of employees. In Section 3.5 we discuss the extensive margins and find an important role for participation and multiple job-holding.

In the regressions that follow, the sum of the coefficients equals the coefficient in the typical Okun’s law regression of output growth on the change in the unemployment rate in expression (1). Specifically, for any variable $X_{jt}$ with $j = 1, ..., J$ denoting each of the $J$ margins of adjustment that we consider in expression (9), let $x_{jt} = \log X_{jt}$. Then we take the year on year difference, denoted $\Delta_4$, to calculate a smooth yearly rate of change (which we will discuss as percentage changes). The regressions then take the form:

$$\Delta_4 x_{jt} = \mu_j + \beta_j \Delta_4 U_t + \varepsilon_{jt}. \quad (11)$$

Throughout, we define cyclicality with respect to the unemployment rate. Since the unemployment rate falls in booms and rises in recessions, a negative value for $\beta_j$ means that the variable is procyclical—it tends to rise in booms and fall in recessions.

Table 1 reports the estimate of $\beta$ in the usual Okun regression, such as that in (1), as well as the estimates of the $\beta_j$ for each margin. Row (1) shows the estimate of the Okun coefficient for $\beta$, which is -2.25. As noted above, we measure output by averaging the income and expenditure sides of the national accounts. Not shown, the estimate of $\beta$ with real expenditure is -2.20 whereas with real income it is not statistically significantly different at -2.31. Thus, the income and expenditure side measures yield similar results and we proceed with the average.\(^{11}\)

Rows (2) and (3) decompose the Okun coefficient into the contributions of total hours and labor productivity, as in equation (2). The total hours coefficient in row (2) has a value of -2.09. Thus, in an accounting sense, most of the Okun coefficient reflects the large associated decline in hours. The

\(^{10}\)Quarter-to-quarter changes yield qualitatively similar results.

\(^{11}\) [Do we keep what follows?] We show the decomposition in a separate table in the Appendix (Table 4).
labor productivity coefficient of -0.16 in row (3) is marginally significant (at the 90% confidence level), but is roughly an order of magnitude smaller. Over the full sample, productivity is thus modestly procyclical—it tends to rise in booms, when unemployment falls; and it tends to fall in recessions, when unemployment rises. This procyclicality is consistent with the stylized facts from the macro literature (see, e.g., Basu and Fernald 2001 for a discussion and references).

The remaining rows of Table 1 further decompose hours and labor productivity into their constituent elements. First consider total hours. Row (2a) shows that about 80 percent (1.68 percentage points) of the decline in total hours reflects a decline in total employees. Nevertheless, row (2b) shows that hours per worker also falls systematically when the unemployment rate rises. Thus, while the majority of adjustment of total hours take place at the extensive, rather than the intensive, margin, both margins matter quantitatively.

Rows (3a)-(3c) of Table 1 report the estimates on the growth-accounting-based decomposition of labor-productivity growth using equation (8). As expected, both capital deepening, \( \alpha (\Delta k - l) \) and labor quality, \((1 - \alpha) \Delta q\) are countercyclical—they work to raise labor productivity when the unemployment rate rises. In contrast, row (3c) shows that measured TFP growth, \( \Delta z \), with a coefficient estimate of -0.84, is strongly procyclical.

The final two rows of Table 1 further decompose TFP growth. Row (3c.1) shows that utilization, \( \Delta u \), with a coefficient of -1.03, drives the procyclicality. In contrast, row (3c.2) shows that utilization-adjusted TFP, \( \Delta a \), with a coefficient of 0.19, is mildly countercyclical. In other words, the procyclicality of TFP mainly reflects the (endogenous) procyclicality of factor utilization, i.e., labor effort and capital’s workweek. The utilization margin is crucial for understanding why TFP is strongly procyclical and labor productivity weakly so. Indeed, after controlling for utilization, row (3c.2) shows that utilization-adjusted TFP, \( \Delta a \), is actually countercyclical with respect to unemployment. These findings are in line with BFK and Galí (1999). They find that, on impact, technology improvements lead to reduced input use. Since our identification of utilization follows BFK, it’s not surprising that we find that utilization-adjusted TFP and unemployment comove positively.

Out of all these findings, perhaps the most important is the large response of total hours worked to a change in unemployment – as row (2) shows, the response is roughly two-to-one. This is much more than in typical DSGE models with unemployment (e.g., Galí, Smets, and Wouters (2011), or Christiano, Eichenbaum, and Trabandt (2013), which generally assume that the number of people employed moves close to one-to-one with unemployment. The reason is that those models have a structure with limited margins of labor adjustment. These models do not allow for endogenous changes in labor-force participation or an intensive margin. [Possibly discuss further]

Three main takeaways from this section are: (1) the response of total hours to fluctuations in the unemployment rate is twice as large as is assumed in much of the DSGE literature; (2) when looking
at the cyclicality of productivity, one should look at the cyclicality of TFP not labor productivity, and (3) much of the procyclicality of TFP comes not from technology (which is countercyclical) but from the strongly procyclical utilization margin.

### 3.3 Secular trends

How stable are the static finding? For example, Stiroh (2009), Gali and Gambetti (2009), and Barnichon (2010) point out that the cyclicality of labor productivity has changed over time. Other things equal, this shift should influence the Okun coefficient, in line with (3). Barnichon (2010) and Gali and Gambetti (2009) explain the change in cyclicality of labor productivity through changes in institutions (e.g., flexibility of labor markets), the systematic behavior of monetary policy, and the mix of shocks hitting the economy. Have these factors had other effects on the reduced-form Okun relationship? Before turning to responses conditional on particular shocks in Section 4, we consider a simple diagnostic of whether margins of adjustment are stable by constructing 40-quarter-rolling-window regression estimates that mirror those reported in Table 1. We find surprising consistency of the overall Okun coefficient—surprising, since the contributions of labor productivity and hours per worker turn out to change a lot, but in offsetting ways.

We organize these results into Figures 1, 2, and 3. Figure 1 reports estimations of the regressions intercepts along with the Okun coefficient and the two broad components: total hours and productivity. Figure 2 further breaks down the total hours component into hours per worker and total workers. Figure 3 breaks down productivity into its components as in expression (9).

The intercepts in Figure 1, panel (a), show the time variation in potential output. Productivity growth slows just as hours growth picks up (reflecting the baby boom) in the 1970s. Recently, both hours and productivity both slow.

Turning to the slope coefficients, Figure 1 panel (b) shows that the Okun relationship has been fairly stable for much of the post-WW2 era. Samples that end in the mid-1990s and after show more volatility, but we cannot generally reject that the coefficient is stable around its long-run value.\(^{12}\)

But the components of the Okun relationship do not show the same stability. Starting with samples that end in the mid-1990s, productivity switches from being procyclical with respect to unemployment to being countercyclical. At the same time, the coefficient on total hours markedly declined.

Figure 2 provides a more detailed look at the total hours component. The conditional averages and

\(^{12}\)I quickly looked at this by doing rolling regressions, putting \(-2.37*dU\) on the rhs along with \(dU\); then I tested whether the coefficient on \(dU\) is significant. The -2.37 is the average beta in rolling samples prior to 2007. There is a brief period in the late 1990s when the t-stat exceeds (minus) two in magnitude; but, of course, we expect that 5 percent of the time the t-stat will exceed 2 in magnitude. We could bootstrap the t-stats if that’s helpful. I also quickly looked at subsamples: There is NOT a significant change in coefficient during the Great Moderation period of 1984:4-2007:4, relative to the pre-Great Moderation period.
the slope coefficients show that the bulk of the decline in total hours is coming from the employment margin. The hours per worker component has been remarkably stable and its contribution is relatively smaller than the employment margin. We return to the evidence on the hours response in Section 3.5 where we discuss the household data, and in Section 4, where we find that technology shocks have a larger negative hours response than demand shocks.

Next, we turn to productivity in Figure 3. Figure 3 panel (b) shows that the key (proximate) driver of the shift from procyclical to countercyclical labor productivity growth is utilization. In samples ending after the mid-1990s the contribution of the utilization margin wanes noticeably. The absence of a relationship between utilization and unemployment during this period meant the other variables, which are all countercyclical (including capital deepening and labor quality, where the contributions are relatively stable) pushed labor productivity itself to become countercyclical.

Note that, while the utilization-adjusted TFP (technology) component is volatile, it remains countercyclical for most of the subsamples. The exception is samples ending in the mid-1980s, where utilization-adjusted TFP was procyclical. Gali, Lopez-Salido, and Valles (2003) identify technology shocks with long-run restrictions and find that, after the early 1980s, technology improvements were expansionary for employment variables, roughly consistent with our correlations for the 1980s. However, with our identification, the change in the sign of the covariance between unemployment and utilization-adjusted TFP is short-lived.

In sum, the decomposition over time points to greater responsiveness of total hours – mostly employment – to changes in unemployment, and a largely offsetting change in the cyclicity of labor productivity. The labor productivity changes, in turn, reflect especially the reduced association between changes in unemployment and factor utilization. The association between unemployment and utilization-adjusted TFP changed relatively little between the early period and the late period.

3.4 Business cycle fluctuations

Okun’s Law not only turns out to be stable over time but over the business cycle. We begin with a simple graphical comparison of selected recession episodes, then turn to a more formal regression analysis. Graphically, the relationship of unemployment changes to output, hours, and labor productivity looks qualitatively similar during the Great Recession as in previous deep recessions. This suggests caution in putting too strong a structural interpretation on the changing cyclicality of labor productivity. The regressions also show little evidence that recessions are different than expansions, or that the Great Recession differs from previous recessions.

\[13\text{\cite{Text I cut because I don’t understand it–they’re about flexibility, not directly about the UE/employment link.}\] Possible explanations for this decline in the employment factor include: changes in employer-employee relationships and unionization, globalization of supply chains, and capital substituting technology. Many of these explanations have been explored elsewhere, for example, in Elsby et al. (2013).
First, we compare the behavior of output growth and changes in the unemployment rate (Okun’s law) over the recession and recovery phases relative to their full sample average relationship. We do the same for the relationship between total hours and productivity against changes in the unemployment rate. However, for productivity, we split the sample in 1985. The choice of a 1985 break point is loosely justified by the time variation in the cyclicality of labor productivity and roughly coincides with the Great Moderation period (see, e.g., McConnell and Pérez-Quirós 2000). Figure 4 is organized into four panels: panel (a) displays the Okun relationship; panel (b) displays the total hours versus unemployment rate relationship; and panels (c) and (d) display the productivity versus unemployment rate relationship for the pre- and post-1985 subsamples, respectively.

The simple scatter plot in panel (a) of Figure 4 shows that, initially, output drops more quickly than the unemployment rate increases. As the recession wanes and the recovery ensues, the opposite appears to be the case. We observe this pattern in every recession since the beginning of the sample, including the Great Recession. This finding is consistent with Daly, Fernald, Jordà and Nechio (2014).

Total hours does not explain this loop-pattern. Panel (b) shows that total hours tend to move along the estimated long-run relationship rather than around it. Instead, the cyclicality depicted in panel (a) is most closely associated with what happens with productivity.

Panels (c) and (d) in Figure 4 highlight two interesting features. First, as suggested by Figure 1, the slope changes from negative pre-1985 to positive post-1985. Second, despite that change, the loop-pattern seen in panel (a) of this figure remains qualitatively similar during deep recessions. Productivity is the main proximate cause of the looping pattern during recessions. Not shown, this looping pattern reflects particularly utilization. Thus, despite the change in the unconditional cyclicality of labor productivity, the relationship remains consistent during deep recessions.

Second, turning from the figures to formal regressions, we now examine how each of the margins of adjustment varies depending on the stage of the business cycle using National Bureau of Economic Research (NBER) recession dates. Although we have seen some changes in these margins over time, Figure 4 suggest that differences in recessions are not the cause of the changes we’ve seen. This is not a priori obvious, since different recessions may have been caused by different shocks. In addition, in order to isolate possible distortions coming from the Great Recession, we allow for the coefficients in that period to vary from those in other recessions.

Specifically, we allow the data to choose whether it wants to assign the same values or not. Therefore, the analysis is based on the margins projections discussed in Section 2 augmented with a set of dummies, that is, we use the following reduced-form regressions:

\[
\Delta_4 x_{jt} = \sum_{k=1}^{K} \mu_{kj} I_{kt} + \sum_{k=1}^{K} \beta_{kj} I_{kt} \Delta_4 U_t + \varepsilon_{jt},
\]
where $I_{kt} \in \{0, 1\}$ for $k \in \{$expansion, recession, Great Recession recovery from Great Recession$\}$. That is, we allow the intercept and slope coefficients to vary as a function of whether the economy is in expansion, recession, Great Recession or recovering from the Great Recession. The index $j$ refers to each margin considered, just as in expression (11).

Table 2 shows these regression results. In addition to reporting coefficient estimates and standard errors (in parentheses), we also report a p-value in squared brackets. This p-value corresponds to a test of the null hypothesis that the corresponding coefficient differs significantly from the coefficient in expansions.

We start with the slope coefficients, which are the main parameters of interest, and defer for a few paragraphs discussion of the recovery from the Great Recession. Strikingly, until this recovery, we cannot in general reject that the $0s$ are the same during recessions (including the Great Recession) as during expansions. Consider the Okun coefficient from regressing output growth on unemployment changes. It is striking how stable this coefficient is: it fluctuates from a value of -1.98 in expansions, -2.08 in recessions, and -1.83 in the Great Recession. The null that the coefficients in recessions are equal to the coefficients in expansions cannot be rejected at conventional confidence levels.

The same finding of constancy of slope coefficients over the business cycle also holds for total hours worked, for labor productivity, and for most components of labor productivity. It is notable that the behavior of labor productivity was fairly "normal," at least by this metric, during the Great Recession. In real time, many commentators argued that productivity was behaving anomalously (usually that it was particularly strong). Fernald (2014b), in contrast, argues that the performance of productivity was typical, though both he and Daly et al (2014) suggest that data revisions were important for reaching this conclusion.

All components of labor productivity also have a relatively stable relationship with unemployment changes during recessions and during expansions. The stability holds through the Great Recession for all variables other than utilization-adjusted TFP, which is, statistically, even more countercyclical than usual during the Great Recession.\footnote{Interestingly, for utilization-adjusted TFP, prior to the Great Recession the point estimates suggest that the "contractionary" association of technology improvements with unemployment increases shows up in expansions. That is, the point estimates suggest that, in recessions, changes in utilization-adjusted TFP and unemployment are largely unrelated. Recessions, in this identification, are not "caused" by technology improvements.}

In terms of intercepts, output and labor productivity are both statistically lower during recessions than during expansions. In other words, there is some nonlinearity in the estimates, in that these variables are lower than would be expected given the increases in the unemployment rate.

In growth-accounting terms, the downward intercept shift appears to arises from factor utilization, which falls more in recessions than predicted given the increase in the unemployment rate. This intercept shift reinforces the procyclicality of TFP growth over much of the sample. That is, in
recessions, the regression not only loads procyclically on unemployment changes (so TFP growth falls when unemployment rises); it also loads procyclically on the recession dummy itself (so TFP growth is lower during recessions, after controlling for unemployment increases).

During the Great Recession and its recovery, the intercept terms are harder to interpret since they are at the very end of the sample. Thus, they largely reflect the slowing trend growth of the labor force and productivity that are apparent in the top panel of Figure 1.

During the recovery from the Great Recession, growth in output and productivity has been relatively lackluster despite sizeable declines in the unemployment rate. This shows as a positive shift in the slope coefficients for these variables—output is less negatively associated with changes in the unemployment rate, and productivity is more positively related. The same is, to some extent, true of TFP and utilization.

We conclude from this section that the consistency in Okun’s Law that we found in Section 3.3 is also, for the most part, true across the business cycle. Note that, prior to the Great Recession, expansions and recessions occur both before and during the Great Moderation period. So this business-cycle cut of the data does not pick up the changing composition of Okun’s Law over time—in particular, the shift from procyclical to countercyclical labor productivity that was apparent in the rolling regressions.

Nevertheless, the results here suggest that we might not want to overinterpret the changing composition of Okun’s Law. First, the “loops plots” discussed at the beginning of this section suggest that, in response to big shocks, the dynamics of the economy remained qualitatively similar over time. Second, slope coefficients for the components of output were, for the most part, unchanged during the Great Recession from previous recessions and expansions. Hence, although we found in Section 3.3 that the underlying reduced-form relationships have changed, relationships during deep recessions remain relatively consistent over time. This consistency could point towards explanations that emphasize relative shock variances rather than deep structural changes in institutions.\(^{15}\) Thus, when there is a severe shock, the economy appears to still respond in the “typical” way.

We return to the question of how responses depend on shocks in Section 4 which offers a more granular analysis depending on the type of shock (in the short run and the longer run).

### 3.5 Extensive and intensive margins in household data

Household-survey data confirm the finding that the cyclicality of hours and productivity changed in offsetting ways, as found in Section 3.3. They also show the importance of multiple job holdings as well as the participation margin in explaining the magnitude of the employment changes.

---

\(^{15}\)I am not entirely sure that I’m thinking properly about the implications, but there’s something there. That is, you’d think structural changes would lead the Great-Recession results to look quite different—as many people suggested at the time, but which we don’t find.
On the first point, we re-examine claims by Hagedorn and Manovski (2011) that productivity remains procyclical if hours are measured using household data. They conjecture that there could have been an increase in cyclical measurement error in the establishment survey. That is, in recessions, measured hours might have fallen more than true hours. Such a pattern would mechanically lead to a larger measured decline in hours in response to an increase in the unemployment rate, while leading to a more positive (or less negative) coefficient on productivity. But since the household data show a similar pattern for hours as the establishment survey, it is not simply an issue of mismeasurement in one survey versus another.

The two measures of hours and employment that we use in this section both come primarily from monthly employment surveys by the BLS. They have different strengths and weaknesses. Our baseline measures of business-sector hours and employment come from the Productivity and Cost release. These data rely primarily on the monthly survey of establishments (the Current Establishment Survey, or CES). The establishment survey is supplemented with information from the household survey (the Current Population Survey, or CPS) on agricultural workers, the self-employed, and unpaid family workers. The CES sample is much larger than the CPS, which reduces sampling error. A concern with the CES data is that the BLS needs to use a model to estimate establishment births and deaths. However, annual revisions to these data benchmark them to near universal unemployment insurance records, which include new firms and exclude dead ones. Thus, revised data greatly reduce non-sampling error related to the birth-death model. Nevertheless, because of non-reporting, some non-coverage, and interpolation between benchmarks, some error may remain.

The alternative measure, in contrast, comes entirely from the CPS. The CPS measure covers the entire civilian economy, not just the business sector. This household sample is much smaller than the establishment sample. In addition, the household survey provides estimated population ratios rather than levels of employment. Because of immigration and emigration, there are errors in estimating the population to which these ratios are applied, which may lead to cyclical errors in estimated employment. As a practical matter, the estimated population used by the BLS is smooth during the year but then has jumps—sometimes sizeable—each January when updated population estimates are available.

In order to compare the establishment (or CES) versus household (or CPS) measures, it is important to ensure that we have comparable coverage of the economy. We do this two ways, to derive either total-civilian-economy measures or, more narrowly, business-sector measures. In both cases, we use unpublished (but freely available) BLS estimates of non-business-sector employment and hours, which are based on data from both the CES and CPS. First, to derive an establishment-based

\[16\] These data differ from the "headline" household-sector employment figures because they adjust for people who have jobs but are not, in fact, working during the survey month; for example, they might be on vacation or on maternity leave.
total-civilian economy measure, we add the non-business data to the business-sector data. With this adjustment, both the CES and CPS measures correspond to the total civilian economy.\textsuperscript{17} Second, to derive an implied CPS "business sector" measure, we take the same estimate for non-business employment and hours and subtract it from the CPS total-economy measure. With this adjustment, the CPS "business sector" measure is conceptually comparable to the estimates shown in Table 1 or Figures 1, 2, and 3.

Table [CPS\_CES--to be added] shows results from regressions of the form of (11), where we project four-quarter changes in labor-market components on the four-quarter change in the unemployment rate. The difference relative to the corresponding terms of Table 1 is that Table [CPS\_CES] covers the entire civilian economy.

Whether we look at the full sample or the pre/post-Great-Moderation samples, the coefficient on hours worked is very similar between the CES and CPS datasets. But the split between employment and hours/worker is different. The CPS shows less of response in bodies, and more response in hours per person. This pattern across the surveys is a priori reasonable. Conceptually, when a person loses a second job, there is one less worker in the establishment survey but fewer hours per person in the household survey.\textsuperscript{18}

Importantly, both surveys show an increased responsiveness of hours to a change in the unemployment rate after 1984.

Indeed, figure [CPS\_Prod\_Hours--to be added] replicates the bottom panel of Figure 1 using the CPS business measure of hours. This rolling measure allows more nuance in timing than using simple subsamples. The pattern shown with the CPS data is very similar to what was shown with the CES data in Figure 1. In particular, CPS labor productivity turns from strongly procyclical with respect to unemployment to somewhat countercyclical. At the same time, the coefficient on CPS business hours worked become much more negative after the 1980s. Thus, the CPS data the offsetting changes in labor productivity and hours worked that underlie the stability of the Okun coefficient.

In sum, we find no evidence for the Hagedorn and Manovski assertion that, with household data, productivity remained procyclical after the 1980s. The reason they failed to find the shift turns out to be that they construct their measure of CPS-based productivity incorrectly. They mix non-farm business output in the numerator with total-civilian-economy employment in the denominator. In the data, the business sector is cyclical whereas the non-business sector is not. Hence, their numerator

\textsuperscript{17}Both the BLS and Cicciuba and Prescott (2012) estimate military hours and employment. Because the two estimates of military hours worked differ, we exclude them.

\textsuperscript{18}If we had ended the Great Moderation sample in 2007 rather than 2014, there would have been a larger discrepancy across surveys. Specifically, there would have been a larger negative response of hours in the establishment survey. The rolling regressions for the business sector, shown below, capture those differences in timing and show that it does not change the conclusions in an important way. Specifically, in the household as well as the establishment data, employment falls more in the Great Moderation period, and productivity changes from procyclical to countercyclical.
is inherently more procyclical than their denominator. Using the same mismatching coverage, we replicate their spurious finding that labor productivity appears to remain procyclical.

We now turn to the question of what margins of adjustment are important from the point of view of households? As noted in Section 2, without additional extensive and intensive margins, the coefficient on hours would be close to one in magnitude, not close to 2. The CPS data provide evidence on those margins that supplements that in the establishment data.

First, the intensive margin is quantitatively important. When the unemployment rate goes up, Table [CPS_CES—to be added] shows that about a third of the decline in hours reflects a decline in hours per person. This includes hours per worker at a given job—what is, conceptually picked up in the establishment data; it also includes the loss of second or third jobs—leading to a wedge between the hours/person response in the CPS and the hours/worker response in the CES.

Second, when the unemployment rate goes up there is a sizeable decline in the labor force after 1984. Not shown, this mainly reflects a decline in the labor-force-participation rate, with a small further decline in population. We summarize the declining labor force as reflecting the importance of the extensive margin of participation in explaining why hours worked falls more after 1984 than before.19

Finally, though not shown, we note that there was a larger change in the magnitude of the coefficients for the business sector than for the overall economy. Over time, the differences between the business and non-business sectors have become even more pronounced as output and employment in the non-business sector turned countercyclical. One hypothesis, [for which we have no evidence ;-)], is that the non-business sector (such as government) could have became countercyclical as a risk-sharing/insurance/stabilizing response to increasing flexibility of the business sector.

To conclude, the most important lesson for DSGE modelers is the need for both an extensive and an intensive margin of adjustment in the labor market. These include participation and multiple-job-holding as well as hours per person. Equally, when matching data, it is important to calibrate the extensive and intensive margins from the same survey. Specifically, it would be inappropriate to calibrate the intensive margin from the establishment side but the extensive margin from the household side, since multiple-job-holdings (conceptually, the gap between the two surveys) would not be accounted for.

---

19 The coefficient on labor-force participation is even larger if we end the sample in 2007. Although the participation rate has fallen dramatically since 2007, the unemployment rate increased sharply but then reversed course. Hence, the declines in participation are only loosely related, temporally, to changes in the unemployment rate. Note also that we can only imperfectly test whether the gap in number of workers in the establishment and household data is multiple job holdings. The reason is that data on multiple job holdings go back only to 1994, whereas we can quantify the gap between the CES and CPS back to 1948. Since 1994, the multiple-job-holding rate responds strongly negatively to changes in the unemployment rate, consistent with the interpretation here.
4 Dynamic adjustment multipliers by shock

So far, we have analyzed unconditional relationships and found that the Okun coefficient is relatively stable over time, even though its composition between labor productivity and hours has changed considerably. We now impose further structure on the analysis by estimating how the relationships depend on the shocks that hit the economy. After all, one might well expect that the mix of shocks should matter for unconditional estimates of the output-unemployment relationship.

It turns out that, after conditioning on different shocks, we can explain both the stability of the overall Okun relationship and how its components have changed over time. Each of the shocks we consider turns out to imply a relatively similar unconditional relationship between output growth and unemployment changes—so a change in the mix of shocks does not, in fact, imply a change in simple versions of the estimated Okun relationship. However, the mix of shocks does matter for the decomposition into labor productivity versus hours. If technology shocks have become relatively more important since the mid-1980s (as argued by Barnichon, 2010, and Gali and Gambetti, 2009), then the conditional responses can explain why labor productivity has turned countercyclical, and why the response of hours has become more negative.

We consider the following four shocks: (1) a monetary policy shock, (2) an oil price shock, (3) a shock to utilization-adjusted TFP. Rather than specifying macroeconomic models from which these shocks can be drawn, we borrow these shocks directly from the literature. Specifically, the monetary shock comes from Christiano, Eichenbaum and Evans (1999). The oil price shock follows Hamilton (1996). The utilization-adjusted TFP shock comes from the Fernald (2014a) data that we have been using. Taking it as a shock means taking seriously the assumptions outlined in Section 2, such as constant returns and perfect competition. A detailed explanation of how these shocks are obtained and modified is provided in the Appendix. In addition and as a robustness check, the Appendix also reports results using alternative measures of shocks: (1) the monetary policy shock based on Romer and Romer (2004); (2) the fiscal shock from Ramey (2011) based on government defense expenditures; (3) as well as a shock based on an alternative measure of government defense expenditures; (4) a shock to TFP for consumer goods producers; (5) and a shock to TFP for investment goods producers.

To start, we use the whole sample and calculate how each shock affects each margin of adjustment over time using a simple regression. Specifically, we regress each margin of adjustment on the shock and up to its twelve lags (for example, Ramey and Shapiro 1998 use a similar approach to compute impulse response coefficients). We estimate the dynamic multipliers associated with the coefficients...
of the shock terms in this regression. Figures 5-7 report the accumulated value of the dynamic multipliers so as to smooth the trajectories displayed and to be able to read off the overall effect at each period. The Figures also report 95% confidence bands.

Figure 5 reports multipliers in response to the monetary shock. This shock generates what looks like a standard demand-induced business cycle response. Specifically, in response to contractionary monetary policy, output declines over the first year and then begins to stabilize. Both total hours and productivity margins decline. Most of the decline in total hours is due to adjustments on the number of employees. Hours per worker moves relatively little. Productivity also declines, driven by a reduction in utilization rates displayed in Figure 5. (Utilization-adjusted TFP does not respond, which is consistent with our use of this variable below as an exogenous measure of technology.)

Oil price increases, shown in Figure 6, also look like a contractionary shock to aggregate demand. Output contracts, and both hours and labor productivity fall. The reduction in total hours, however, is driven especially by a decline in hours-per-worker. This greater use of the intensity margin could reflect the shorter persistence of the downturn relative to a monetary contraction. The shorter persistence creates more of an incentive to hoard labor. Again, the productivity decline is not driven by utilization-adjusted TFP but rather a decline in utilization rates.

Figure 7 shows how the behavior of the margins of adjustment to a technology shock. These multipliers look quite different than in Figures 5 and 6, with some interesting differences and similarities between them. The technology shock has little effect on output immediately, but over time becomes expansionary. The increase in output is mainly driven by the gains in labor productivity, which in turn reflects the direct effect of utilization-adjusted TFP. Utilization itself actually declines for some time. In the short run, total hours worked declines due to both a reduction in the number of employees and hours-per-worker. Because the downturn in labor demand is relatively short-lived compared with the monetary shock, it may create considerable incentives for labor hoarding.

4.1 Impulse response functions over time

Not only these margins can adjust differently depending on which shock hits the economy but it is also possible that the reaction of each of those margins changed over time. In this section, we find evidence that responses do vary over time. One key takeaway is that utilization responds less to various shocks over time. This change is consistent with the reduced importance of utilization over time that we found in Section 3.3.21

There are at least two reasons to expect variations in the impulse responses. First, the estimated impulse responses to technology and oil shocks depends on the endogenous response of monetary policy—and that reaction is often thought to have changed over time. For example, Gali, Lopez-

---

21 A question is whether we’d be better off doing pre-Great Moderation versus Great Moderation time periods?
Salido, and Valles (2003) find variation over time in the endogenous reaction of monetary policy to technology shocks. Second, increasing flexibility of the economy over time should also modify the impulse responses to shocks. Gali and Gambetti (2009) and Barnichon (2010) find evidence for both of these effects. (They also find evidence that technology shocks become more important over time, a point we return to in the next subsection.)

To investigate time variation, we estimate impulse response functions while constraining the data to rolling windows of 40 quarters at a time. More specifically, for each 40-quarter rolling window, we regress each margin of adjustment on the shock and up to its eight lags.\footnote{We use eight lags instead of twelve due to the smaller sample size.}

We report the results in Figures 8-10. Figure 8 highlights the sizable negative medium-term effects of monetary shocks during the 1970s and 1980s. More recently, those effects have become more modest and are close to zero. Oil and technology-shock effects on all variables, reported in Figures 9 and 10, show much larger variation in both size and signs over time.

A comparison between the set of Figures 5-7 and the set of Figures 8-10 show substantial variation in the response of margins to shocks over time. Interestingly, some of the commonly-known patterns explored in the literature seem to be mostly driven by responses during certain periods of time. For example, a comparison between Figures 5 and 8 suggest that the shape of the response of output to monetary shocks in Figure 5 seem to driven by the earlier sample.

More importantly in trying to explain the somewhat puzzling stability of the Okun coefficient, Figures 9 and 10 seem to provide some clue. Recall that our OLS time series analysis of Figures 1-3 showed that while the Okun coefficient remained stable, its labor productivity and total hours components changed substantially, particularly during the 1990s and early 2000s, with the former slope coefficient increasing and the latter slope coefficient decreasing (see Figure 1 panel (b)). As the panel (b) of Figures 2 and 3 showed, movements in total hours came from a decrease in the slope coefficient of number of employees, while changed in labor productivity were linked to variations in utilization and technology shocks themselves.

Figures 9 and 10 show that during this same period (between 1990s and early 2000s) the effects of oil and technology shocks on the number of employees (and hence in total hours) become more negative and more long lasting. In contrast, the effects of these two shocks on labor productivity became more positive and more long lasting.

Importantly, the response of utilization to shocks in all cases became attenuated over time. For example, with technology shocks, consider samples that end after the early 1980s (i.e., that start during the Great Moderation period from the early- to mid-1980s on). Hours worked fall sharply and persistently—but utilization does not. That contrasts with earlier time periods when the responses were all in the same direction. Thus, the evidence is consistent with increasing flexibility of the
economy leading to less use of the utilization margin. Since the utilization margin is, empirically, the main cause of procyclical labor productivity in the data, reduced use of that margin would contribute to the changing cyclicality of labor productivity.

4.2 When the dust settles

The nature of the shock clearly has different implications for the margins by which the economy adjusts in the short-run. However, in previous sections we also have highlighted the relative stability of the overall Okun relationship. These two findings turn out to be consistent.

In particular, Gali and Gambetti (2009) and Barnichon (2010) both find that technology shocks have become relatively more important over time. In this section, we find that such a shift is consistent with the patterns we see. The reason is that, despite differences in short-run dynamics, different shocks turn out to imply fairly similar unconditional output-unemployment relationships. But the unconditional decomposition between hours and productivity is affected by the mix of shocks: Relative to demand shocks, technology shocks imply a more negative relationship between hours and unemployment but a more positive relationship between labor productivity and unemployment. This is exactly the pattern documented in Section 3.3. Thus, the secular pattern in the coefficients is consistent with a relative shift towards technology shocks.

In addition, increased flexibility may also have contributed to the offsetting movements in labor productivity and employment. This is not a priori obvious, in that increased flexibility would most obviously reduce the hours-per-worker responsiveness to changes in unemployment. But some forms of flexibility might also have made “bodies” more responsive to changes in the unemployment rate, along the lines found in Section 3.5. These include the increased importance of labor-force participation—perhaps reflecting a shift towards two-earner families—and immigration.

The starting point of the analysis in this section is expression (9) and the sequence of regressions based on this expression and summarized in equation (11). One way to isolate fluctuations in the change of the unemployment rate that are due to the each shock considered above is to follow an instrumental variable (IV) approach in expression (11). The instrument is the shock and the instrumented variable is the change in the unemployment rate. The IV estimates average the dynamic effects found in the previous section. Intuitively, the IV procedure relates the variation in the left-hand-side variable explained by the instrument to the variation in the right-hand-side variable explained by the instrument. Thus, it gives the unconditional coefficient that would be estimated if the only shock was to the instrument. This allows us to connect the static results reported earlier to the dynamic multipliers estimated in the previous section.

23 We should do the IV regressions for the pre- and post-1984 periods to close the loop with the time-variation in responses that we discussed in the previous section.
Specifically, we reestimate the OLS coefficients reported in Table 1 using each shock at a time (and twelve of its lags) as an instrumental variable. Coefficients are estimated using an two-step instrumental variable approach in expression, where the instrument is the shock and the instrumented variable is the change in the unemployment rate. For each variable $x$, we estimate $\Delta_4 x_{jt} = \mu_j + \beta_j \Delta_4 \hat{U}_t + \varepsilon_{jt}$, where $\Delta_4 x_{jt}$ is the four-quarter growth rate of $x$ and $\Delta_4 \hat{U}_t$ is the fitted value obtained from the regression of four-quarter percentage-point change in unemployment rate on twelve lags of each shock (instrument).

The results are reported in Table 3. The broad message that all these estimates convey is simple: The overall Okun coefficient (the response of hours) does not vary substantially across different shocks over the long-term, but the composition of the responses varies.

The estimated values reported in Table 3 are close to the estimates reported in Table 1 based on OLS. With few exceptions, variation in the loadings on the different margins do not vary substantially with the type of shock. Consider first the total hours versus productivity split as in expression (2). For most shocks, total hours respond more than productivity except with the technology shock. The technology shock implies a more negative hours response but a more positive response of labor productivity.

The IV results help us think about the overall implications of the variability of the margins over time reported in Figures 1-3; the variability over the business cycle reported in Table 2 and Figure 4; and the dynamic adjustment multipliers in Figures 5-7. The average estimates of the margins of adjustment in Table 3 are very similar to those reported in Table 1 suggesting that despite some short-term variability, the economy tends to settle into specific patterns as it adjusts to different perturbations. One way to visualize this result is with panel (a) in Figure 4. Even though the Okun relationship displayed is tightly estimated, the recurrent cyclical loops characterizing each recession illustrate how this periodic source of variability dissipates into long-standing stable relations.

5 Conclusion

Macroeconomists and policymakers struggle to understand the channels by which modern economies adjust to shocks of different nature. Whether adjustments are made through staffing levels or hours, capital deepening or utilization rates, or any other available margin has important implications for identifying suitable policy responses and characterizing the macroeconomic environment. This paper uses the novel growth-accounting framework of Fernald (2014a) to provide a more detailed look into the margins of adjustment than has been hitherto the case.

Our contributions fall into two broad categories. On one side we establish a number of stylized facts that enrich some of the assumptions typically made in the DSGE literature. On the other
side, our findings enhance the rules-of-thumb upon which policymakers have come to rely on. These rules-of-thumb work well “on average,” but our research shows that in the short-run the responses of each margin of adjustment can vary considerably from norm, albeit in predictable patterns.

We highlight several 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 two percent when unemployment rises by one percentage point. The structure of typical DSGE models with unemployment imposes a relationship that is rarely much larger than one-to-one. The reason is the need for an intensive and extensive margin of adjustment.

Second, output declines faster than the unemployment rate increases at the start of the recession. This decline reverses course as the recession progresses and the recovery begins. The brunt of this cyclical pattern is explained by a similar pattern in productivity rather than in total hours. In recessions, productivity goes from being countercyclical to procyclical. The contribution of each productivity margin depends heavily on the type of shock hitting the economy.

Third, in response to all the shocks we analyze, the adjustment rests primarily with the utilization rate. These results tie into a large literature that emphasizes the importance of unobserved variations in factor intensity as an explanation of movements in productivity (see Basu and Fernald 2001 and references therein). In addition, this result ties into many DSGE models that find that a utilization margin helps to propagate shocks.

The main lesson for policymakers is that the standard Okun law result, while a reliable guidepost in general, conceals a much more nuanced reality. Even this rule-of-thumb is subject to sizeable fluctuations depending on the stage of the business cycle. Within the broad relationship between output and unemployment, there is considerable variation in the margins by which the economy adjusts to different shocks. And all these lessons do not even deal with the difficulties introduced by data available in real-time relative to later revisions (see, e.g. Daly et al. 2014).

References


Table 1: Margins of adjustment

<table>
<thead>
<tr>
<th>Dependent variables:</th>
<th>Slope estimates:</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Output ($\Delta y$)</td>
<td>-2.25*** (0.09)</td>
</tr>
<tr>
<td>(2) Hours ($\Delta l$)</td>
<td>-2.09*** (0.06)</td>
</tr>
<tr>
<td>(2a) Employees ($\Delta n$)</td>
<td>-1.68*** (0.05)</td>
</tr>
<tr>
<td>(2b) Hours per employee ($\Delta h$)</td>
<td>-0.41*** (0.03)</td>
</tr>
<tr>
<td>(3) Labor productivity ($\Delta y - \Delta l$)</td>
<td>-0.16* (0.09)</td>
</tr>
<tr>
<td>(3a) Capital deepening ($\alpha (\Delta k - \Delta l)$)</td>
<td>0.62*** (0.02)</td>
</tr>
<tr>
<td>(3b) Labor quality ($(1-\alpha) \Delta q$)</td>
<td>0.06*** (0.01)</td>
</tr>
<tr>
<td>(3c) TFP ($\Delta z$)</td>
<td>-0.84*** (0.09)</td>
</tr>
<tr>
<td>(3c.1) Utilization ($\Delta v$)</td>
<td>-1.09*** (0.08)</td>
</tr>
<tr>
<td>(3c.2) Utilization-adjusted TFP ($\Delta a$)</td>
<td>0.25*** (0.08)</td>
</tr>
</tbody>
</table>

For each variable $x$, the entries shown are the slope coefficients from estimating $\Delta x_{jt} = \mu + \beta \Delta U_t + \epsilon_{jt}$, where $\Delta x_{jt}$ is the four-quarter growth rate of $x$ and $\Delta U_t$ is the four-quarter percentage-point change in unemployment. The column of entries measures output as the average of real business expenditure and income. The sample runs from 1949Q1 to 2014Q1.
Table 2: Margins of adjustment – Normal times versus recessions

<table>
<thead>
<tr>
<th>Dependent variables:</th>
<th>Intercept</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expansion</td>
<td>Recession</td>
</tr>
<tr>
<td>(1) Output ($\Delta y$)</td>
<td>3.94***</td>
<td>2.24***</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.34)</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.00]</td>
</tr>
<tr>
<td>(2) Hours ($\Delta l$)</td>
<td>1.16***</td>
<td>0.75***</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.24)</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.11]</td>
</tr>
<tr>
<td>(2a) Employees ($\Delta n$)</td>
<td>1.30***</td>
<td>1.58***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.23)</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.24]</td>
</tr>
<tr>
<td>(2b) Hours per employee ($\Delta h$)</td>
<td>-0.15***</td>
<td>-0.83***</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.14)</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.00]</td>
</tr>
<tr>
<td>(3) Labor productivity ($\Delta y-\Delta l$)</td>
<td>2.78***</td>
<td>1.48***</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.37)</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.00]</td>
</tr>
<tr>
<td>(3a) Capital deepening ($\alpha(\Delta k-\Delta l)$)</td>
<td>0.84***</td>
<td>1.13***</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.10)</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.00]</td>
</tr>
<tr>
<td>(3b) Labor quality ($\alpha(1-\alpha)\Delta q$)</td>
<td>0.21***</td>
<td>0.37***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.05)</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.00]</td>
</tr>
<tr>
<td>(3c) TFP ($\Delta z$)</td>
<td>1.74***</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.37)</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.00]</td>
</tr>
<tr>
<td>(3c.1) Utilization ($\Delta u$)</td>
<td>0.26**</td>
<td>-1.24***</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.34)</td>
</tr>
<tr>
<td></td>
<td>[0.02]</td>
<td>[0.00]</td>
</tr>
<tr>
<td>(3c.2) Utilization-adjusted TFP ($\Delta a$)</td>
<td>1.47***</td>
<td>1.22***</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.33)</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.46]</td>
</tr>
</tbody>
</table>

For each business-sector variable $x$, the entries shown are the coefficients from estimating $\Delta x_{jt} = \sum_{k=1}^{K} \mu_{kj} l_{kt} + \sum_{k=1}^{K} \beta_{kj} l_{kt} \Delta u_{t} + \epsilon_{jt}$, where $l_{kt} \in \{0,1\}$ for $k \in \{Expansion, Recession, GreatRecession, Recovery\}$. The index $j$ refers to each margin considered. The table reports coefficient estimates and the standard error in parentheses, we also report a p-value in squared brackets. This p-value corresponds to a test of the null hypothesis that the corresponding coefficients differ significantly from the coefficient in expansions. Output is measured as the average of real expenditure and real income. Recession dates are obtained from NBER. The sample runs from 1949Q1 to 2014Q1.
Table 3: Margins of adjustment – instrumental variables by type of shock

<table>
<thead>
<tr>
<th>Dependent variables:</th>
<th>Monetary</th>
<th>Oil</th>
<th>TFP</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Output (Δy)</td>
<td>-2.50***</td>
<td>-1.84***</td>
<td>-1.62***</td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
<td>(0.23)</td>
<td>(0.32)</td>
</tr>
<tr>
<td>(2) Hours (Δl)</td>
<td>-2.27***</td>
<td>-1.92***</td>
<td>-2.64***</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.15)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>(2a) Employees (Δn)</td>
<td>-1.99***</td>
<td>-1.31***</td>
<td>-1.94***</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.15)</td>
<td>(0.19)</td>
</tr>
<tr>
<td>(2b) Hours per employee (Δh)</td>
<td>-0.29***</td>
<td>-0.62***</td>
<td>-0.70***</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.09)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>(3) Labor productivity (Δy-Δl)</td>
<td>-0.22</td>
<td>0.08</td>
<td>1.02***</td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
<td>(0.23)</td>
<td>(0.38)</td>
</tr>
<tr>
<td>(3a) Capital deepening (α(Δk-Δl))</td>
<td>0.78***</td>
<td>0.71***</td>
<td>0.83***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.06)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>(3b) Labor quality ((1-α)Δq)</td>
<td>0.11***</td>
<td>0.05</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>(3c) TFP (Δz)</td>
<td>-1.11***</td>
<td>-0.65***</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.24)</td>
<td>(0.37)</td>
</tr>
<tr>
<td>(3c.1) Utilization (Δv)</td>
<td>-0.94***</td>
<td>-1.00***</td>
<td>-2.38***</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.21)</td>
<td>(0.37)</td>
</tr>
<tr>
<td>(3c.2) Utilization-adjusted TFP (Δa)</td>
<td>-0.17</td>
<td>0.35*</td>
<td>2.55***</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.2)</td>
<td>(0.53)</td>
</tr>
</tbody>
</table>

Coefficients are estimated using an two-step instrumental variable approach in expression, where the instrument is the shock and the instrumented variable is the change in the unemployment rate. For each variable x, the entries shown are the slope coefficients from estimating $\Delta_4x_{jt} = \mu_j + \beta_j \Delta_4U_t + \varepsilon_{jt}$, where $\Delta_4x_{jt}$ is the four-quarter growth rate of x and $\Delta_4U_t$ is the fitted value obtained from the regression of four-quarter percentage-point change in unemployment rate on twelve lags of each shock (instrument). Output is measured as the average of real expenditure and real income. The monetary shock is obtained from an update of Christiano et al. (1999). The oil shock is obtained from Hamilton (1996) and the sample runs from 1949Q1 to 2014Q1. The TFP shock is obtained from Fernald (2014) and the sample runs from 1949Q1 to 2014Q1.
The figure reports the relationships between unemployment and output, total hours, and productivity over time. Each series corresponds to the 40-quarter-rolling-window regression estimates of the intercept, in panel (a), and the slope coefficient, in panel (b), in $\Delta_4 x_{jt} = \mu_j + \beta_j \Delta_4 U_t + \varepsilon_{jt}$, where $\Delta_4 x_{jt}$ is the four-quarter growth rate of $x$ (output, total hours, labor productivity) and $\Delta_4 U_t$ is the four-quarter percentage-point change in unemployment. The sample runs from 1949Q1 to 2014Q1.
The figure reports the relationships between unemployment and number of employees, and hours-per-worker over time. Each series corresponds to the 40-quarter-rolling-window regression estimates of the intercept, in panel (a), and the slope coefficient, in panel (b), in $\Delta x_{jt} = \mu_j + \beta_j \Delta U_t + \varepsilon_{jt}$, where $\Delta x_{jt}$ is the four-quarter growth rate of $x$ (number of employees, hours-per-worker) and $\Delta U_t$ is the four-quarter percentage-point change in unemployment. The sample runs from 1949Q1 to 2014Q1.
Figure 3: Margins of adjustment – labor productivity components

The figure reports the relationships between unemployment and capital deepening, labor quality, capital utilization and utilization-adjusted TFP over time. Each series corresponds to the 40-quarter-rolling-window regression estimates of the intercept, in panel (a), and the slope coefficient, in panel (b), in $x_{jt} = \mu_j + \beta_j \Delta U_t + \varepsilon_{jt}$, where $\Delta x_{jt}$ is the four-quarter growth rate of $x$ (capital deepening, labor quality, capital utilization, utilization-adjusted TFP) and $\Delta U_t$ is the four-quarter percentage-point change in unemployment. The sample runs from 1949Q1 to 2014Q1.
Figure 4: Business cycle loops – output, total hours and labor productivity

The figure tracks the behavior of output growth, total hours and labor productivity and the changes in the unemployment rate over the recessions and recovery phases focusing on three NBER recession starting dates: 1973Q4, 2001Q1 and 2007Q4. Panel (a) displays the Okun relationship; panel (b) displays the total hours versus unemployment rate relationship; and panels (c) and (d) display the productivity versus unemployment rate relationship for the pre- and post-1985 subsamples, respectively. The scatter in panels (a) and (b) shows data between 1949Q1 and 2014Q1, in panel (c) correspond to data between 1949Q1 and 1984Q4, and panel (d) correspond to data between 1985Q1 and 2014Q1.
Figure 5: Impulse response functions – monetary shocks

The figure reports the accumulated value of the dynamic multipliers associated with the coefficients of the monetary shock from the regression of each margin of adjustment on the shock, and up to its twelve lags. Monetary shock is obtained from Christiano, Eichenbaum and Evans (1999). Sample runs from 1949Q1 to 2014Q1. Dashed lines correspond to 95% confidence bands.
Figure 6: Impulse response functions – oil shock

The figure reports the accumulated value of the dynamic multipliers associated with the coefficients of the oil shock from the regression of each margin of adjustment on the shock, and up to its twelve lags. Oil shock is obtained from Hamilton (1996). Sample runs from 1974Q1 to 2014Q1. Dashed lines correspond to 95% confidence bands.
Figure 7: Impulse response functions – TFP shock

The figure reports the accumulated value of the dynamic multipliers associated with the coefficients of the TFP shock from the regression of each margin of adjustment on the shock, and up to its twelve lags. TFP are obtained from Fernald (2014). Sample runs from 1949Q1 to 2014Q1. Dashed lines correspond to 95% confidence bands.
Figure 8: Impulse response functions – monetary shocks

The figure reports the accumulated value of the dynamic multipliers in the first, fourth and eighth quarters following the monetary shock. These effects are obtained from the regression of each margin of adjustment on the shock, and up to its eighth lags using rolling windows of 40 quarters. Monetary shock is obtained from Christiano, Eichenbaum and Evans (1999). Sample runs from 1949Q1 to 2014Q1. Shades correspond to 95% confidence bands.
Figure 9: Impulse response functions – oil shocks

The figure reports the accumulated value of the dynamic multipliers in the first, fourth and eighth quarters following the oil shock. These effects are obtained from the regression of each margin of adjustment on the shock, and up to its eighth lags using rolling windows of 40 quarters. Oil shock is obtained from Hamilton (1996). Sample runs from 1974Q1 to 2014Q1. Shades correspond to 95% confidence bands.
Figure 10: Impulse response functions – technology shocks

The figure reports the accumulated value of the dynamic multipliers in the first, fourth and eighth quarters following a shock to utilization-adjusted TFP. These effects are obtained from the regression of each margin of adjustment on the shock, and up to its eighth lags using rolling windows of 40 quarters. TFP are obtained from Fernald (2014). Sample runs from 1949Q1 to 2014Q1. Shades correspond to 95% confidence bands.
A Appendix

A.1 Expenditure versus income sides

Recently, Nalewaik (2010) raises the question of whether gross domestic product (GDP) or gross domestic income (GDI) provides a more accurate reading on economic activity, especially around turning points. As a robustness check, we use both expenditure-side and income-side measures of output. 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.

In particular, the first column in Table 4 shows results using unpublished BLS data on the total economy; these data are primarily from the establishment survey, but are augmented with data on active military employment as well as agricultural employment, self-employment, and household employment from the household survey. Some recent literature argues for using the household survey as the primary source, instead of the establishment survey; see Ramey (2012) and Hagedorn and Manovski (2013). The second column in Table 4 shows results using these data. The row numbers used in the table correspond to those in Table 1.

Table 4 shows that the high response of total hours to an unemployment rate change is not explained by our focus on the more cyclically sensitive business sector data, nor is it limited to the establishment survey. In both columns, hours fall just under two percent when the unemployment rate rises by one percentage point. In the household survey, more of the response comes from hours per worker, and less from a change in the number of people working, but the total response is similar. This suggests that our results accurately reflect the fact that a wide range of margins are important. For example, the final line of Table 4 shows that labor-force participation is quantitatively important in explaining the response of the number of people working. Other margins, such as changes in number of multiple-job holders, also contribute. Together, the results imply that models that ignore these margins potentially miss quantitatively important aspects of the economy’s adjustment to shocks.

We now consider how the output-unemployment relationship has changed over time. Figure 11 plots 40-quarter rolling estimates of the Okun coefficient $\beta_j$ when output is measured using either real income or real expenditures. Figure 11 shows the striking divergence in the estimated Okun coefficient between the income- and expenditure-based measures of output 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.

---

24 We thank John Glaser (from the Bureau of Labor Statistics) for providing us with the data.
25 CPS hours work data start in 1976, restricting the sample to 1976Q3 to 2012Q4.
26 Multiple job-holding may explain the different mix between individuals and hours between the two surveys. Suppose the unemployment rate rises and some individuals lose a second job. In the establishment survey, that shows up as one employee fewer. In the household survey, the person still has a job – but would report fewer hours worked.
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-based measures of output are more correlated with other measures of activity (say, ISM surveys); and are more closely related to what forecasters are saying. More pointedly, he argues that the product-based measure of output has become increasingly unreliable. 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.

Despite this divergence, Table 4 shows that our results are qualitatively unchanged when using one measure or the other.

A.2 Total economy hours worked

Table 5 reestimated the total hours response using two broader datasets with wider coverage than just the business sector based data of Table 1. One dataset is based primarily on the establishment survey augmented with data on active military employment as well as agricultural employment, self-employment. The second dataset is based and household employment from the household survey. The estimates based on these two more detailed datasets confirm that the roughly two-to-one response of total hours growth to changes in the unemployment rate hold.

A.3 Alternative shocks and instruments

Figures 12-15 and Table 6 replicate the results reported in the paper on Figures 5-7 and Table 3 but considers, instead alternative measures shocks: (1) the monetary policy shock based on Romer and Romer (2004),27 (2) the fiscal shock from Ramey (2011) based on government defense expenditures, (3) as well as a shock based on an alternative measure of government defense expenditures. It also considers (4) a shock to TFP for consumer goods producers, and (5) a shock to TFP for investment goods producers.

While Figures 12 and 13 bring similar lessons than Figures 5 and 6, the productivity shocks on the consumer and investment sectors differ substantially from the aggregate TFP shock reported in Figure 7.

A shock in the consumption sector is associated with a positive response of output whereas the investment productivity shock is contractionary. An explanation for this difference comes from the behavior of total hours. In contrast, productivity improves in both sectors, not surprisingly given the nature of the shock. In the case of the investment TFP shock, both employees and hours per worker decline along with utilization even as adjusted TFP is improving. Meanwhile, the response in employees, hours per worker and utilization rates is more muted when the shock comes from the consumption sector.

27We use the sum for the preceding year of quarterly VAR monetary innovations, following Christiano, Eichenbaum, and Evans (1999), Burnside (1996), and others. Following Burnside (1996), we measure monetary policy as innovations to the 3-month Treasury bill rate from a VAR with GDP, the GDP deflator, an index of commodity prices, the 3-month T-bill rate, and M1.
One way to reconcile these differences is to consider a sticky-price, two-sector model such as Basu, Fernald and Liu (2014). In that model, although a productivity shock will lower the price of investment goods eventually, in the short-run price-stickiness causes investment to be relatively expensive. As a result, the initial effect of the shock is contractionary. When the productivity shock is to the consumption sector instead, short-run price stickiness makes investment goods relatively cheaper, which in turn expands investment and output. In addition, there is a wealth effect coming from expected future gains in the consumption sector that also pushes economic activity up today.

A.4 Fernald (2014) Quarterly Growth-Accounting Data

These data are available at http://www.frbsf.org/economics/economists/jfernald/quarterly_tfp.xls. They include quarterly growth-accounting measures for the business-sector, including output, hours worked, labor quality (or composition), capital input, and total factor productivity from 1947:Q2 on. In addition, they include a measure of factor utilization that follows BFK. 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. The data are described in greater detail in Fernald (2014).

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.

\[28\] 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).
(iv) Factor shares: Interpolated and, where necessary, extrapolated from the annual data on factor shares, $\alpha$ 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 $\left(\frac{H_i}{N_i}\right)$ by industry $i$ from the monthly employment report of the BLS. These are used to estimate a series on industry utilization $\Delta \ln Y_i = \beta_i \Delta \ln \left(\frac{H_i}{N_i}\right)$, where $\beta_i$ is a coefficient estimated by BFK. Fernald (2014) then calculates an aggregate utilization adjustment as $\Delta \ln Y = \Sigma_i w_i \Delta \ln Y_i$, 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.29

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 (2014). 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.

A.5 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 3/4 of GDP (from the national accounts) and employment.30 The non-business sector is mainly government services, nonprofits, and household workers.

---

29 The output data also differ, both in vintage and data source, from the annual data used by BFK.
30 We thank John Glaser (from the Bureau of Labor Statistics) for providing us with the data.
The Tornquist approximation to chained GDP implies the following:

\[ \Delta y_{total} = w_{bus} \Delta y_{bus} + (1 - w_{bus}) \Delta y_{nbus} \]

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

\[ \beta_{total} = w_{Bus} \beta_{Bus} + (1 - w_{bus}) \beta_{nbus}, \]

where \( \beta_j \) is from \( \Delta y_{jt} = \mu_j + \beta_j \Delta U_t + \varepsilon_{jt} \).

Figure 16 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 August 13, 2014). Clearly, the cyclicality of output for the overall economy comes almost entirely from the business sector. Indeed, the non-business sector displays little cyclicality with respect to unemployment, apart from a brief period in the early 1970s.

<table>
<thead>
<tr>
<th>Table 4: Margins of adjustment – expenditure versus income sides</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Real Expenditure</strong></td>
</tr>
<tr>
<td>(1) Output (( \Delta y ))</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(2) Hours (( \Delta l ))</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(2a) Employees (( \Delta n ))</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(2b) Hours per employee (( \Delta h ))</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(3) Labor productivity (( \Delta y - \Delta l ))</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(3a) Capital deepening (( \alpha(\Delta k - \Delta l) ))</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(3b) Labor quality (( (1-\alpha) \Delta q ))</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(3c) TFP (( \Delta z ))</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(3c.1) Utilization (( \Delta v ))</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(3c.2) Utilization-adjusted TFP (( \Delta a ))</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

For each variable \( x \), the entries shown are the slope coefficients from estimating \( \Delta x_{jt} = \mu_j + \beta_j \Delta U_t + \varepsilon_{jt} \), where \( \Delta x_{jt} \) is the four-quarter growth rate of \( x \) and \( \Delta U_t \) is the four-quarter percentage-point change in unemployment. The column of entries measures real business output from the expenditure and income sides. The sample runs from 1949Q1 to 2014Q1.
Table 5: Comparing Establishment and Household Survey Hours

Slope estimates:

<table>
<thead>
<tr>
<th>Dependent variables:</th>
<th>Establishment survey</th>
<th>Household survey</th>
</tr>
</thead>
<tbody>
<tr>
<td>(2) Hours ($\Delta l$)</td>
<td>-2.09*** (0.06)</td>
<td>-1.71*** (0.08)</td>
</tr>
<tr>
<td>(2a) Employees ($\Delta n$)</td>
<td>-1.68*** (0.05)</td>
<td>-1.16*** (0.05)</td>
</tr>
<tr>
<td>(2b) Hours per employee ($\Delta h$)</td>
<td>-0.41*** (0.03)</td>
<td>-0.56*** (0.05)</td>
</tr>
</tbody>
</table>

Additional:

Civilian employment

-1.12*** (0.05)

Labor force participation rate

-0.07*** (0.02)

For each variable $x$, the entries shown are the slope coefficients from estimating $\Delta_4 x_{jt} = \mu_j + \Delta_4 U_t + \varepsilon_{jt}$, where $\Delta_4 x_{jt}$ is the four-quarter growth rate of $x$ and $\Delta_4 U_t$ is the four-quarter percentage-point change in unemployment. The table uses alternative data sources on employment and hours, which correspond to the total economy. The “Establishment Survey” column is from unpublished BLS total-economy data, which relies predominately on the establishment survey for employment and (for production workers) hours per worker. The “Household Survey” column shows number of persons at work and average hours of all persons at work from the household survey (data obtained from Haver Analytics). The memo items on civilian employment and labor-force participation are from the summary tables in the monthly employment report. The sample runs from 1976Q3 to 2014Q1.
Table 6: Margins of adjustment – instrumental variables by type of shock

<table>
<thead>
<tr>
<th>Dependent variables:</th>
<th>Monetary</th>
<th>Oil spending</th>
<th>Government spending</th>
<th>Defense spending</th>
<th>TFP Consumption</th>
<th>TFP Investment</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Output ($\Delta y$)</td>
<td>-2.55***</td>
<td>-2.18***</td>
<td>-1.84***</td>
<td>-2.13***</td>
<td>-2.13***</td>
<td>-2.54***</td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
<td>(0.2)</td>
<td>(0.44)</td>
<td>(0.52)</td>
<td>(0.16)</td>
<td>(0.25)</td>
</tr>
<tr>
<td>(2) Hours ($\Delta l$)</td>
<td>-2.44***</td>
<td>-1.96***</td>
<td>-1.80***</td>
<td>-3.15***</td>
<td>-2.38***</td>
<td>-2.44***</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.13)</td>
<td>(0.29)</td>
<td>(0.45)</td>
<td>(0.11)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>(2a) Employees ($\Delta n$)</td>
<td>-2.05***</td>
<td>-1.42***</td>
<td>-1.39***</td>
<td>-2.01***</td>
<td>-1.69***</td>
<td>-1.90***</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.13)</td>
<td>(0.28)</td>
<td>(0.33)</td>
<td>(0.1)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>(2b) Hours per employee ($\Delta h$)</td>
<td>-0.39***</td>
<td>-0.54***</td>
<td>-0.40**</td>
<td>-1.14***</td>
<td>-0.69***</td>
<td>-0.48***</td>
</tr>
<tr>
<td></td>
<td>(0.1)</td>
<td>(0.08)</td>
<td>(0.16)</td>
<td>(0.32)</td>
<td>(0.07)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>(3) Labor productivity ($\Delta y-\Delta l$)</td>
<td>-0.11</td>
<td>-0.22</td>
<td>-0.04</td>
<td>1.02</td>
<td>0.25</td>
<td>-0.1</td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
<td>(0.2)</td>
<td>(0.44)</td>
<td>(0.64)</td>
<td>(0.17)</td>
<td>(0.25)</td>
</tr>
<tr>
<td>(3a) Capital deepening ($\alpha(\Delta k-\Delta l)$)</td>
<td>0.74***</td>
<td>0.64***</td>
<td>0.44***</td>
<td>1.37***</td>
<td>0.94***</td>
<td>0.65***</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.13)</td>
<td>(0.28)</td>
<td>(0.06)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>(3b) Labor quality ($(1-\alpha)\Delta q$)</td>
<td>0.15***</td>
<td>0.02</td>
<td>0.09</td>
<td>0.03</td>
<td>0.04*</td>
<td>0.14***</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.03)</td>
<td>(0.06)</td>
<td>(0.08)</td>
<td>(0.02)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>(3c) TFP ($\Delta z$)</td>
<td>-0.99***</td>
<td>-0.87***</td>
<td>-0.57</td>
<td>-0.37</td>
<td>-0.73***</td>
<td>-0.87***</td>
</tr>
<tr>
<td></td>
<td>(0.29)</td>
<td>(0.21)</td>
<td>(0.45)</td>
<td>(0.56)</td>
<td>(0.17)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>(3c.1) Utilization ($\Delta v$)</td>
<td>-1.27***</td>
<td>-0.99***</td>
<td>-1.42***</td>
<td>-1.76***</td>
<td>-1.81***</td>
<td>-1.32***</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.18)</td>
<td>(0.41)</td>
<td>(0.53)</td>
<td>(0.17)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>(3c.2) Utilization-adjusted TFP ($\Delta a$)</td>
<td>0.29</td>
<td>0.12</td>
<td>0.85**</td>
<td>1.39**</td>
<td>1.08***</td>
<td>0.45**</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(0.18)</td>
<td>(0.41)</td>
<td>(0.63)</td>
<td>(0.17)</td>
<td>(0.22)</td>
</tr>
</tbody>
</table>

Coefficients are estimated using an two-step instrumental variable approach in expression, where the instrument is the shock and the instrumented variable is the change in the unemployment rate. For each variable $x$, the entries shown are the slope coefficients from estimating $\Delta_4 x_{jt} = \mu_j + \beta_j \Delta_4 \hat{U}_t + \varepsilon_{jt}$, where $\Delta_4 x_{jt}$ is the four-quarter growth rate of $x$ and $\Delta_4 \hat{U}_t$ is the fitted value obtained from the regression of four-quarter percentage-point change in unemployment rate on twelve lags of each shock (instrument). Output is measured as the average of real expenditure and real income. The first column reports results using a monetary shock obtained from Romer and Romer (2004). The second column reports oil shocks obtained from Hamilton (1996). The third column reports the results using a fiscal shock obtained from Ramey (2011). The fourth column reports results using a fiscal shock obtained from changes in defense spending. The last two columns reports results obtained from a consumption and an investment TFP shocks from Fernald (2014). The sample runs from 1949Q1 to 2014Q1.
Figure 11: Okun coefficients: real income and real expenditure sides

The figure reports the relationships between unemployment and output over time. Output is measured from either the income or the expenditure sides. Each series corresponds to the 40-quarter-rolling-window regression estimates of the intercept, in panel (a), and the slope coefficient, in panel (b), in $\Delta x_{jt} = \mu_j + \beta_j \Delta U_t + \varepsilon_{jt}$, where $\Delta x_{jt}$ is the four-quarter growth rate of $x$ (output measured from income and expenditure sides) and $\Delta U_t$ is the four-quarter percentage-point change in unemployment. The crosses on each series represent periods when the differences in the two coefficients are statistically significant. The sample runs from 1949Q1 to 2014Q1.
Figure 12: Impulse response functions – monetary shocks

The figure reports the accumulated value of the dynamic multipliers associated with the coefficients of the monetary shock from the regression of each margin of adjustment on four lags of itself, the shock, and up to twelve lags of the shock. Monetary shock is obtained from Romer and Romer (2004) and the sample runs from 1969Q1 to 1996Q4. Sample runs from 1969Q1 to 1996Q4. Dashed lines correspond to 95% confidence bands.
Figure 13: Impulse response functions – oil shock

The figure reports the accumulated value of the dynamic multipliers associated with the coefficients of the oil shock from the regression of each margin of adjustment on four lags of itself, the shock, and up to twelve lags of the shock. Oil shock is obtained from Hamilton (1996). Sample runs from 1974Q1 to 2014Q1. Dashed lines correspond to 95% confidence bands.
Figure 14: Impulse response functions – consumption-goods TFP shock

The figure reports the accumulated value of the dynamic multipliers associated with the coefficients of the consumption-goods TFP shock from the regression of each margin of adjustment on four lags of itself, the shock, and up to twelve lags of the shock. Consumption-goods TFP are obtained from Fernald (2014). Sample runs from 1949Q1 to 2014Q1. Dashed lines correspond to 95% confidence bands.
Figure 15: Impulse response functions – investment-goods TFP shock

The figure reports the accumulated value of the dynamic multipliers associated with the coefficients of the investment-goods TFP shock from the regression of each margin of adjustment on four lags of itself, the shock, and up to twelve lags of the shock. Investment-goods TFP are obtained from Fernald (2014). Sample runs from 1949Q1 to 2014Q1. Dashed lines correspond to 95% confidence bands.
Figure 16: Okun coefficient: business and non-business sectors

The figure reports the relationships between unemployment and output over time. Each series corresponds to the 40-quarter-rolling-window regression estimates of the intercept, in panel (a), and the slope coefficient, in panel (b), in $\Delta_4 x_{jt} = \mu_j + \beta_j \Delta_4 U_t + \epsilon_{jt}$, where $\Delta_4 x_{jt}$ is the four-quarter growth rate of $x$ (business, non-business and total output) and $\Delta_4 U_t$ is the four-quarter percentage-point change in unemployment. Non-business output is from NIPA Table 1.3.3. The sample runs from 1949Q1 to 2014Q1.