Shocks and Adjustments: The View through Okun's Macroscope[*]

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Abstract

Considerable macroeconomic literature focuses on measuring the shocks that hit the economy and understanding how they propagate over time. We explore these propagation mechanisms empirically by examining the supply-side margins of adjustment used by firms and households. Concretely, these margins of adjustment provide the empirical microfoundations for the strong empirical regularity known as "Okun's Law", which relates movements in unemployment and output. We examine these margins both unconditionally and in response to particular shocks. This supply-side perspective sheds light on the key margins of adjustment that are needed in macroeconomic models in order to match key features of the data. Our analysis also sheds light on how margins of adjustment have changed over time, and on the changing cyclicality of productivity.

"Given the path of output, changes in unemployment depend on the movements of (1) the labor force, (2) average weekly hours, and (3) productivity." Okun (1974)

"The answer became famous as Okun's Law, one of the most reliable empirical regularities of macroeconomics." Tobin (1996)

1. INTRODUCTION

Considerable literature documents historical characteristics of the business cycle. Much of this literature (e.g., Kydland and Prescott, 1991; Backus and Kehoe, 1992; and Backus, Kehoe and Kydland, 1994) focuses on the variances and covariances of output and the expenditure side of GDP (consumption, investment, government expenditures and net exports). Models of the business cycle, analysis of the welfare costs of business cycles, and studies of the role of economic policy primarily build upon such statistical properties. More recently, business cycle analysis has focused extensively on identifying macroeconomic shocks and understanding how those shocks propagate (see, for example, the *Handbook* chapter by Ramey, 2017).

This paper investigates the cyclical propagation of shocks to the U.S. economy through the lens of the aggregate production function. What margins do firms use to respond to different shocks? Do they adjust hours per worker or the labor force? Do they adjust the workweek of capital or the effort required from employees? Importantly, do they respond differently to different shocks–such as a spike in oil prices, or changes in credit constraints, or changes in technology?

We focus this analysis on a concrete question: What margins of adjustment are needed to understand the strong empirical relationship between changes in unemployment and output–that is, the empirical regularity known as "Okun's Law"? We have known at least since Okun (1962) that movements in output and unemployment are closely intertwined. The unconditional relationship has remained remarkably stable for much of the last 50 years, as Ball, Leigh and Loungani (2013) and others have shown. At the same time, macroeconomic modeling has increasingly allowed business cycle models to incorporate unemployment. Examples include (Andolfatto, 1996; Gali, 1996; Galí, 2010; Barnichon, 2010; and Blanchard and Galí, 2010. Much though not all of this literature relies on search-and-matching frictions in labor markets based on the Diamond-Mortensen-Pissarides model (Pissarides, 2000, Chapter 1).

This shift in focus speaks directly to the manner different economies have recovered from the Great Recession and the challenges that lay ahead. For example, the surprising gains in employment experienced in the U.S. over the last few years are equally matched by dismal readings in productivity that have some researchers ringing the alarm bells of hysteresis and secular stagnation (see, e.g., Eggertsson and Mehrotra, 2014; Summers, 2014; and others), presaging an era of low productivity growth (see, e.g., Gordon, 2015).

In the next few sections we investigate fundamental moments calculated over the last 50 years between the unemployment rate and the various components of output viewed from the production side. This benchmark analysis reveals that the phenomenon of the Great Moderation, first discovered by McConnell and Pérez-Quirós (2000) (and later coined in Stock and Watson, 2003), is clearly visible in the manner firms behave. We will show, among other things, that firms have shifted from adjustments in hours-per-worker to adjustments in their work force. Not surprisingly, as firms trim staffing levels (usually by letting go of the least productive workers), productivity improves, thereby giving rise to another well documented feature of the American business cycle (Fernald and Wang, 2015): productivity has shifted from being procyclical to being countercyclical. Our work will provide a more detailed explanation for this shift.

These changes could have strong implications for how we build economic models to the extent that they reflect shifts in corporate behavior rather than shifts in the shocks firms typically face. Therefore, it is important to document two features of the post-WW2 experience: (1) the extent to which firms respond differently to different shocks; and, (2) the extent to which the nature of shocks that hit the economy has changed over time.

Absent a fully specified macroeconomic model, it may seem a hopeless task to disentangle how firms respond to different shocks. One of the main contributions of this paper is to propose a novel empirical strategy based on modern semiparametric time series methods and identification through instrumental variables. In particular, we use local projections (see Jordà, 2005) and instruments that have featured in the literature for a collection of economic shocks. These shocks are: (1) an interest rate shock (identified as in Romer and Romer, 2004 and updated by Cloyne and Hürtgen, 2014); an oil shock (based on Hamilton, 2003); a shock to credit conditions (based on Gilchrist and Zakrajšek, 2012); and a shock to total factor productivity adjusted for utilization (based on Fernald, 2014b). Using these shocks, we are able to trace the response of output and its components as well as the response of the unemployment rate. These responses can then be used to replicate our historical analysis but conditional on different experiments using Classical Minimum Distance (CMD). We will show that the nature of the shock has important implications for the margins firms

prefer to use to make adjustments.

The stability of Okun's law over the last 50 years, a convenient staff for policy makers, hides the tremendous transformation of the aggregate American corporate landscape. We feel such transformation has yet to be fully incorporated into the way macroeconomic models are built, calibrated and tested. Changes in labor markets, technology, and finance will undoubtedly continue to shape this new landscape. We view our contribution as setting the foundations over which better macroeconomic models can be formulated.

2. EMPIRICAL APPROACH

Fluctuations and the statistical properties of aggregate output are a focal point in macroeconomics. Much of our paper explores the factors behind the movements in output over the business cycle. In particular, we depart from a mechanical decomposition of aggregate output in total hours worked and labor productivity. Similarly, we also consider how total hours worked can be decomposed in number of workers and hours per worker.[1] Based on this decomposition, we shed light on the importance of taking into account how the various margins of adjustment respond to different macroeconomic shocks and how their responses help understand output fluctuations and the path followed by the economy.

Over the past few decades an increasing number of central banks have developed and estimated medium-scale New Keynesian DSGE models in order to study output fluctuations and the business cycle. These models are well suited for theoretical analysis and seem to provide sound empirical and forecasting properties. One common shortcoming of these models, however, is the small, or complete lack of a, role for unemployment as well as for the margins that firms use to adjust to shocks. More recently, Galí, Smets and Wouters (2011) fill this gap by developing and estimating a large-scale DSGE model that allows for changes to the unemployment rate, while Barnichon (2010) considers a partial-equilibrium model that allows for firms to adjust both the intensive and the extensive margins. These papers, among others (e.g. Fernald and Wang, 2015), highlight the importance of allowing for adjustments the on these margins to better understand the dynamics of the aggregate output.

A convenient starting platform from which to analyze the cyclical properties of aggregate

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[1]In addition to the aggregate margins of adjustment from the point of view of firms, there are several other household margins of adjustment. These include changes in labor-force participation reflecting household decisions on retirement and female participation, immigration/emmigration flows, or multiple job holdings. This dimension of the problem clearly preoccupied Okun as the opening quote of the paper reveals. These are definitely important factors that deserve to be investigated further, but are left for another paper.

production and its components is with Okun's Law. Tobin's quote at the beginning of the paper summarizes a sentiment that has been revived many times over the years – the remarkable record of stability documented in, e.g. Prachowny (1993) and Ball, Leigh and Loungani (2013). The baseline specification of Okun's Law relates the growth rate in real output, Δy, with the change in the rate of unemployment, ΔU:

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

The coefficient β directly captures the (reduced-form) comovement of output and unemployment. The unemployment rate is perhaps one of the better cyclical indicators there is.

It is easy to show that β in expression (1) is equal to the sum of the β's from component-wise Okun regressions based on the mechanical decomposition of aggregate output growth discussed earlier. For example, the OLS estimate of β from equation (1) equals the sum of the coefficients from the linear projections of growth in hours, denoted Δl, and growth in labor productivity, denoted $\Delta LP = (\Delta y - \Delta l)$, on unemployment changes, denoted ΔU. That is, $\hat{\beta} = \hat{\beta}^l + \hat{\beta}^{LP}$, where the coefficients $\hat{\beta}^l$ and $\hat{\beta}^{LP}$ come from the following regressions:[2]

$$\Delta l = \beta^l \Delta U + \epsilon^l \quad \text{and} \quad \Delta y - \Delta l = \beta^{LP} \Delta U + \epsilon^{LP}. \tag{2}$$

In the short-run, changes in the number of workers will be approximately the negative of changes in the unemployed and therefore a reasonable guess for $\hat{\beta}^l$ would be a coefficient of -1 or slightly higher. Thus, output should change by about $-(1 - \alpha)\Delta U$ where α is the capital-share. Assuming the value of the labor-share at about $1/3$, the change in output should be about $-(2/3)\Delta U$. In that case, $\hat{\beta}^l$ would be roughly -1, and $\hat{\beta}^{LP}$ would be roughly α, that is $1/3$. These back-of-the-envelope values are helpful benchmarks to keep in mind as we take expressions (1) and (2) to the data. In addition, they are helpful reminders of appropriate values to be used in common calibration exercises.

2.1. Instrumental Variable Local Projections

The elasticity of the growth rate in each component of output with respect to changes in the unemployment rate measures the sensitivity of that component to business cycle fluctuations in the practical sense. These fluctuations are the result of a variety of shocks

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

that hit the economy. The extent to which we can isolate the dynamic response of the components of output and of the unemployment rate to each type of shock allows one to measure shock-specific Okun elasticities. These elasticities educate us about the margins businesses favor in response to one shock or another.

Estimating these shock-specific elasticities from the data requires combining statistical tools in a novel manner. First, we use local projections (Jordà, 2005) to obtain estimates of the dynamic responses of output, its components and the unemployment rate. These responses are calculated for a variety of *treatments*, that is, perturbations caused by a variety of economic factors. In order to properly identify each treatment experiment, we extend the original local projection framework by using instrumental variables (see, e.g. Jordà, 2005; Jordà, Schularick and Taylor, 2015; and Owyang, Ramey and Zubairy, 2013). The underlying notion is that, for example, shocks to the interest rate will likely have different implications than shocks to oil prices (e.g., Galí, Lopez-Salido and Valles, 2003 and He and Krishnamurthy, 2013). Sometimes firms will adjust via hours worked. Other times they will adjust staffing levels instead. Or maybe they will prefer to adjust via labor productivity.

With the responses of the components of output and the unemployment rate obtained from instrumental variable local projections (LP-IV), we estimate shock-specific Okun elasticities using a classical minimum distance approach (CMD). LP-IV estimates of the responses are basically moments of the sample. Each shock-specific elasticity is itself a function of these moments. The LP-IV approach provides a simple way to both achieve identification and also to obtain the covariance matrix of the responses. Using this covariance matrix estimate, we construct optimally weighted estimates of shock-specific elasticities based on CMD and thus provide formal classical inference for these parameter estimates as well.

More specifically, let X_{jt} with $j = 1, ..., J$ denote output and its different components and hence let $x_{jt} = \log X_{jt}$. That is, $x_{jt} \in \{\Delta y_t, \Delta l_t, \Delta n_t, \Delta h_t, \Delta LP_t\}$. Denote the year on year difference[3] as Δ_4. Thus $\Delta_4 x_{jt}$ is the smooth yearly rate of change of X_{jt} (which we will discuss as percentage changes). Okun Law elasticities for each of the components can be estimated using regressions of the type:

$$\Delta_4 x_{jt} = \mu_j + \beta_j \Delta_4 U_t + \varepsilon_{jt}. \tag{3}$$

Throughout the paper we define cyclicality with respect to the unemployment rate based on this regression. Since the unemployment rate falls in booms and rises in recessions, a

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[3]Calculations based on quarter-to-quarter changes yield qualitatively similar results.

negative value for $\hat{\beta}_j$ means that the variable is *procyclical*, i.e., it tends to rise in booms and fall in recessions. Otherwise, we say the variable is *countercyclical*.

Next, instead of evaluating expression (3) using fluctuations in the raw data, suppose that we isolate fluctuations in x_{jt} and U_t that are explained by a given perturbation δ_i to a *treatment* variable w_{it} for $i = 1, ..., 4$ corresponding to each of the four factors we consider. As an example, think of the treatment variable as a monetary policy intervention. We are interested in calculating the average change in the future values of x_{jt} and U_t when $w_{it} = w_i + \delta_i$ compared to $w_{it} = w_i$. The difference in average responses under the *treatment* and *control* scenarios summarizes counterfactual movements in x_{jt} and U_t from which to obtain shock-specific Okun elasticities, as we will show momentarily.

Let the generic notation $s_{t+h} \in \{\Delta_h U_{t+h}, \Delta_h x_{1,t+h}, ..., \Delta_h x_{J,t+h}\}$, where Δ_h is the h-difference operator and where the size of the intervention is denoted δ_i. In addition, define R_t as a vector of controls that includes exogenous and predetermined values of s_t and w_{it}, although in general, one could potentially include additional variables. We define $I(s, h, w_i, \delta_i, R)$ as:

$$I(s, h, w_i, \delta_i, R) \equiv E(s_{t+h}|w_{it} = w_i + \delta_i; R_t) - E(s_{t+h}|w_{it} = w_i; R_t), \qquad (4)$$

for each experiment $i = 1, ..., 4$ as it evolves over $h = 0, ..., H - 1$ periods after impact.

In general, for a given experiment δ_i, $I(s, h, w_i, \delta_i, R)$ could vary with the level of the intervention variable, w_i, as well as the values of the control set, R_t. A 25 basis points (bps) decline in interest rates when the level is at 6% may have a different effect than when rates are at 1%, for example. Moreover, the same rate cut may have different effects in recession than in expansion. However, in what follows and to maintain the discussion accessible, we approximate the expectations in expression (4) using a linear model. Linearity makes the effects of δ_i invariant to w_i and R_t. For that reason, we simply write $I(s, h, \delta_i)$ from here on.

If the observables in R_t where sufficient to identify exogenous movements in w_{it}, the expectations in expression (4) could be calculated using the a set of regressions such as:

$$s_{t+h} = \alpha_{ih}^s + w_{it}\lambda_{ih}^s + R_t\Gamma_{ih}^s + e_{t+h}^s \qquad i = 1, ..., 4; h = 0, 1, ..., H - 1 \qquad (5)$$

where recall that $s_{t+h} \in \{\Delta_h U_{t+h}, \Delta_h x_{1,t+h}, ..., \Delta_h x_{J,t+h}\}$. It is easy to see that $\hat{I}(s, h, \delta_i) = \hat{\lambda}_{ih}^s \delta_i$.

However, we recognize that unobservable variables correlated with the intervention variable, w_{it}, and the outcome, s_t, could bias estimates based on expression (5). In order to ward off against such a situation, we will estimate expression (5) using instrumental

variables (IV) for each of the types of intervention considered, and denote the approach LP-IV. Instrumental variables have been used for identification in the VAR literature (see, e.g. Mertens and Ravn, 2013 and Gertler and Karadi, 2015) and with local projections (see, e.g. Owyang, Ramey and Zubairy, 2013 and Jordà, Schularick and Taylor, 2015). We note that when we estimate expressions such as (5) using IV methods we will allow up to 8 lags of the outcome variable, the unemployment rate and the intervention variable. The horizon over which we calculate (4) goes from h = 0, 1,..., 8.

The four interventions that we consider are: (1) to monetary policy measured by interest rates on the 3-month treasury bill rate instrumented by the series of shocks from Romer and Romer (2004) and extended in Cloyne and Hürtgen (2014); (2) to credit conditions measured by the average (cross-sectional) credit spread on senior unsecured corporate bonds issued by nonfinancial firms obtained from Gilchrist and Zakrajšek (2012) and instrumented with the shock series provided therein; (3) to oil markets measured by the West Texas Intermediate (WTI) oil price instrumented by the series of supply shocks identified by Hamilton (2003); and (4) to technology measured by shocks to utilization-adjusted TFP or $TFP^\star$ as constructed in Basu, Fernald and Kimball (2006).

LP-IV estimates of λ_{ih}^s can then be used to estimate shock-specific Okun elasticities using Classical Minimum Distance (CMD). More specifically, collect estimates $\hat{\lambda}_{ih}^s$ into a vector $\hat{\boldsymbol{\lambda}}_i^s = (\hat{\lambda}_{i,0}^s, ..., \hat{\lambda}_{i,8}^s)'$. Thus, $\hat{\boldsymbol{\lambda}}_i^s$ is of dimension 9×1. Moreover, under standard IV regularity assumptions (see, e.g. Wooldridge (2010)):

$$\sqrt{T}(\hat{\boldsymbol{\lambda}}_i^s - \boldsymbol{\lambda}_i^s) \xrightarrow{d} N(0, \Omega_i^s) \qquad i = 1, ..., 4; s = 1, ..., J, U. \tag{6}$$

In order to obtain shock-specific Okun elasticities, denoted β_{ij}, define the CMD objective function based on expression (3) as:

$$Q(\hat{\boldsymbol{\lambda}}_i^s; \beta_{ij}) = (\hat{\boldsymbol{\lambda}}_i^j - \hat{\boldsymbol{\lambda}}_i^U \beta_{ij})' M (\hat{\boldsymbol{\lambda}}_i^j - \hat{\boldsymbol{\lambda}}_i^U \beta_{ij}), \tag{7}$$

where M is the optimal weighting matrix. In order to minimize $Q(\hat{\boldsymbol{\lambda}}_i^s; \beta_{ij})$, set the first order conditions with respect to β_{ij} equal to zero and thus obtain the estimator:

$$\hat{\beta}_{ij} = (\hat{\boldsymbol{\lambda}}_i^{U'} M \hat{\boldsymbol{\lambda}}_i^U)^{-1} (\hat{\boldsymbol{\lambda}}_i^{U'} M \hat{\boldsymbol{\lambda}}_i^j). \tag{8}$$

Using expression (6) and setting $M = (\Omega_i^j)^{-1}$, it is straightforward to show that:

$$\sqrt{T}(\hat{\beta}_{ij} - \beta_{ij}) \xrightarrow{d} N(0, \nu_{ij}) \tag{9}$$

where:

$$\nu_{ij} = [\hat{\lambda}_i^{U'}(\Omega_i^j)^{-1}\hat{\lambda}_i^U]^{-1} \tag{10}$$

In practice one would substitute a heteroskedasticity and autocorrelation (HAC) robust estimate of Ω_i^j in expression (10) to obtain an estimate of ν_{ij}. In combination with expression (9), it is easy to conduct formal standard classical inference on $\hat{\beta}_{ij}$. A great deal of the technical details necessary to obtain this result has been omitted for clarity. Moreover, although not explicitly stated, we have used standard assumptions used in the majority of empirical work. Generalizations of this estimation procedure to potential pathologies in the data are possible but would distract from the main result. Expressions (9) and (10) are easily implementable using standard econometrics software –expression (8) is a weighted least-squares step. Before concluding the section we take a moment to note that the results presented in this section have wide applicability. For example, one could consider estimating the parameters of a more complex DSGE model by exploiting structurally identified impulse responses estimated using LP-IV and then deriving the CMD conditions that match the deep parameters in the first-order conditions of the DSGE model with the impulse response coefficients. This generalization is well beyond the scope of this paper, however.

2.2. Data

The data for the analysis that follows comes from relatively new, detailed, and carefully constructed quarterly growth-accounting data for the U.S. business sector from Fernald (2014a). Our dataset, which runs from 1949Q1 through 2015Q2, contains observations on each component described in earlier, as well as the components in which labor productivity can be further decomposed, as we briefly discussed. The construction of the data is as consistent as possible with production theory. Further details appear in Appendix A.1. However, several features of these data are worth highlighting here.

First, output is constructed as 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.[4]

Second, in addition to standard growth-accounting terms, the Fernald (2014*a*) dataset has an empirical measure of factor utilization. Utilization here is a quarterly implementation of what Basu, Fernald and Kimball (2006) measured annually. The authors 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. Basu, Fernald and Kimball (2006) and Fernald (2014*b*) 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.[5]

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 Labor Productivity and Costs release, which in turn decomposes hours into employment and hours per worker. These employment and hours data are based primarily on surveys of establishments.[6]

When comparing the household and establishment surveys, it is important to be consistent in coverage, since the household data cover the total civilian economy whereas the establishment-side data in the Labor Productivity and Costs release by the BLS (and in the Fernald, 2014*a* dataset) covers the narrower business sector. To be consistent, we use unpublished (but freely available on request) BLS data on employment and hours in the non-business civilian sector. By adding these measures to the corresponding productivity-and-cost measures, we can create an establishment-based measure of hours and employment

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[4]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 et al. (2013) recommend taking a weighted average of the two.

[5]The differences in parameters across industries, per se, do not 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.

[6]In results available upon request, we also look at household-survey data. 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. However, Cociuba, Prescott and Ueberfeldt (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. 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.

to compare with the household data.[7] We find that the establishment and household surveys are broadly consistent with one another. Hence, the changes we identify appear robust across datasets.[8]

Turning to the macroeconomic shocks, of the many reasons why the economy fluctuates we focus on four: (1) monetary policy; (2) credit conditions; (3) oil prices; and (4) technology. We use instrumental variables directly available in the literature for each of these factors. Exogenous fluctuations in interest rates come from an update by Cloyne and Hürtgen (2014) of the Romer and Romer (2004) monetary shocks. The shocks are the prediction errors made by Federal Reserve staff when producing Greenbook forecasts. Exogenous fluctuations in credit conditions are measured using the bond spread shock from Gilchrist and Zakrajšek (2012). This variable consists of the (option-adjusted) excess bond premium. Exogenous fluctuations in the supply of oil come from Hamilton (2003) and consist of an adjustment intended to identify supply side shocks using price data. Exogenous fluctuations in total factor productivity come from Fernald (2014a) and represent shocks to adjusted TFP or $TFP^\star$. A detailed explanation of how these shocks are obtained, a discussion on the exclusion restriction and instrument validity are provided in the original sources.

3. Adjusting to shocks

We begin this section by first evaluating whether the responses of the outcome variables to each of our four shocks are consistent with basic economic intuition. Figure 1 provides the responses of output growth, the unemployment rate, and the treatment variable using LP-IV for each of the four experiments, namely shocks to interest rates, credit, oil, and technology. The responses of the subcategories of output are omitted in the interest of space, but are available upon request. Figure 1 is based on the full sample up to the Great Recession, that is, 1949Q1–2007Q4. Results extended to 2015Q2 appear in Appendix A.3.

Figure 1 is organized as follows. Each row provides the response of output (left-hand column), the unemployment rate (middle column), and the response of impulse variable receiving the shock (right-hand column). All responses are consistent with economic intuition. Increases in interest rates, bond spread and oil prices cause output to decline and

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[7]Alternatively, we can subtract the non-business measures from the household-survey measures to create household-based business measures.

[8]This conclusion contrasts with claims by Hagedorn and Manovskii (2011), who appear to find sizable 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 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.

Figure 1: *Impulse responses to shocks in the interest rate, the bond premium, oil prices and TFP**
Full sample
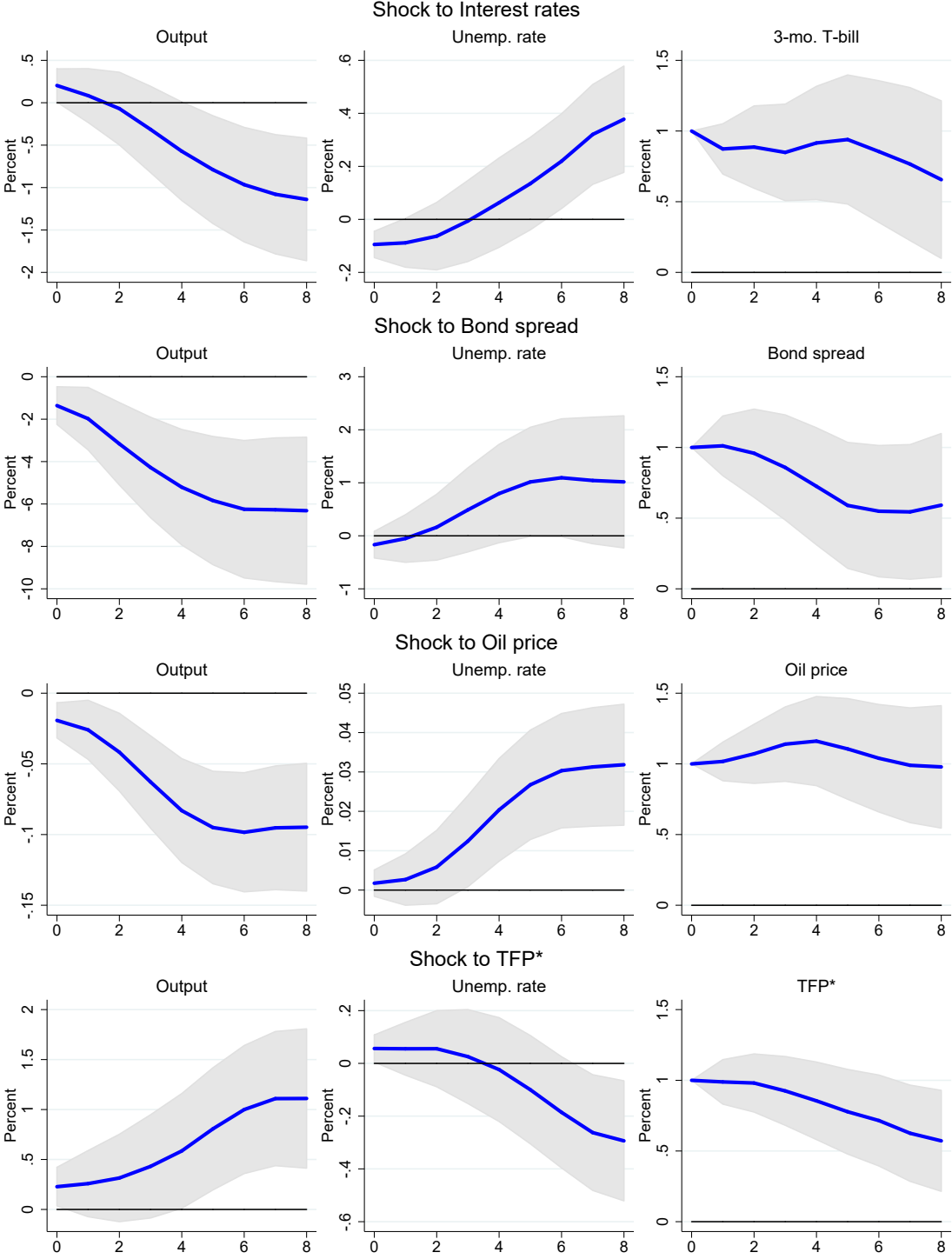
Notes: The figure reports the response of output and unemployment to the shocks indicated. The effect of the shock on its corresponding impulse series is reported in right column of charts. Responses are scaled to unity at time 0. The sample runs from 1949Q1 to 2007Q4, except for interest rates and bond spread, whose samples run from 1969Q1 to 2007Q4 and from 1973Q1 to 2007Q4, respectively.

the unemployment rate to increase whereas a positive technology shock has the opposite effect. Note that for the first 3 quarters unemployment is mildly positive. However, this is entirely consistent with the initial displacement of workers caused by new technology reported in the literature (see, e.g. Basu, Fernald and Kimball, 2006).

Based on Figure 1, we proceed to report estimates of shock-specific Okun elasticities in Table 1. The table is organized as follows. Column (1) provides the traditional static results based on the full sample analysis. These results are a natural benchmark. Columns (2)-(5) report LP-IV estimates based on the responses in Figure 1 in combination with the CMD procedure described in Section 2.1. More specifically, column (2) reports Okun elasticities to shocks in interest rates; column (3) to credit shocks; column (4) to oil shocks; and column (5) to technology shocks.

The estimates in column (1) are best thought of as an average over the full sample, that is, they average across all sorts of shocks and business cycle states. Loosely speaking, they can also be thought of as the values to which the component-wise Okun coefficients are expected to settle to over time. Standard errors are reported in parenthesis. These are calculated by CMD using the optimal weighting matrix obtained from the LP-IV procedure as explained in expression (10). Finally, the table reports the smallest value of the F-statistic for the instruments in the first stage. For all variables, this value is well above conventional critical values for standard weak instrument testing.[9]

Each row in the table is organized by component. Row (1), labeled "Output" reports the usual Okun coefficient, which is decomposed into rows (2) and (3), total hours worked and labor productivity respectively. Finally, the total hours category, row (2), is further decomposed into adjustments via total workers, row (2a) and adjustments via hours per worker, row (2b).

Estimates of the Okun coefficient reported in Table 1 are exactly additive, meaning that the coefficient estimate in row (1) is the sum of the coefficients in rows (2) and (3). Similarly, the coefficient in row (2) is the sum of the coefficients in rows (2a) and (2b). This feature is mechanical, but does not apply for the elasticities reported in columns (2)–(5). There are no intrinsic restrictions that would ensure similar additivity. And yet, the coefficient estimates are roughly additive, a good back-of-the-envelope check of the results based on our new estimation procedure.

It is helpful to discuss the static Okun patterns reported in column (1) first. The estimates

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[9]Note that the weak IV test value is missing from column (5). The reason is that the coefficient is obtained using local projections estimated by OLS. The reason is that, as we will discuss later, $TFP^\star$ is the observable, not the shock.

Table 1: *Shock-specific Okun elasticities. Full sample*

	Static (1)	Interest rates (2)	Bond spread (3)	Oil price (4)	$TFP^\star$ (5)
(1) Output	-2.32*** (0.09)	-3.06*** (0.59)	-3.77*** (0.86)	-2.63*** (0.57)	-2.83*** (0.70)
(2) Hours	-2.05*** (0.06)	-2.51*** (0.45)	-3.12*** (0.66)	-2.08*** (0.43)	-2.31*** (0.52)
(2a) Employees	-1.63*** (0.06)	-1.40*** (0.25)	-2.32*** (0.39)	-1.23*** (0.21)	-0.96*** (0.26)
(2b) Hours per employee	-0.42*** (0.04)	-0.45** (0.16)	-0.62** (0.22)	-0.57** (0.17)	-0.83*** (0.21)
(3) Labor productivity	-0.27** (0.10)	-1.11** (0.35)	-0.04 (0.53)	-0.03 (0.33)	-0.13 (0.39)
Min. Weak IV F-stat	n/a	20.7	12.8	22.2	n/a
N	236	140	124	224	224

Notes: ***/**/* indicates significance at the 99/95/90% confidence level. Column (1) are static Okun elasticities. Columns (2)-(5) are shock-specific Okun elasticities. Standard errors are reported in parentheses. Min. weak IV F-test refers to the smallest value of the first stage F-statistic for the instruments and is used to evaluate the strength of the instruments. The test does not apply to columns (1) and (5) and this is indicated with n/a. The sample runs from 1949Q1 to 2007Q4, except for interest rates and bond spread, whose samples run from 1969Q1 to 2007Q4 and from 1973Q1 to 2007Q4, respectively.

of the Okun coefficient reported in that column is -2.32, virtually the same value Okun estimated over 50 years earlier himself[10] The majority of this elasticity is explained by the total hours response reported in row (2) with a value of -2.05. About 80% of the decline in total hours reflects adjustments in employees. The coefficient for this category reported in row (2a) is -1.63 versus the -0.42 value corresponding to the hours per employee margin reported in row (2b). Thus while most of the adjustment of total hours takes place at the extensive rather than the intensive margins, both matter quantitatively.

The labor productivity coefficient of -0.27 in row (3) is roughly an order of magnitude smaller. Over the full sample, productivity is thus modestly procyclical, i.e., it tends to rise in booms, when unemployment falls; and it tends to fall in recessions, when unemployment rises. This weak procyclicality of labor productivity is consistent with the stylized facts from the macro literature (see, e.g., Basu and Fernald, 2001 for a discussion and references).

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[10]As noted above, we mneasure output by averaging the income and expenditure sides of the national accounts. In unreported results, we find that the estimate based on output measured by real expenditures is -2.15 whereas output measured with real income is -2.26. In both cases the estimates are not significantly different from the benchmark estimates reported in Table 1.

Compared to the static results, note that the shock-specific Okun elasticities for output in row (1) are generally larger (in absolute terms) than those reported in column (1). An exogenous increase in interest rates (column (2)) causes output to decline by more for a given increase in the unemployment rate (-3.06 versus -2.32), a result that seems to be largely driven by a larger decline in labor productivity (-1.11 versus -0.27). The response of total hours is more comparable (-2.51 versus -2.05).

Interestingly, a tightening of credit conditions, reported in column (3), has a similar effect on output (-3.77 vs. -2.32 for the static case). In contrast to the monetary experiment, total hours become more responsive (-3.12 vs. -2.05) mostly through bodies, whereas labor productivity is far less responsive (-0.04 vs. -0.27). On the other hand, oil prices and technology exhibit Okun elasticities that mirror almost perfectly the static estimates reported in column (1) in every category. Both of these type of shocks are probably closer to what one could consider a standard supply shock.

3.1. Economic implications

Adjustments through the intensive versus the extensive labor margins are pivotal to understand the economy's response to interest rate shocks, see e.g. Galí and Gambetti (2009) and Barnichon (2010) who highlight this point by constructing models that allow firms to adjust their labor use through alternative margins. Barnichon (2010), in particular, builds a model that allows firms and households to adjust on their effort, and firms to adjust hours per worker and the number of employees in response to different shocks. In his model, because the adjustment of employees is subject to hiring frictions, firms first rely on the intensive margin, adjusting hours worked. Workers, however, have a convex disutility in hours and effort. Firms cannot therefore rely solely on these two margins and also resort to adjustments in the number of employees.

In response to a positive non-technology shock (a monetary shock, in his model), firms first increase intensive margins (hours and productivity) before increasing the number of employees. As a result, the model predicts a negative relation between unemployment and both hours per worker and labor productivity. These predictions are consistent with the results reported in Table 1, column (2): the coefficients of hours per employee and of labor productivity are both negative and statistically significant.

A positive technology shock, on the other hand, raises firms' productivity. Initially firms meet demand by decreasing hours per worker and effort, eventually adjusting down the number of employees. Consequently, labor productivity undershoots its long term

equilibrium initially. In this case, the model predicts a negative relationship between hours per employee and unemployment, but the correlation between the latter and labor productivity is undetermined. These features are in line with the findings reported on Table 1, column (5). The coefficient on hours per worker is negative, but the coefficient on labor productivity is not statistically significant.

While Barnichon (2010) does not consider oil prices nor bond spread shocks, one can use his model to gather some intuition about the patterns reported on Table 1. Consider first an increase in oil prices. Since it is costly to adjust the employment margin, firms would first reduce effort and hours per worker, and later also reduce employment. This helps justify the findings of column (4) and the negative association between unemployment and both hours per employee and labor productivity, although the latter is not statistically significant.

Turning to the bond spread, if a positive shock implies solely an increase in credit funding costs to firms, the model would predict dynamics similar to those following an oil price increase. Firms adjust to higher funding costs by lowering investment and production, with an initial reduction in hours per worker and effort before then reducing employment. The prediction that the relationship between unemployment, and hours per worker and labor productivity are negative are supported by the data, as reported in Table 1, column (3).

These results straddle a period of time many refer to as the Great Moderation. It is therefore important to examine the robustness of our findings to a more careful analysis where the sample is partitioned in 1985. The choice of the 1985 break point is rather uncontroversial, as it coincides with the date favored by, e.g., McConnell and Pérez-Quirós (2000), Stock and Watson (2003), Galí and Gambetti (2009), and Barnichon (2010). This analysis is done in the next section.

4. The Great Moderation

This section examines the stability of the benchmark results presented in the previous section. The specific subsamples that we consider are from 1949Q1 to 1984Q4 and 1985Q1 to 2007Q4, thus omitting the Great Recession as before. The corresponding impulse response functions for output, unemployment, total hours and labor productivity are provided in Appendix A.2, broken down by subsample and organized as in Figure 1.

Table 2 presents the results organized by component just as in Table 1. Columns (1) and (2) provide the subsample estimates corresponding to column (1) in Table 1 to provide

a benchmark. As before, columns (1) and (2) are best thought of as averages across all shocks and business cycles over each subsample. The remaining columns redo the exercises reported in Table 1 for each subsample and type of shock. In particular, columns (3) and (4) report responses to a monetary shock in the pre-1984 and post-1984 subsamples respectively. Similarly, columns (5) and (6) report responses to the bond spread shock; columns (7) and (8) report responses to an oil price shock; and columns (9) and (10) report responses to a technology shock.

The static estimates of the Okun coefficient reported in row (1) and columns (1) and (2) suggest little difference across samples, -2.38 vs. -2.12. This is not always the case when focusing across shocks nor is this apparent stability visible even in the subcomponent analysis for columns (1) and (2). To the best of our knowledge, this important feature has not been highlighted in the literature before.

Consider the static results in columns (1) and (2) first. The coefficient for total hours becomes about 1/3 larger (from -1.96 to -2.89) with the Great Moderation. The brunt of the change is in the number of employees (-1.56 to -2.35) rather than hours per employee, which remain largely constant (-0.40 to -0.54). It is striking that with the advent of the so-called "gig-economy" and more flexible work schedules, on aggregate the declines in innovation and workers' bargaining power appear to have a much larger effect. The more interesting shift happens in labor productivity. It shifts from being procyclical (-0.42) to becoming strongly countercyclical (0.77), a result that others have noted (see, e.g. Stiroh, 2009; Gordon, 2010; Galí and van Rens, 2014; and Fernald and Wang, 2015).

The literature has suggested that the changing cyclicality of labor productivity can be explained by the changing role of monetary shocks during the Great Moderation. Barnichon (2010) and Galí and Gambetti (2009) argue that during the Great Moderation, structural changes in the economy (such as, the decline in hiring and firing costs, rising share of temporary workers, the decline of unions and the increase in flexibility in labor markets) may have changed how the economy responds to monetary shocks, and even changed the sign of the correlation between labor productivity and unemployment. In addition, Galí, Lopez-Salido and Valles (2003) argue that monetary policy has become more accommodative to technology shocks, reducing the response of the unemployment to the latter shocks.

How do our results compare against this literature? Columns (9) and (10), which correspond to the Okun elasticities from technology shocks, provide support to the arguments in Galí, Lopez-Salido and Valles (2003) and others. The Okun coefficient ir row (1) goes from -3.09 to 0.19. Moreover, turning to columns (3)–(10), the pattern that emerges is very

revealing. In this respect, labor productivity is, if anything, more procyclical since the Great Moderation started when one considers monetary, credit, and oil related shocks. The coefficients reported in row (3) either remain about the same or become more negative. The countercyclicality of productivity seems to be a phenomenon that is largely associated with technology, whose coefficients goes from 0.05 to 0.42.

The results reported in Table 1 suggest that the unconditional negative relationship between labor productivity and unemployment in the full sample results can only be obtained in response to monetary shocks, as all other shocks at hand yield statistically inconclusive results. This finding, however, disappears in the subsample analysis.

Taking a broader perspective, two results stand out. First, 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 that allowed for in typical Dynamic Stochastic General Equilibrium (DSGE) models with unemployment, which reflect the back-of-the-envelope arithmetic discussed in the previous section. Most models do not allow for enough margins of adjustment. Second, the Okun coefficient is relatively stable over time. This is surprising given the Great Moderation, and the shift in the cyclicality of labor productivity from procyclical to countercyclical.

5. The distribution of shocks since the Great Moderation

The Great Moderation has been associated to a number of explanations. Firms' willingness to adjust workforce over workweek is a good example, a willingness often blamed on a combination of deunionization and skill-biased technological change (see, e.g. Acemoglu, Aghion and Violante, 2001). However, shifts in the bargaining power of workers are a plausible explanation for the U.S. and the U.K., but the Great Moderation transcended to almost every advanced economy (Stock and Watson, 2005), even those where unions remained strong. Explanations have naturally turned to phenomena with a more international reach. Among them, better monetary policy through inflation targeting (Boivin and Giannoni, 2006), more stable commodity prices (Nakov and Pescatori, 2010), and even dumb luck (Ahmed, Levin and Wilson, 2004). The debate rages on.

Many of the explanations on the causes of the Great Moderation are often complementary rather than exclusionary. Our focus has been to examine the manner firms adjust to each of these potential explanations, and hence, characterize firm behavior rather than arbitrating across explanations. In this section, the focus is on describing shifts in the distribution of the main drivers examined in the previous section: interest rates, oil prices

(expressed as a growth rate), bond premiums and productivity (also expressed as a growth rate).

Table 2: *Shock-specific Okun elasticities. Pre- and Post-1984 samples*

	Static		Interest rates		Bond spread		Oil price		TFP*	
	(1) Pre-1984	(2) Post-1984	(3) Pre-1984	(4) Post-1984	(5) Pre-1984	(6) Post-1984	(7) Pre-1984	(8) Post-1984	(9) Pre-1984	(10) Post-1984
(1) Output	-2.38*** (0.11)	-2.12*** (0.21)	-2.72*** (0.65)	-7.01*** (1.30)	-1.14*** (0.30)	-5.89*** (1.39)	-2.54*** (0.53)	-4.64*** (1.02)	-3.09*** (0.74)	0.19 (0.97)
(2) Hours	-1.96*** (0.07)	-2.89*** (0.13)	-2.00*** (0.49)	-4.39*** (1.06)	-1.89*** (0.23)	-3.94*** (1.02)	-2.08*** (0.38)	-3.27*** (0.79)	-2.59*** (0.50)	-1.17 (0.90)
(2a) Employees	-1.56*** (0.07)	-2.35*** (0.10)	-1.28*** (0.23)	-3.27*** (0.63)	-1.00*** (0.10)	-3.42*** (0.62)	-1.35*** (0.17)	-1.69** (0.51)	-1.18*** (0.24)	-0.65 (0.51)
(2b) Hours per employee	-0.40*** (0.04)	-0.54*** (0.09)	-0.19 (0.13)	-0.69 (0.53)	-0.33*** (0.06)	-1.04 (0.56)	-0.16 (0.15)	-1.56*** (0.45)	-0.70*** (0.21)	-1.62** (0.50)
(3) Labor productivity	-0.42*** (0.11)	0.77*** (0.21)	-0.75 (0.47)	-0.60 (1.07)	-0.30 (0.25)	-0.84 (1.12)	-0.09 (0.30)	-1.26 (0.77)	0.05 (0.39)	0.42 (0.77)
N	144	92	56	84	40	84	140	84	140	84

Notes: ***/**/* indicates significance at the 99/95/90% confidence level. Columns (1) and (2) correspond to the results reported in Table 1 in column (1). Columns (3)-(8) report estimates using LPIV and the resulting impulse response functions. Columns (9) and (10) reports estimates using LP and the resulting impulse response functions. Standard errors are reported in parentheses. The pre-1984 sample runs from 1949Q1 to 1984Q4, while the post-1984 sample runs from 1985Q1 to 2007Q4, except for interest rate and bond spread, whose pre-1984 samples run from 1969Q1 to 1984Q4 and from 1973Q1 to 1984Q4, respectively.

We begin with summary statistics stratified by era, before and after 1984, and reported in Table 3. The table reports mean, standard deviation (S.D.), skewness and the first autocorrelation (ρ_1). Simple tests of the equality of means across samples suggest that for bond spread and technology shocks, the center of the distributions have shifted in a significant manner. Interest rates are much less volatile and relatively more symmetric about the mean than they used to be. Not surprisingly, interest rates are highly persistent. Although the mean for oil prices has not shifted significantly, the volatility of oil prices is much higher during the Great Moderation era. Bond spreads have nearly doubled. $TFP^\star$ is growing considerably slower in the post-1984 era, with negative skewness.

Table 3: *Summary statistics before and after the Great Moderation*

	Interest Rate		Oil prices		Bond Spread		TFP*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-1984	Post-1984	Pre-1984	Post-1984	Pre-1984	Post-1984	Pre-1984	Post-1984
Mean	5.00	4.70	1.60	1.30	1.10	1.70	1.50	1.10
p-value	[0.49]		[0.81]		[0.00]		[0.06]	
S.D.	3.30	1.90	8.50	13.50	0.30	0.70	1.70	1.40
Skewness	1.10	-0.20	7.20	-0.80	1.40	1.40	0.10	-0.70
ρ_1	0.97	0.97	0.18	0.16	0.83	0.93	0.69	0.74
N	144	92	144	92	48	92	144	92

Notes: *Mean* refers to the sample mean; *p-value* refers to the p-value of the null that the sample mean between samples is the same; *S.D.* refers to standard deviation; *Skewness* refers to the skewness coefficient; and ρ_1 refers to the coefficient of first order serial correlation. The pre-1984 sample runs from 1949Q1 to 1984Q4, while the post-1984 sample runs from 1985Q1 to 2007Q4, except for interest rate and bond spread, whose pre-1984 samples run from 1969Q1 to 1984Q4 and from 1973Q1 to 1984Q4, respectively.

The main takeaway from the analysis can therefore be summarized as follows. Although there have been noticeable differences in the distribution of the treatment factors that we considered in the analysis, to a great extent the overall effect of each of all these factors (with perhaps the exception of interest rates), has not changed as dramatically as one would expect. Thus, it is perhaps not surprising that the overall estimate of the Okun coefficient across samples reported in Table 2 has not varied very much even though, as we document in that table, the margins that, on aggregate, firms use to adjust to shocks appear to have shifted considerably.

Altogether, we find both that the nature of shocks hitting the economy and firms' responses to these shocks have changed. In some cases, such as for the bond spread and oil

price shocks, the coefficients on some of the margins have shifted considerably. Something similar can be said about technology shocks. Table 2 shows that the coefficients estimated over the Great Moderation yield a clear departure from the pre-1984 patterns. Therefore, these findings provide some evidence that, at least in response to these shocks, shifts in the firms' aggregate behavior have played a role in explaining the differences between firms' responses between the pre- and the post-1984 periods.

The different dynamics of interest rate shocks come as no surprise since, as shown by Leeper, Sims and Zha (1996) and Galí, Smets and Wouters (2011), monetary shocks have played a different role during the Great Moderation, and have been responsible for a smaller fraction of the variances of output and unemployment. In addition, Table 2 shows that the components of the Okun coefficient seem to also have changed during that period in response to an interest rate shock, with an increase (in absolute value) in the coefficients of both the Okun coefficient and number of employees.

6.   What explains the cyclicality of productivity?

As Section 4 showed, the cyclicality of labor productivity has switched over the sample. It went from being procyclical to becoming countercyclical. We explore the mechanisms that may explain this switch in more detail in this section. To do this, we move from simple identities to a more formal growth accounting framework as in Basu, Fernald and Kimball (2006).

Specifically, suppose output Y depends on three terms: capital services $W \times K$, effective labor services $L \times Q \times \Phi$, and technology, A. Capital services, in turn, depend on the stock of capital, K, and the workweek of capital (the number of hours capital is actually in operation), W. Effective labor services depend on hours L; the average "quality" of each hour, Q (which captures age, experience, and other observables); and effort Φ per quality-adjusted hour. Note that capital utilization shows up in W and labor hoarding in Φ. A is technology. We suppress time subscripts for simplicity. The production function can therefore be expressed as:

$$Y = F\left(W \times K; L \times Q \times \Phi; A\right). \tag{11}$$

Next, take log differences and impose the usual growth-accounting assumptions: (1) that the representative firm produces with constant returns; (2) that it faces perfect competition; and (3) that it takes factor prices as given. Under these assumptions, cost-minimization

implies that output elasticities are equal to factor shares. We denote the capital's share by α and the 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. We explore this time variation further in the empirical analysis that follows.[11]

With these assumptions, the production function in equation (11) takes the form (expressed in growth rates):

$$\Delta y = \alpha \left(\Delta k + \Delta w \right) + (1 - \alpha) \left(\Delta l + \Delta \phi + \Delta q \right) + \Delta a, \tag{12}$$

where, again, we use lower case to indicate the logs of the variables and Δ to denote first differences. We have normalized the elasticity of output with respect to technology to be one.

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

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

Defining the contribution of factor utilization (the workweek of capital and labor effort) to growth as $\Delta v \equiv \alpha \Delta w + (1 - \alpha) \Delta \phi$, we can then use expression (12) to write $\Delta z = \Delta v + \Delta a$. That is, TFP growth reflects variations in factor utilization and in technology. We will refer to the empirical counterpart of Δa as "utilization-adjusted TFP" or $TFP^\star$, which is the shorthand we have been using for referring to technology shocks in earlier parts of the paper. Δa is technology for the case of perfect competition and an aggregate production function.[12] This is the measure we have used in the preceding analysis.

Expression (12) can now be rearranged in terms of labor productivity, $(\Delta y - \Delta l)$, where:

$$\begin{aligned} \Delta y - \Delta l &= \alpha \left(\Delta k - \Delta l \right) + (1 - \alpha) \Delta q + \left(\alpha \Delta w + (1 - \alpha) \Delta \phi \right) + \Delta a \\ &\equiv \alpha \left(\Delta k - \Delta l \right) + (1 - \alpha) \Delta q + \Delta v + \Delta a. \end{aligned} \tag{13}$$

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[11] 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. Some studies document secular changes in shares, such as, Elsby, Hobijn and Şahin (2013). They discuss the decline in the labor share observed over the past two decades. That said, whether constant or time-varying shares, the choice has little effect on the analysis provided below. 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, however.

[12] Consistent with our assumptions, Basu, Fernald and Kimball (2006) find that utilization is the most important non-technological factor affecting measured TFP over the business cycle.

Table 4: *Labor productivity responses to different shocks. Pre- and Post-1984 samples*

	Static		Interest rates		Bond spread		Oil price		TFP*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Pre-1984	Post-1984	Pre-1984	Post-1984	Pre-1984	Post-1984	Pre-1984	Post-1984	Pre-1984	Post-1984
(3) Labor productivity	-0.42***	0.77***	-0.75	-0.60	-0.30	-0.84	-0.09	-1.26	0.05	0.42
	(0.11)	(0.21)	(0.47)	(1.07)	(0.25)	(1.12)	(0.30)	(0.77)	(0.39)	(0.77)
(3a) Capital deepening	0.60***	0.80***	0.71***	1.32***	0.56***	0.59	0.54***	0.77***	0.78***	0.36
	(0.03)	(0.07)	(0.15)	(0.28)	(0.08)	(0.32)	(0.12)	(0.21)	(0.16)	(0.26)
(3b) Labor quality	0.05***	0.09*	0.25***	0.16	0.12***	0.46**	0.06	0.18	0.09	0.29*
	(0.01)	(0.03)	(0.05)	(0.16)	(0.02)	(0.16)	(0.03)	(0.13)	(0.05)	(0.14)
(3c) TFP	-1.06***	-0.11	-1.23*	-1.84	-0.88***	-2.26	-0.87*	-2.29*	-1.07*	-0.16
	(0.12)	(0.21)	(0.50)	(1.10)	(0.24)	(1.26)	(0.36)	(0.93)	(0.50)	(0.99)
(3c1) Utilization	-1.49***	-0.81***	-1.06**	-1.09	-1.11***	-0.60	-0.65	-2.36**	-2.81***	-1.75*
	(0.12)	(0.18)	(0.39)	(0.78)	(0.26)	(0.93)	(0.36)	(0.74)	(0.51)	(0.69)
(3c2) TFP*	0.43***	0.70**	-0.57	0.90	0.48*	-0.44	0.14	0.96	1.29***	0.33
	(0.10)	(0.24)	(0.34)	(1.36)	(0.20)	(1.38)	(0.29)	(0.94)	(0.37)	(1.19)
N	144	92	56	84	40	84	140	84	140	84

Notes: ***/**/* indicates significance at the 99/95/90% confidence level. Columns (1) and (2) replicate results reported in Table **??**. Columns (3)-(8) report estimates using LPIV and the resulting impulse response functions. Columns (9) and (10) reports estimates using LP and the resulting impulse response functions. Standard errors are reported in parentheses. The pre-1984 sample runs from 1949Q1 to 1984Q4, while the post-1984 sample runs from 1985Q1 to 2007Q4, except for interest rate and bond spread, whose pre-1984 samples run from 1969Q1 to 1984Q4 and from 1973Q1 to 1984Q4, respectively.

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*, Δv; or *technology*, Δa.

Based on this discussion, we revisit the labor productivity results first reported in Table 2. Thus, Table 4 reports the labor productivity estimates in row (3) of Table 2 to help the reader, and then provides a similar analysis for each of the subcomponents of labor productivity using expression (13).

Table 4 is quite revealing. Once again, while labor productivity coefficients for interest rates and credit shocks look similar on the surface, there are dramatic changes taking place in the subcomponents. First, we discuss the overall shifts reported in columns (1) and (2) for the static case. The shift in the cyclicality of labor productivity is largely explained by shifts in utilization rates. $TFP^{\star}$ is slightly more countercyclical after 1985. The shift is more dramatic when considering the interest rate estimates in columns (3) and (4). Notice that row (3c2) corresponding to $TFP^{\star}$ switches from being countercyclical (-0.57 to 0.90). Interestingly, although labor productivity has similar values in row (3) for interest rate and bond spread shocks, the switch in row (3c2) for the bond spread is exactly the opposite of that just discussed for interest rates. $TFP^{\star}$ goes from being countercyclical to procyclical instead (0.48 to -0.44).

Oil markets offer a different perspective. Here labor productivity becomes much more procyclical, in large part explained by the shift in the utilization margin. Estimates in row (3c1) switch from -0.65 to -2.36 even as $TFP^{\star}$ is becoming more countercyclical, 0.14 to 0.96.

Since workers could be displaced more easily as unemployment increases, labor productivity also rises, becoming countercyclical. The change in cyclicality of labor productivity comes as a result of a change in all of its components, particularly factor utilization. The increase in the coefficients of capital deepening, of labor quality, and of utilization basically reflects a compositional effect. As unemployment rises and the number of employees declines, capital deepening (capital-labor ratio) and labor quality increase as qualified workers are more likely to remain employed. Utilization is still negatively correlated with unemployment, although this correlation is weaker in the post-1984 sample—the larger displacement of workers is accompanied by a smaller decline in factor utilization, relative to the pre-1984 sample.

7. Conclusion

The U.S. economy has generated growth of about 2% per capita over 100 years, a remarkable feat of stability. Underneath that stability, punctuated by the avatars of geopolitical events,

financial crises and the business cycle, hides an ever-changing economy. Through the lens of the economy's production function, we have investigated the manner labor and capital markets interact in the face of technological and institutional change since WW2, focusing on the before and the after of the Great Moderation.

Longstanding relationships among the big macroeconomic aggregates, such as Okun's Law, have stood remarkably still over this period. Yet beneath this deceiving calm, currents of change criss-crossed the economic ocean floor. Enduring benchmarks on which macroeconomic models have been designed and calibrated turn out to have evolved in some ways known and unknown. The latter have been the focus of this paper.

Our paper makes several contributions. We show that firms have increasingly preferred to adjust workforce over workweek, and therefore hours have become more responsive to unemployment fluctuations. Intensive and extensive margins play important roles: utilization rates, capital deepening and labor quality all vary in ways that had not been fully appreciated (exceptions include Barnichon, 2010 and Galí and Gambetti, 2009). Productivity, one of the fundamental forces of prosperity, has switched from being countercyclical to being procyclical. The implications of such a shift are difficult to underestimate. It begs the question: Does countercyclical policy matter not just in the short-run, but also in the medium and long-runs? Our results indicate that much depends on the nature of the shock the economy experiences in any given moment.

Our paper makes other contributions. On the methodological front, we have provided a new approach to investigate how fundamental moments of the economy vary depending on the shock experienced. In addition, we have discussed a different approach to evaluating the relative explanatory power of exogenous forces, whose impact and volatility have also changed. In aggregate, firms adjust to different shocks differently.

Factor utilization turns out to play an important role, in particular, providing important evidence in support of a large literature that emphasizes the importance of unobserved variations in factor intensity as an explanation for movements in productivity (see Basu and Fernald, 2001 and references therein). Moreover, this result ties into many DSGE models that find that a utilization margin helps propagate shocks.

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A. APPENDIX

A.1. Fernald (2014a) Quarterly Growth-Accounting Data

These data are available at http://www.frbsf.org/economic-research/economists/jfernald/quarterly_tfp.xls. They include quarterly growth-accounting measures for the business-sector, including output, hours worked, labor quality (or composition), capital input, and total factor productivity from 1947:Q2 on. In addition, they include a measure of factor utilization that follows Basu, Fernald and Kimball (2006). They are typically updated one to two months after the end of the quarter (for example, data through 2011:Q4 were posted on February 2, 2012, following the release of BLS Labor Productivity and Costs 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.[13]

The data are described in greater detail in Fernald (2014a). 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

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[13]To name six minor differences: (i) BLS covers private business, Fernald (2014a) covers total business. (ii) BLS uses expenditure-side measures of output, whereas Fernald (2014a) 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 (2014a) 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).

data on inventory stocks and interpolate/extrapolate the annual BLS estimates of land input. Note that the data also allow me to calculate sub-aggregates, such as equipment and software capital, or structures capital.

(iv) Factor shares: Interpolated and, where necessary, extrapolated from the annual data on factor shares, α and $(1 - \alpha)$, from the BLS multifactor productivity database.

(v) Labor composition: Interpolated and extrapolated from annual measures in the BLS multifactor productivity data.

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

(vi) Hours-per-worker $\left(\frac{H^i}{N^i} \right)$ 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 β^i is a coefficient estimated by Basu, Fernald and Kimball (2006). Fernald (2014b) then calculates an aggregate utilization adjustment as $\Delta \ln Y = \Sigma_i w_i \Delta \ln Y_i$, where is the industry weight from Basu, Fernald and Kimball (2006) (taken as the average value over the full sample).

The resulting utilization-adjusted series differs conceptually from the Basu, Fernald and Kimball (2006) purified technology series along several dimensions. Those authors 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 Basu, Fernald and Kimball (2006) 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.[14]

For this paper, we modify the labor-quality adjusted TFP and utilization-adjusted TFP measures relative to the figures in the downloadable spreadsheet. The Fernald (2014a) 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

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[14]The output data also differ, both in vintage and data source, from the annual data used by Basu, Fernald and Kimball (2006).

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.2. Adjusting to shocks: pre- and post-1984

Figure A1 reports estimates of the responses based on equation (5) for output, unemployment rate, total hours and labor productivity based on LPIVs for the interest rate, credit spread and oil price shocks, and based on LPs for the TFP* shock. These impulse response functions provide input to the construction of the corresponding coefficients reported on main text Table 2. We do not report the impulse responses for the remaining components of output in the interest of space, although they are available upon request.

Figure A1 is organized as follows. Each row provides the response of output, unemployment, total hours and labor productivity to each type of shock. For each variable, the panel reports the impulse response function estimated in the pre- and the post-1984 subsamples. Solid circles indicate that the response in the pre-1984 sample is statistically significant at the 10% level, while open circles indicate that the response in the post-1984 sample is statistically significant at the 10% level.

A.3. Including the Great Recession

Throughout the paper, at the cost of loosing data points, we have excluded data since the Great Recession. This was so because we did not want to have the turmoil of the Great Recession years possibly biasing our results.

In this Section we redo the main text Tables 1 and 2 but allow the post-1984 sample to include the Great Recession and the recovery, i.e., the sample runs from 1985 to 2015Q2. Results are reported in Tables A1 and A2. For completeness, in these tables we also include results corresponding to the components of labor productivity (in analogy to the main text Table 4).

In very general terms, results change somewhat in the sample including the Great Recession. A few differences worth noting arise.

Starting with Table A1, the full sample analysis yields a positive and statistically significant (at 10%) coefficient for labor productivity in response to the bond spread shock, while in the pre-Great Recession sample, this coefficient was negative and not statistically significant. The inclusion of the Great Recession and recovery period implies the addition of data points in which these bond spread shocks were the most volatile. In addition,

Figure A1: *Impulse responses to shocks in the interest rate, the bond premium, oil prices and TFP⋆: pre- and post-1984 samples*
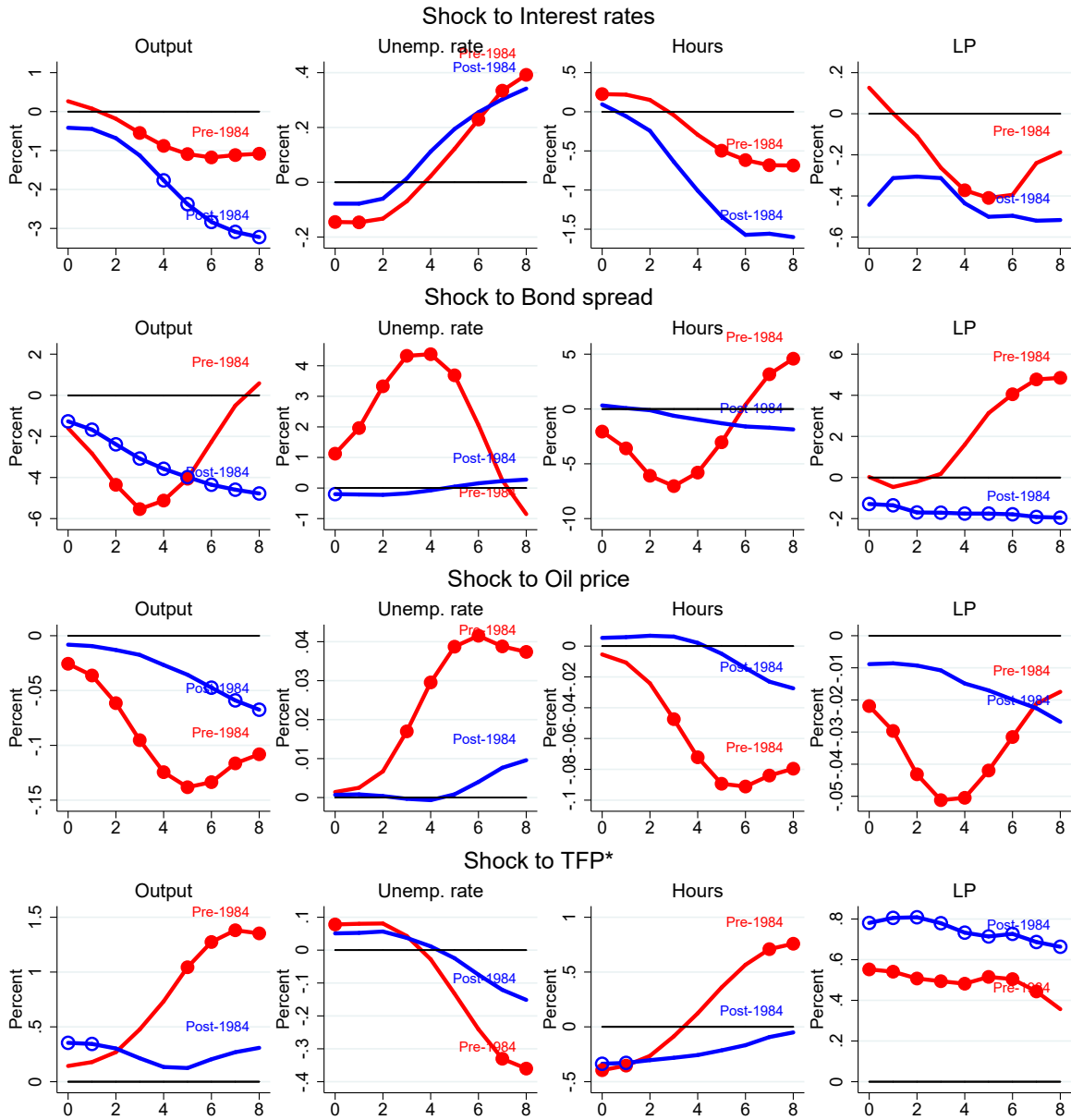
Notes: The figure reports the response of output, unemployment, hours worked and labor productivity to the shocks indicated. Shocks (unreported) are normalized to unit at time 0. Solid circles indicate that the response in the pre-1984 sample is statistically significant at the 10% level, while open circles indicate that the response in the post-1984 sample is statistically significant at the 10% level. The pre-1984 sample runs from 1949Q1 to 1984Q4, while the post-1984 sample runs from 1985Q1 to 2007Q4, except for interest rate and bond spread, whose pre-1984 samples run from 1969Q1 to 1984Q4 and from 1973Q1 to 1984Q4, respectively.

thinking through this change under the lens of Barnichon (2010)'s model, the financial constrains of the Great recession affected not only firms, but also the households' financing costs and optimization decision. The severity of the crisis and the singularity of movements in bond spreads in that period may have affected the economy through other channels than those allowed for in the model, for example, by possibly affecting households' confidence (e.g., Angeletos and La'O, 2013 and Benhabib, Wang and Wen, 2015). These singular developments may be behind the aforementioned change in magnitude and statistical significance in the correlation between labor productivity and unemployment. Table A2 concurs with this discussion by showing that the positive and statistically significant coefficient on labor productivity in response to the bond spread shock appears in the 1985-2015 subsample only.

In addition, Table A2 also shows a somewhat changed role for interest rate shocks, with much more muted coefficients relative to the results for the 1985-2007 sample reported in Table 2. This comes as no surprise, as since and during the Great recession, the use of interest rates as a monetary policy tool has been limited.

Table A1: *Dynamic component-wise responses to different shocks*
Including the Great Recession

	Table 1 (1)	Interest rates (2)	Bond spread (3)	Oil price (4)	TFP* (5)
(1) Output	-2.21*** (0.09)	-3.52*** (0.89)	-2.14*** (0.50)	-2.43*** (0.49)	-2.78*** (0.62)
(2) Hours	-2.08*** (0.06)	-2.64*** (0.69)	-2.64*** (0.38)	-2.13*** (0.39)	-2.42*** (0.47)
(2a) Employees	-1.66*** (0.06)	-1.29*** (0.38)	-2.21*** (0.24)	-1.33*** (0.21)	-1.46*** (0.26)
(2b) Hours per employee	-0.41*** (0.03)	-0.45 (0.26)	-0.47*** (0.11)	-0.56*** (0.14)	-0.76*** (0.18)
(3) Labor productivity	-0.13 (0.09)	-1.30* (0.55)	0.51* (0.25)	0.07 (0.28)	-0.23 (0.33)
(3a) Capital deepening	0.64*** (0.02)	0.84*** (0.19)	0.58*** (0.12)	0.73*** (0.12)	0.62*** (0.15)
(3b) Labor quality	0.06*** (0.01)	0.29** (0.10)	0.17*** (0.04)	0.04 (0.04)	0.19*** (0.05)
(3c) TFP	-0.82*** (0.09)	-2.48*** (0.63)	-0.16 (0.30)	-0.76* (0.33)	-1.34*** (0.41)
(3c1) Utilization	-1.30*** (0.09)	-0.68 (0.55)	-0.76** (0.24)	-0.92** (0.29)	-2.48*** (0.40)
(3c2) TFP*	0.48*** (0.08)	-1.00 (0.60)	0.42 (0.28)	0.44 (0.27)	0.84* (0.34)
Min. Weak IV F-stat	n/a	21.8	28.7	18.5	n/a
N	266	148	152	254	254

Notes: ***/**/* indicates significance at the 99/95/90% confidence level. Column (1) is based on a simple OLS of each variable on unemployment. Columns (2)-(4) report estimates using LPIV and the resulting impulse response functions. Column (5) report estimates using LPOLS and the resulting impulse response function. Standard errors are reported in parentheses. Min. weak IV F-test refers to the smallest value of the first stage F-statistic for the instruments and is used to evaluate the strength of the instruments. The test does not apply to columns (1) and (5) and this is indicated with n/a. Standard errors are reported in parentheses. The sample runs from 1949Q1 to 2015Q2, except for interest rates and bond spread, whose samples run from 1969Q1 to 2007Q4 and from 1973Q1 to 2012Q4, respectively.

Table A2: *Dynamic component-wise responses to different shocks*
Including the Great Recession

	Table 1		Interest rates		Bond spread		Oil price		TFP*	
	(1) Pre-1984	(2) Post-1984	(3) Pre-1984	(4) Post-1984	(5) Pre-1984	(6) Post-1984	(7) Pre-1984	(8) Post-1984	(9) Pre-1984	(10) Post-1984
(1) Output	-2.38*** (0.11)	-1.88*** (0.14)	-2.72*** (0.65)	1.05 (1.40)	-1.14*** (0.30)	-2.01*** (0.48)	-2.54*** (0.53)	-2.92*** (0.83)	-3.09*** (0.74)	-1.27 (0.81)
(2) Hours	-1.96*** (0.07)	-2.42*** (0.08)	-2.00*** (0.49)	-2.33* (1.14)	-1.89*** (0.23)	-2.65*** (0.38)	-2.08*** (0.38)	-3.38*** (0.79)	-2.59*** (0.50)	-1.68* (0.78)
(2a) Employees	-1.56*** (0.07)	-1.97*** (0.08)	-1.28*** (0.23)	0.09 (0.74)	-1.00*** (0.10)	-2.38*** (0.27)	-1.35*** (0.17)	-2.59*** (0.61)	-1.18*** (0.24)	-1.66*** (0.49)
(2b) Hours per employee	-0.40*** (0.04)	-0.42*** (0.05)	-0.19 (0.13)	0.23 (0.51)	-0.33*** (0.06)	-0.48*** (0.11)	-0.16 (0.15)	-0.89*** (0.23)	-0.70*** (0.21)	-0.99*** (0.24)
(3) Labor productivity	-0.42*** (0.11)	0.55*** (0.13)	-0.75 (0.47)	0.38 (0.98)	-0.30 (0.25)	0.60* (0.26)	-0.09 (0.30)	0.62 (0.62)	0.05 (0.39)	0.18 (0.51)
(3a) Capital deepening	0.60*** (0.03)	0.73*** (0.04)	0.71*** (0.15)	-0.18 (0.28)	0.56*** (0.08)	0.58*** (0.11)	0.54*** (0.12)	0.99*** (0.23)	0.78*** (0.16)	0.55* (0.24)
(3b) Labor quality	0.05*** (0.01)	0.12*** (0.02)	0.25*** (0.05)	0.03 (0.19)	0.12*** (0.02)	0.17*** (0.04)	0.06 (0.03)	0.11 (0.08)	0.09 (0.05)	0.27*** (0.08)
(3c) TFP	-1.06*** (0.12)	-0.29* (0.13)	-1.23* (0.50)	0.46 (1.04)	-0.88*** (0.24)	-0.10 (0.30)	-0.87* (0.36)	-0.51 (0.63)	-1.07* (0.50)	-1.07 (0.65)
(3c1) Utilization	-1.49*** (0.12)	-0.84*** (0.12)	-1.06** (0.39)	-2.04* (0.92)	-1.11*** (0.26)	-0.70** (0.24)	-0.65 (0.36)	-1.41** (0.45)	-2.81*** (0.51)	-1.47** (0.49)
(3c2) TFP*	0.43*** (0.10)	0.55*** (0.13)	-0.57 (0.34)	0.48 (1.15)	0.48* (0.20)	0.64 (0.35)	0.14 (0.29)	1.27 (0.76)	1.29*** (0.37)	-0.07 (0.70)
N	144	122	56	92	40	112	140	114	140	114

Notes: ***/**/* indicates significance at the 99/95/90% confidence level. Columns (1) and (2) are based on a simple OLS of each variable on unemployment. Columns (3)-(8) report estimates using LPIV and the resulting impulse response functions. Columns (9) and (10) reports estimates using LPOLS and the resulting impulse response functions. Standard errors are reported in parentheses. The pre-1984 sample runs from 1949Q1 to 1984Q4, while the post-1984 sample runs from 1985Q1 to 2015Q2 for oil and TFP*. For interest rate and bond spread the pre-1984 samples runs from 1969Q1 to 1984Q4 and from 1973Q1 to 1984Q4, and post-1984 samples run from 1985Q1 to 2007q4 and from 1985Q1 to 2012Q4, respectively.