The Cyclical Behavior of the Price-Cost Markup

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Abstract

A countercyclical markup of price over marginal cost is a key transmission mechanism for demand shocks in New Keynesian (NK) models. This paper re-examines the foundation of those models by studying the cyclicality of the price-cost markup in the private economy. We find that how the markup is measured matters for its unconditional cyclicality. Measures of the markup based on the inverse of the labor share are moderately procyclical, but are moderately countercyclical for some generalizations of the production function. NK models predict that the cyclicality of the markup should vary depending on the nature of the shock. Consistent with the NK model, we find that the markup is procyclical conditional on TFP shocks and countercyclical conditional on investment-specific technology shocks. In contrast, we find that the markup increases in response to a positive demand shock. Thus, the transmission mechanism for the effects of demand shocks in sticky-price NK models is not consistent with the data.

JEL codes: E3, J3
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1 Introduction

The markup of price over marginal cost plays a key role in sticky-price New Keynesian (NK) macroeconomic models. In these models, a demand shock raises output and marginal cost, but since prices are sticky, the markup of price over marginal cost falls. As pointed out by Broer et al. (2019), a lower markup leads to higher output during booms largely through its effect on profits. In particular, lower markups reduce profits, generating a negative wealth effect that induces households to raise their labor supply. Even in the medium-scale NK models that also incorporate sticky wages, countercyclical movements in the price markup play a key role in the transmission of monetary and fiscal policy shocks. For example, in the estimated dynamic stochastic general equilibrium model from Smets and Wouters (2007), the price markup is countercyclical in response to a monetary shock. The two-agent New Keynesian and heterogeneous-agent New Keynesian (HANK) models also rely heavily on countercyclical price markups to amplify shocks. As Debortoli and Galí (2018, p. 31) point out, "in both models the amplification/dampening of aggregate shocks depends critically on the cyclical properties of markups (or equivalently the labor share). . ." Indeed, price markups are required to be so countercyclical in the leading HANK models that expansionary monetary shocks cause profits to fall.[1]

The dependence of Keynesian models on a countercyclical price markup is a feature only of the models formulated since the early 1980s. From the 1930s through the 1970s, the Keynesian model was founded on the assumption of sticky wages.[2] Some researchers believed that the implications of this model were at odds with the cyclical properties of real wages, leading to a debate known as the "Dunlop-Tarshis" controversy.[3] In response to the perceived disparity between the data and predictions of the traditional Keynesian model, the literature shifted in the early 1980s to relying on sticky prices rather than sticky wages for the transmission of shocks.[4] While the medium-scale

1. Kaplan, Moll and Violante (2018, p. 716)

2. Such as Keynes (1936); Phelps (1968); Taylor (1980).

3. In fact, Dunlop (1938) and Tarshis (1939) were repeatedly misquoted by the literature as showing that real wages were procyclical. Neither of them showed this. Both authors showed that money wages and real wages were positively correlated, and Tarshis went on to show that real wages were in fact negatively correlated with aggregate employment. Dunlop (1998) discusses the debate in his retrospective article.

4. Gordon (1981); Rotemberg (1982).

NK models add wage stickiness, virtually all current NK models rely on countercyclical price markups in response to demand shifts.

Is the price markup countercyclical in the data? There is no consensus, because estimating the cyclicality of the markup is one of the more challenging tasks in macroeconomics. Theory prescribes a comparison of price and marginal cost; however, available data typically include only average cost. As we will discuss, researchers have used a variety of techniques to measure the markup directly, or have inferred its movements using indirect evidence. Some researchers have estimated the markup to be procyclical while others have estimated it to be countercyclical.

In this paper, we assess how various measures of the aggregate markup move over the business cycle and how they respond to leading macroeconomic shocks. We find that how the markup is measured matters for its unconditional cyclicality — that is, its relationship with an indicator of the business cycle. Markups measured as the inverse of the labor share are moderately procyclical, but markups based on more general production functions are procyclical or countercyclical depending on the details of the empirical implementation.

Our main emphasis is on the *conditional* cyclicality of the markup — that is, how the markup responds to a particular type of shock. If business cycles are driven by a multitude of shocks, not just demand shocks, the unconditional cyclicality is not dispositive.[5] Because sticky-price NK models predict the markup should behave differently in response to different shocks, the conditional cyclicality is the appropriate way to evaluate these models.

Unlike our estimates of the unconditional cyclicality, the sign of the conditional cyclicality does not depend on the empirical measure of the markup. Consistent with the NK model, we find that the markup is procyclical conditional on total factor productivity (TFP) shocks and countercyclical conditional on investment-specific technology (IST) shocks. In contrast to the sticky-price NK model predictions, we find that the markup *increases* in response to expansionary monetary policy shocks and government spending shocks. Thus, we conclude that the transmission mechanism for these policy shocks in sticky-price NK models is not consistent with the data.

5. Fleischman (1999) made this point forcefully for real wages, demonstrating empirically that real wages are procyclical conditional on technology shocks, but countercyclical conditional on labor supply shocks and aggregate demand shocks.

One possible route to resolving this inconsistency would be for a return to the traditional Keynesian emphasis on wage rigidities instead of price rigidities. Indeed, several recent papers have advocated such a shift. For example, Broer et al. (2019) advocate shifting from price stickiness to wage stickiness based on insights from heterogeneous agent models, while Auclert and Rognlie (2017) do so based on undesirable interactions between Greenwood, Hercowitz and Huffman (1988) preferences and flexible wages.

2 Relationship to the literature

Industrial organization economists have a long history of studying the cyclicality of price-cost margins. Macroeconomists only began studying this issue in the mid-1980s when macro models started to emphasize price setting behavior of firms. Four principal methods have been used to measure the markup directly and two additional methods have been used to assess the cyclicality of the markup indirectly.

The first of the direct methods uses the standard industrial organization concept of a price-cost margin constructed from revenues and variable costs. Domowitz, Hubbard and Petersen (1986) use this method in a panel of four-digit SIC manufacturing industries and find that margins are significantly procyclical. Anderson, Rebelo and Wong (2018) use confidential detailed data from the retail industry and measure markups by comparing well-measured individual product prices to the replacement cost of the good. This latter cost measure should be a very good proxy for marginal cost. They find that markups are acyclical or mildly procyclical.

The second method builds on Hall's (1986) generalization of the Solow residual to estimate the cyclicality of markups. For example, Haskel, Martin and Small (1995) extend Hall's framework to allow for time-varying markups and apply it to a panel of two-digit U.K. manufacturing industries. They find that markups are markedly procyclical. Marchetti (2002) applies a similar framework to two-digit manufacturing industries in Italy. He finds no clear pattern of cyclicality of markups; in only 2 of 13 industries does he find consistent evidence across specifications of countercyclical markups.

The third method uses generalized production functions with quasi-fixed factors to estimate markups relative to marginal cost estimated from stochastic Euler equations. Using this type of approach, Morrison (1994) finds weakly procyclical markups in Canadian manufacturing, and Chirinko and Fazzari (1994) find acyclical or procyclical markups in firm-level data. Galeotti and Schianterelli (1998) test the Rotemberg

and Saloner (1986) game-theoretic hypothesis and find that, consistent with this hypothesis, markups depend negatively on the current level of output but positively on the growth of output.

The fourth method uses variable inputs to estimate marginal cost. The most widely-used variable input is labor since it aligns with the measured markup in NK models. Under standard assumptions, such as Cobb-Douglas (C-D) production functions and no overhead labor, this method implies that the markup is inversely proportional to the labor share. Since the labor share is countercyclical during the post-WWII period, this measure of markups implies that markups are on average procyclical. Most of the papers using reduced form methods to measure the cyclicality of markups have applied adjustments to the standard model to account for reasons why marginal labor costs might be more procyclical than average labor costs. For example, Bils (1987) argues that the marginal hourly wage paid to workers should be more procyclical than the average wage. He constructs a measure of marginal cost based on estimates of the marginal wage and finds that his markup series has a negative correlation with industry employment in a panel of two-digit industries, suggesting countercyclicality. Rotemberg and Woodford (1991), Rotemberg and Woodford (1999), Oliveira Martins and Scarpetta (2002), and Galí, Gertler and López-Salido (2007) apply additional adjustments to the standard model, such as substituting a constant elasticity of substitution (CES) production function for C-D and allowing for overhead labor.[6] Their applications of these adjustments typically convert procyclical markups (based on standard assumptions) into countercyclical markups. Bils, Klenow and Malin (2018) argue that wages are not allocative in typical employment relationships and formulate other measures of markups using either self-employed workers or intermediate goods. Their measures for the period after 1987 suggest countercyclical markups. De Loecker, Eeckhout and Unger (2019) also use variable inputs, but instead of focusing on only one input, they use Compustat's variable on the cost of goods sold as a measure of all variable inputs in order to infer markups.

The two indirect methods for assessing the cyclicality of the markup use entirely different frameworks. Bils and Kahn (2000) present a model of inventories and stock-outs in which the joint cyclicality of the ratio of sales to inventories and the discounted growth rate of output prices reveals the cyclicality of markups. They use this framework

6. The appendix of Galí, Gertler and López-Salido (2007) gives a particularly clear and concise summary of the adjustments.

to conclude that markups are countercyclical in several two-digit U.S. manufacturing industries. Hall (2012) exploits standard advertising theory to show that countercyclical markups imply that advertising should also be highly countercyclical. He shows, in fact, that advertising is somewhat procyclical.

Finally, a relatively recent literature has documented and offered explanations for the global decline in the labor share.[7] Some of the papers in this literature have introduced additional methods for estimating the markup. Barkai (2017), Gutiérrez (2017), and Gutiérrez and Philippon (2017) assume constant returns to scale and infer markups from measured profit rates. Karabarbounis and Neiman (2018), however, offer arguments against the profit rate approach. As mentioned above, De Loecker, Eeckhout and Unger (2019) use Compustat's variable on the cost of goods sold as a measure of the variable input in order to infer markups. Since the focus of this literature is on trends, none of these papers has analyzed the cyclicality of their measures of markups.

Overall, this literature has used a host of innovative and clever ways to measure markups. Given the mixed results of the literature, it is surprising that the countercyclicality of markups is often treated as a stylized fact.

In this paper, we first revisit the arguments from the literature and then proceed to construct markups based on new data and new methods to implement the theoretical measures. We argue that the cyclicality of the markup sheds light on the NK model only when analyzed conditional on the type of shock.

3 Theoretical framework

This section lays out the theoretical framework that forms the basis of our main estimates of the markup. We first derive general expressions for the markup based on the firm's cost minimization problem. Next, we explain why we think that labor hours is the best margin for measuring the markup. Finally, we show several possible measures of the markup based on assumptions about the production function.

7. See, for example, Karabarbounis and Neiman (2014).

3.1 Deriving the price markup from cost minimization

The theoretical markup, $\mathcal{M}$, is defined as

$$\mathcal{M} = \frac{P}{MC}, \tag{1}$$

where P is the price of output and MC is the nominal marginal cost of increasing output. The inverse of the right hand side of equation 1, MC/P, is also known as the *real marginal cost* in the NK literature.

A cost-minimizing firm should equalize the marginal cost of increasing output across all possible margins for varying production. Thus, it is valid to construct the marginal cost of varying output based on changing any one input. Most of the literature has considered variable inputs in order to avoid the challenges involved in estimating adjustment costs.

Focusing on the cost-minimization problem for variable inputs, consider the problem of a firm that chooses variable inputs x_i, $i = 1, \ldots, N$ to minimize

$$\text{Cost} = \sum_{i=1,\ldots,N} (w_i \cdot x_i) + \text{terms not involving } x\text{s}, \tag{2}$$

subject to

$$\bar{Y} = F(x_1, x_2, \ldots, x_N), \tag{3}$$

where w_i is the factor price, x_i is the variable input, Y is output, and $F(\ldots)$ is the production function. Letting λ be the Lagrange multiplier on the constraint, we obtain the first-order condition for x_i as:

$$w_i = \lambda \cdot \frac{\partial Y}{\partial x_i}. \tag{4}$$

Since the multiplier λ is equal to the marginal cost of raising output, we can substitute equation 4 into equation 1 to derive the markup based on using input x_i to raise output:

$$\mathcal{M}_{x_i} = \frac{1}{s_{x_i}} \cdot \left(\frac{\partial Y}{\partial x_i} \cdot \frac{x_i}{Y} \right) \tag{5}$$

where

$$s_{x_i} = \left(\frac{w_i \cdot x_i}{P \cdot Y} \right) \tag{6}$$

is x_i's factor share of output. The term in parentheses in equation 5 is the elasticity of output with respect to x_i. Thus, the markup can in theory be measured as the product of the inverse of any variable input's share and the output elasticity with respect to that input.

3.2 Why we measure the markup using the labor margin

In principle, one can choose the first-order condition for any variable input as the basis for the markup measure. The traditional variable input studied is the labor input margin. Hamermesh and Pfann's (1996) summary of the literature suggests that adjustment costs on the number of employees are relatively small and that adjustment costs on hours per worker are essentially zero. Bils (1987) and Rotemberg and Woodford (1999) study markups based on the hours per worker margin, and virtually all modern NK models use the total labor hours margin.

Some have criticized the use of the labor margin, arguing that a key part of the marginal cost measure — average hourly wages — may not be a good indicator of the true marginal cost of an extra hour of work. This critique takes two forms. The first is Bils's (1987) argument that the ratio of the marginal wage to the average wage for a particular worker may be procyclical because of an overtime premium or other costs associated with inducing extra hours worked. Using approximations, various simplifying assumptions, and annual industry data, he found that his adjustments to average wages transformed the markup from being procyclical to countercyclical. We revisit Bils's (1987) argument in the supplementary appendix. It derives a ratio of marginal to average wages based on observables and shows that once we replace Bils's (1987) approximations and simplifying assumptions with exact expressions and the richer data that is now available, there is very little cyclical variation in the marginal to average wage ratio. Thus, we conclude that the average wage is a good indicator of the marginal wage for a worker.

The second critique of the labor hours margin and its reliance on average hourly wages is based on ideas from the implicit contract literature.[8] This critique argues that because wages may be payments on an implicit contract in an ongoing employment relationship, they are smoothed relative to the true marginal cost of increasing hours. There are two leading pieces of evidence offered in support of this view. The first is Bils's (1985) finding that new hire wages are more procyclical than existing worker wages. The second is Beaudry and DiNardo's (1991) finding that workers' long-term wages depend on the state of the economy at the time they were first hired.

Based on this evidence, Kudlyak (2014) develops an alternative measure of the marginal cost of labor, the *user cost* of labor. If long-term wage contracts depend on the state of the economy when a worker is hired, then a firm faces an intertemporal trade-off of hiring a worker now versus later. The user cost is equal to the current wage plus the present discounted value of the difference between future wages paid to today's cohort and future wages paid to tomorrow's cohort. Kudlyak finds evidence that her measure of user cost is more procyclical than current wages.

Kudlyak's particular user cost measure is based on an asymmetric treatment of history dependence, however. In particular, she assumes that neither the match productivity nor the separation rate is history dependent — in fact, she assumes that the separation rate is exogenous. The assumption of exogenous separations implies that workers who are stuck in low-wage contracts cannot quit their jobs and that firms stuck paying high-wage contracts cannot fire those workers. Allowing for endogenous separation and cyclical match productivity would completely change the nature and cyclicality of the user cost measure.

In fact, two recent papers call into question the interpretation of the earlier evidence based on exactly the issue of match productivity. First, Hagedorn and Manovskii (2013) show theoretically that changing quality of job matches over the business cycle can lead to composition effects. They demonstrate empirically that the results of Bils (1985) and Beaudry and DiNardo (1991) disappear after controlling for job match quality. The intuition is that the quality of new job matches is also procyclical, so the observed cohort dependence of wages is not due to implicit contracts. Second, Gertler, Huckfeldt and Trigari (2019) document that new hire worker wages are no longer more procyclical than existing worker wages once one adjusts for the cyclicality of the composition of

8. Such as Barro (1977) and Hall (1980).

new hires.[9] Based on their new findings, Gertler, Huckfeldt and Trigari (2019, p. 1) conclude that "the sluggish behavior of wages for existing workers is a better guide to the cyclicality of the marginal cost of labor than is the high measured cyclicality of new hires wages unadjusted for composition effects."

Additional recent work has provided evidence that, even if wages are sticky, they appear to be allocative. Olivei and Tenreyro (2007), Olivei and Tenreyro (2010), and Björklund, Carlsson and Skans (2019) present evidence that monetary shocks have larger effects when they occur just after annual labor contracts are signed, suggesting that wage stickiness has real effects.

Thus, we read the latest findings as supporting the use of average wages as a measure of the marginal cost of labor hours. Based on that evidence, as well as its prominent role in NK models, we therefore choose to measure the markup using the labor input margin.

Of course, one could consider several margins. Other possibilities are offered by Bils, Klenow and Malin (2018) (BKM) and De Loecker, Eeckhout and Unger (2019). One of BKM's alternatives is based on self-employed individuals. They measure the markup as the log difference between the current business income per hour worked and the marginal rate of substitution for self-employed workers. We believe this measure has some weaknesses. For example, it relies on the assumption that the returns to self-employed labor are adequately reflected in current business income. Recent work by Bhandari and McGrattan (2019) estimates that the self-employed spend many hours building up customer bases and other intangible capital and that intangible capital is worth 60 percent of total assets of these businesses. The returns to those intangible assets are realized over a long period of time and are not adequately reflected in current business income. If investment in intangible capital is procyclical, then BKM's markup measure will be biased toward countercyclicality.[10]

9. Basu and House (2016) show empirically, however, that Kudlyak's (2014) user cost measure continues to be very procyclical even after including Hagedorn and Manovskii's (2013) composition bias measures. Gertler, Huckfeldt and Trigari (2019) critique Basu and House's (2016) estimation equation, arguing that the failure to express wages in efficiency units of labor overstates the cyclicality of the user cost. Separately, our critique of the assumption of exogenous separations also applies to the user cost measure employed by Basu and House (2016).

10. In addition, we show in the supplementary appendix that the unconditional markup became more countercyclical after 1995. Because BKM's sample starts only in 1987, their study is more likely to find a countercyclical markup.

BKM's second set of alternative measures relies on variations in intermediate inputs, such as materials, energy, and business services. They find countercyclical markups based on materials and energy, but procyclical markups based on business services. We chose not to construct markups based on intermediate goods because of data limitations. The data on intermediate goods is available only since 1987 and only annually, which makes it difficult to conduct the conditional structural vector autoregression (SVAR) analysis that is the heart of our approach. De Loecker, Eeckhout and Unger's (2019)'s markup measure based on Compustat variable cost of goods sold is available for a longer span, though still only annually. Our supplementary appendix shows that their markup measure is slightly more procyclical than our preferred labor margin measure when compared over the same sample and frequency.

3.3 Production function assumptions

The markup using the labor input margin can be expressed as

$$\mathcal{M} = \frac{1}{s} \cdot \left(\frac{\partial Y}{\partial L} \cdot \frac{L}{Y} \right) \tag{7}$$

where s is the labor share of output and the term in parentheses is the elasticity of output with respect to labor hours L.

The formula for the markup above requires an estimate of the marginal product of labor, necessitating assumptions about the production function. Under the standard assumptions that the production function is Cobb-Douglas (denoted by a superscript "CD") in total hours, the markup is given by

$$\mathcal{M}^{\text{CD}} = \frac{\alpha}{s}, \tag{8}$$

where α is the exponent on labor input in the production function and s is the labor share.

Rotemberg and Woodford (1999) note several reasons why the standard assumption of a production function that is C-D in total hours may lead to estimates of the markup that are biased toward being procyclical. We now consider the most plausible generalizations.

The first generalization allows for the presence of overhead labor. In this generalization, the labor term in the production function is instead $\left(L - \bar{L}\right)^{\alpha}$ where $\bar{L}$ represents

overhead labor hours. With a C-D production function and overhead labor (denoted by "CD, OH"), the markup is given by:

$$\mathcal{M}^{\text{CD, OH}} = \frac{\alpha}{s'}, \tag{9}$$

where

$$s' = \frac{W\left(L - \bar{L}\right)}{PY} \tag{10}$$

is the labor share of variable labor, W is hourly wages, and PY is value added.

A second generalization allows the elasticity of substitution between inputs to deviate from unity. For example, consider the following CES production function:

$$Y = \left[\alpha_L (ZL)^{\frac{\sigma-1}{\sigma}} + \alpha_K (uK)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{11}$$

where Z is labor-augmenting technology, u is capital utilization, K is the stock of capital, σ is the elasticity of substitution between labor and capital, and α_L and α_K are distribution parameters. Computing the elasticity with respect to hours L and substituting into equation 7 yields the markup in the CES case:

$$\mathcal{M}^{\text{CES}} = \underbrace{\frac{1}{s} \cdot \alpha_L \cdot \left(\frac{Y}{ZL}\right)^{\frac{1}{\sigma}-1}}_{\mathcal{M}_{\text{L}}^{\text{CES}}} = \underbrace{\frac{1}{s} \cdot \left[1 - \alpha_K \cdot \left(\frac{Y}{uK}\right)^{\frac{1}{\sigma}-1}\right]}_{\mathcal{M}_{\text{K}}^{\text{CES}}}. \tag{12}$$

This equation shows two ways of writing the CES markup. The first expression, $\mathcal{M}_{\text{L}}^{\text{CES}}$, uses the elasticity with respect to hours and the second expression, $\mathcal{M}_{\text{K}}^{\text{CES}}$, uses Euler's theorem to re-express it as a function of the output-capital ratio. It is important to note that the second expression is based on the labor margin even though capital appears there. In both cases, the first term, $\frac{1}{s}$, is the C-D markup (up to a constant). The impact of the CES generalization depends on the the value of σ and the cyclicality of output per effective hour, $\frac{Y}{ZL}$, or equivalently, the ratio of output to capital input, $\frac{Y}{uK}$. We consider markups based on both versions since measurement of each of the ratios is not straightforward.

We can also combine overhead labor and CES production by substituting $Z(L - \bar{L})$ for labor input. Working through this substitution, we derive the markup for both CES

production and overhead labor:

$$\mathcal{M}^{\text{CES, OH}} = \frac{1}{s'} \cdot \alpha_L \cdot \left[\frac{Y}{Z\left(L - \bar{L}\right)} \right]^{\frac{1}{\sigma}-1} = \frac{1}{s'} \cdot \left[1 - \alpha_K \cdot \left(\frac{Y}{uK} \right)^{\frac{1}{\sigma}-1} \right]. \tag{13}$$

Rotemberg and Woodford (1999) and Galí, Gertler and López-Salido (2007) implement these two generalizations using log-linear approximations around a steady-state and then calibrating parameters based on zero profit conditions and assumptions on steady-state markups. As discussed in section 4.1, we use direct measures that do not rely on approximations.

4 Empirical measures of the markup

The remainder of the paper uses the theory from the previous section to derive new measures of the aggregate price markup and assesses their cyclicality. This section describes how we constructed our measures of the markup. The next two sections report our results for the unconditional and conditional cyclicality. The unconditional analysis updates and expands the previous literature on the markup cyclicality. However, as we emphasized in the introduction, what matters for assessing economic models is how the markup moves in response to shocks. The conditional analysis assesses how our markup measures respond to identified demand and supply shocks.

4.1 Baseline markup

As discussed in section 3, the markup is proportional to the inverse of the labor share when the production function is Cobb-Douglas and there is no overhead labor (equation 8). Ignoring constant terms, the logarithm of the markup for this case is given by:

$$\mu_t^{\text{CD}} = -\ln s_t. \tag{14}$$

where s_t is the labor share. We use the labor share in the private business sector for our baseline measure.[11] The markup is computed from Bureau of Labor Statistics (BLS)

11. Galí, Gertler and López-Salido (2007) use the nonfarm business version of this measure, while Rotemberg and Woodford (1999) favor the nonfinancial corporate business sector. We did not find

data as value added divided by total labor compensation. We use quarterly data from 1947:Q1 through 2017:Q4.

4.2 Overhead labor

As shown in equation 9, the generalization of the markup to allow for overhead labor requires actual estimates of overhead labor. Despite macroeconomists' fondness for relying on overhead labor to explain a variety of phenomenon, few researchers have tried to measure overhead labor directly, either in the macro literature or the labor literature. Most macroeconomists have used very indirect ways to estimate the ratio of overhead to variable labor. For example, Rotemberg and Woodford (1999) use zero-profit conditions and assumptions on the steady-state markup to estimate that the ratio of overhead labor to variable labor is 0.4, implying a ratio of overhead labor to total labor of 0.3. This high value is key to converting the procyclical baseline markup to being countercyclical.

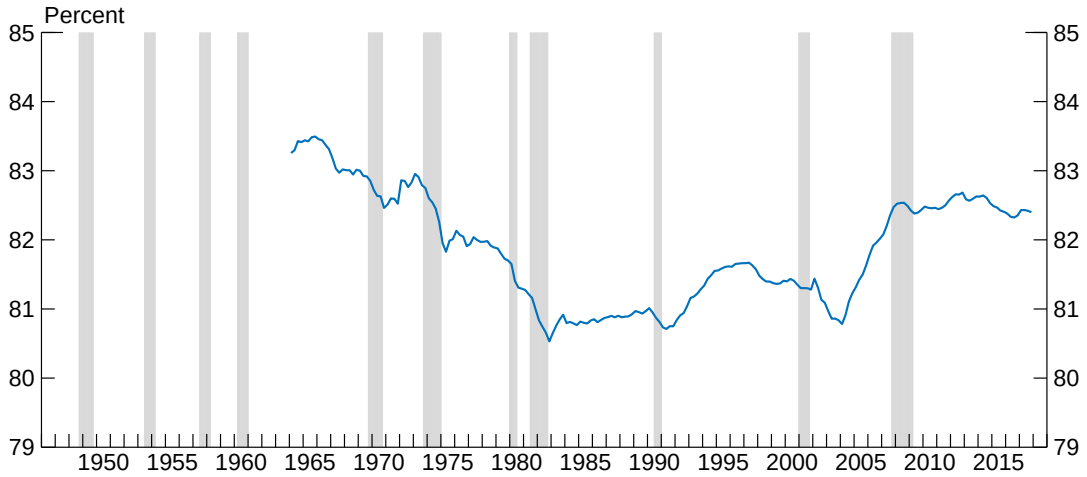
Ramey (1991) argued that the number of nonproduction or supervisory workers is probably an upper bound on the number of overhead workers. It is an upper bound because even nonproduction and supervisory workers shows significant cyclicality of employment. For example, using Hodrick-Prescott (HP) filtered data, we find that the elasticity of the log of employment of nonproduction workers to GDP is positive and statistically significant and is about half of the elasticity of production workers with respect to GDP.

As as test of Ramey's (1991) hypothesis, we compare a direct measure of overhead labor to the share of nonproduction workers within a particular industry. Our direct measure is computed from the number of workers at automobile assembly plants when they are running one shift versus two shifts. If part of employment under one shift consists of overhead labor, then employment should rise by less than 100 percent when a second shift is added. According to Levitt, List and Syverson (2013, p. 675), adding a second shift increased employment at the automobile plant in their study by 80 percent. This implies that overhead labor is 11 percent of total employment when two shifts are running and 20 percent of total employment when one shift is running.[12]

major differences in the cyclicality among these different measures. These results are reported in the supplementary appendix.

12. This ratio is consistent with narrative evidence from automobile industry periodicals during the 1970s and 1980s collected as part of the Bresnahan and Ramey (1994) project.

Figure 1. Share of production workers in total private employment



Source: Authors' calculations using BLS data.
Note: Shaded areas represent periods of business recession as determined by the NBER.

Since automobile assembly plants run two or more shifts 80 percent of the time, the steady-state ratio of overhead to total employment at plants should be closer to 11 percent. In industry data, the share of nonproduction workers at automobile assembly plants averaged 18 percent of total employment over 1958 to 2009.[13] Thus, the direct evidence on employment by shifts in the automobile industry supports our contention that nonproduction workers are an upper bound on overhead labor.

Figure 1 plots the fraction of production workers in total private employment. Production workers averaged roughly 82 percent of total employment since 1964, similar to the share of production labor in the motor vehicle manufacturing sector, and this share is procyclical, as one would expect. We take the employment share from figure 1 as a proxy for the portion of variable labor. Specifically, our measure of variable labor hours adjusts total hours worked in the private business sector by the fraction of production workers in total private employment. Thus, our measure of the markup with a C-D production function that adjusts for overhead labor is the log of current dollar output in private business divided by the wage bill for variable labor. The data appendix provides more detail. Markup measures that adjust for overhead labor start in 1964, when the data on production workers begin.

13. This share is for SIC 3711, calculated using the Manufacturing Industries Database, published by the National Bureau of Economic Research (NBER) and the Census Bureau's Center for Economic Studies.

4.3 CES production function

From equation 12, the logarithm of the CES measure of the markup can be measured by either of the following equivalent methods:

$$\mu_{\mathrm{L}t}^{\mathrm{CES}} = \mu_t^{\mathrm{CD}} + \ln\left[\alpha_L \cdot \left(\frac{Y_t}{Z_t L_t}\right)^{\frac{1}{\sigma}-1}\right] \tag{15}$$

or

$$\mu_{\mathrm{K}t}^{\mathrm{CES}} = \mu_t^{\mathrm{CD}} + \ln\left[1 - \alpha_K \cdot \left(\frac{Y_t}{u_t K_t}\right)^{\frac{1}{\sigma}-1}\right]. \tag{16}$$

Both variations use the labor adjustment margin, but each expresses the elasticity of output to labor in a different way.

Both expressions require a value of the elasticity of substitution (σ). Chirinko (2008) surveys the substantial literature that estimates the elasticity of substitution between capital and labor and concludes that it is in the range of 0.4 to 0.6. Karabarbounis and Neiman (2014) use differential long-run trends in labor shares and the relative price of investment goods across countries and estimate a much higher value, around 1.25. More recently, Chirinko and Mallick (2017) use a low-pass filter on U.S. panel data and find an estimate around 0.4. Since we study capital-labor interactions at a higher frequency, i.e. the business cycle frequency, we believe an elasticity below 1 is more likely than one above 1. Thus, we use the midpoint, 0.5, of Chirinko's (2008) survey as our elasticity of substitution. This particular value has the additional advantage that it gives the two terms in parenthesis in equation 15 and equation 16 an exponent of 1.

The CES generalization is more complicated to implement because there are no direct measures of labor-augmenting technology, Z_t. We consider two measures of the markup using the expression in equation 15 based on two estimates of Z_t. The first assumes that Z_t follows a trend but does not vary cyclically. The second uses Galí's (1999) SVAR method to estimate technology shocks that can be used to create a technology level series. This SVAR identifies technology shocks as those shocks that have permanent effects on labor productivity in the long-run; thus any movements in labor productivity due to cyclical variations in utilization of factors are excluded from this

series. We use a simple bivariate SVAR in productivity growth and per capita hours growth, allowing for four lags.

An alternative approach is expressed in equation 16. In this case, the cyclicality of the CES adjustment depends on the cyclicality of the ratio of output to utilized capital. If this ratio is procyclical, as one would expect with slow-moving capital stocks, then it imparts some countercyclicality to the markup since it enters with a negative sign.

We measure the output-capital ratio using real private business output in the numerator and the productive real capital stock for private business in the denominator. The measure of the capital stock (which excludes consumer durables) is derived from the Bureau of Economic Analysis (BEA)'s fixed asset tables, which are annual. The annual data are interpolated to quarterly frequency using the Denton method, with quarterly real private fixed investment as our indicator series.[14]

We consider three alternatives based on different estimates of capital utilization since there is no readily available series on aggregate capital utilization (u_t).[15] The first assumes that utilization is constant. In practice, capital utilization is procyclical, so assuming constant utilization will make $\frac{Y_t}{u_t K_t}$ appear to be more procyclical than it actually is, resulting in an estimated markup that is more *counter*cyclical than it actually is.

The second alternative is based on a utilization series we construct from available estimates of the workweek of capital. Our method proceeds in several steps. First, we estimate the elasticity of the workweek of capital in manufacturing to output in manufacturing at a business-cycle frequency. Shapiro (1986) constructs a quarterly series on the workweek of capital in manufacturing from 1952 to 1982 based on data on shiftwork from the Area Wage Survey of the BLS. Gorodnichenko and Shapiro (2011) construct an annual series from 1974 to 2004 on the workweek of capital in manufacturing based on the U.S. Census Bureau's Survey of Plant Capacity. For each of these series, we regress the HP–filtered log of the workweek of capital in manufacturing on the HP–filtered log of industrial production in manufacturing. For both series, we estimate an elasticity around 0.3.

The second step involves a decision on how to use that information. Even if Shapiro's (1986) quarterly series extended over our entire sample, it would be incorrect to use

14. See the data appendix for additional details.

15. The Board of Governors of the Federal Reserve System publishes a measure of capacity utilization for the industrial sector, but as Shapiro (1986) notes, this concept is distinct from capital utilization.

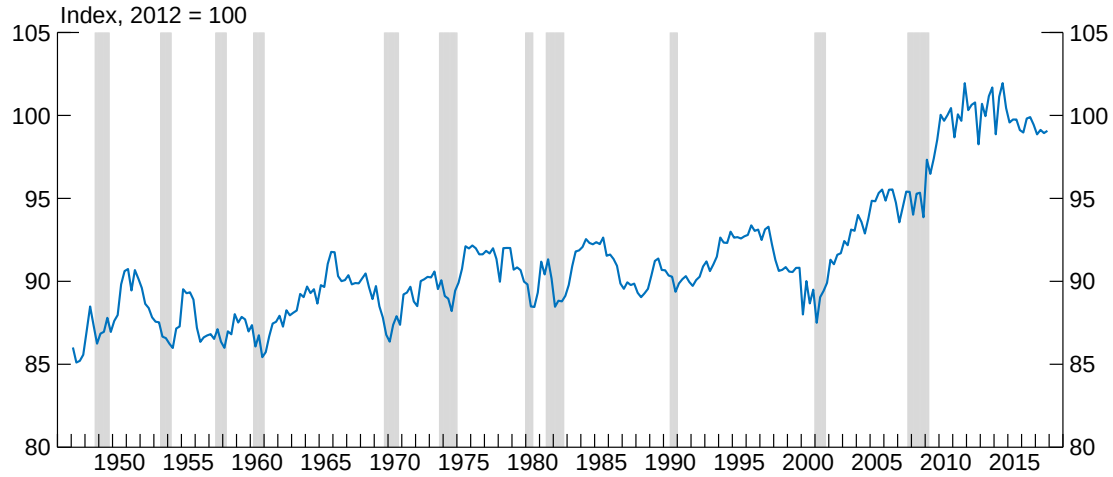
it as our utilization measure for all of private business. This is because manufacturing output is much more procyclical than private business output. Indeed, a regression of the cyclical component of either manufacturing output or the workweek of capital on the cyclical component real private business output yields estimated elasticities above 1.7. To create a capital workweek series suitable for the entire private business sector, we assume that the elasticity of the workweek of capital in private business to the cyclical component of output in private business is also 0.3, as estimated for manufacturing. Thus, we assume that the *cyclical variation* of $\frac{Y_t}{u_t}$ is the same in private business as it is in manufacturing.

The third alternative takes Fernald's (2014) utilization series that he derives in order to estimate utilization-adjusted TFP. This measure is calculated using hours per worker as a proxy for unobserved capital utilization and effort. Note that this measure may over-correct for capital utilization, since it may also include variation in labor effort, and thus make $\frac{Y_t}{u_t K_t}$ less procyclical than it actually is. In sum, the constant utilization measure likely induces a countercyclical bias to the markup and Fernald's (2014) utilization measure likely induces a procyclical bias.

For all measures based on equation 16, units of $\frac{Y_t}{u_t K_t}$ matter. Therefore, we normalize using one of the options recommended by Klump, McAdam and Willman (2012) and Cantore and Levine (2012). In particular, we set α_K equal to 1.1 in equation 16, based on an average capital share of 0.32 and the sample average of $\frac{Y_t}{u_t K_t}$.

To summarize, we derive five potential measures of the markup based on CES production functions. Two measures are based on equation 15 and differ according to how labor-augmenting technological progress Z is estimated. Three measures are based on equation 16 and differ according to how utilization u is estimated. In later sections, we emphasize the measure based on the output-capital ratio and with utilization estimated from the workweek of capital, because we think it has the least cyclical bias of these measures.

Figure 2. The Markup in Private Business



Source: Authors' calculations using BLS data.
Note: Shaded areas represent periods of business recession as determined by the NBER.

5 Unconditional cyclicality of the markup

5.1 Cobb-Douglas production function

Figure 2 plots our baseline measure of the markup.[16] It appears to peak near the middle of expansions, to decline going into a recession, and then to rise coming out of a recession. That said, the cyclicalty is somewhat obscured by an upward trend. The downward trend in the labor share — or upward trend in the markup — has attracted considerable attention in recent years.[17]

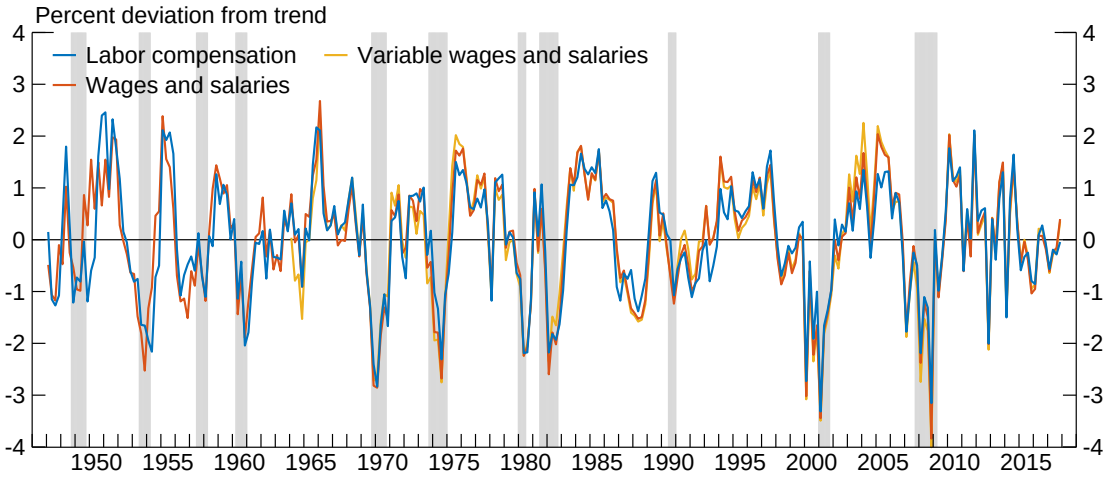
To abstract from these substantial low-frequency movements for assessing the cyclicality, we detrend using the HP filter with a standard smoothing parameter.[18] Figure 3 plots the detrended C-D markup series. The cyclical components of the three markup

16. The supplementary appendix describes several other measures of the markup and examines their cyclicality. Our findings are similar for these other measures.

17. See, Nekarda and Ramey (2009), Elsby, Hobijn and Şahin (2013), Karabarbounis and Neiman (2014), and Gutiérrez and Piton (2019), among others.

18. We also explored other detrending methods, including the Baxter-King (BK) filter, a first-difference filter, and Hamilton's (2018) two-year-difference filter. We found that the HP and BK filters gave very similar results, whereas the first difference filter implied more procyclical markups; these results are reported in the supplementary appendix. We found the two-year-difference filter to be sensitive to low frequency movements.

Figure 3. Detrended Price-Cost Markup, Cobb-Douglas Production Function



Source: Authors' calculations using BLS data.
Notes: Series detrended using the HP filter. Shaded areas represent periods of business recession as determined by the NBER.

measures are broadly similar, typically reaching a cyclical peak mid-way to late in an expansion and reaching a cyclical trough early in a recession.

To assess the unconditional cyclicality more systematically, we estimate the elasticity of the detrended markup with respect to detrended real GDP using the following regression:

$$\mu_t = \beta\, y_t + \epsilon_t,$$

where μ is the cyclical component of the log markup and y is the cyclical component of log real GDP.[19] Following the literature, we consider only contemporaneous correlations here and reserve the full dynamic analysis for our later analysis of conditional correlations. To account for serial correlation, we report Newey and West (1987) standard errors. We prefer the elasticity over the correlation because it describes the magnitude of the response as well as the cyclicality.

Line 1 of table 1 reports the cyclicality of our baseline markup measure calculated from 1947 to 2017. The markup is mildly procyclical, with an estimated elasticity of 0.2.

19. Hall (2012) assesses cyclicality with respect to labor market variables rather than GDP. Because the cyclical behavior of productivity changed dramatically in the mid-1980s and because some shocks, such as technology shocks, are often found to drive output and labor in opposite directions, we chose GDP as the best measure of cyclicality.

Table 1. Unconditional Cyclicality of the Price-Cost Markup

Measure	*Elasticity*	*Standard error*
CD production function, 1947–2017		
1. Labor compensation	.20**	(.07)
2. Wages and salaries	.10	(.07)
CD production function, overhead labor, 1964–2017		
3. All worker wages and salaries	.12	(.08)
4. Prod. worker wages and salaries	.04	(.08)
CES production function, 1947–2017		
5. μ_L, naive technology trend	.46***	(.12)
6. μ_L, SVAR technology trend	.41***	(.10)
7. μ_K, constant capital utilization	−.32***	(.07)
8. μ_K, variable utilization (Shapiro)	−.18**	(.07)
9. μ_K, variable utilization (Fernald)	.00	(.08)
CES production function, overhead labor, 1964–2017		
10. μ_L, naive technology trend	.28	(.17)
11. μ_L, SVAR technology trend	.25*	(.13)
12. μ_K, constant capital utilization	−.54***	(.09)
13. μ_K, variable utilization (Shapiro)	−.39***	(.09)
14. μ_K, variable utilization (Fernald)	−.24**	(.09)

Notes: Elasticity of detrended log markup with respect to detrended log real GDP; series detrended using the HP filter. Standard errors that are robust to serial correlation are reported in parentheses; '***', '**', '*' indicates significance at the 0.1-, 1-, and 5-percent level. For CES production function, elasticity of substitution between capital and labor $\sigma = 0.5$. See section 4.3 for a description of the CES markup measures.

That is, when real GDP is 1 percent above its trend, this markup measure is 0.2 percent above its trend, on average.

To gain perspective on the magnitude of this elasticity, it is useful to compare it to the elasticity of the labor wedge, defined to be the gap between the firm's marginal product of labor and the household's marginal rate of substitution. The labor wedge measures distortions relative to the competitive representative agent model with no distortions, and can be split into the sum of the price-cost markup and the wage markup over marginal rate of substitution. The labor wedge has been analyzed by numerous authors and has been found to be strongly countercyclical.[20] Using Galí, Gertler and López-Salido's (2007) baseline parameterization of the marginal rate of substitution, we find that the elasticity of the cyclical component of the wedge to the cyclical component of GDP in our sample is −1.1. Thus, an elasticity of the price markup to GDP of 0.2 implies that the wage markup accounts for more than 100 percent of the countercyclicality of the labor wedge.[21]

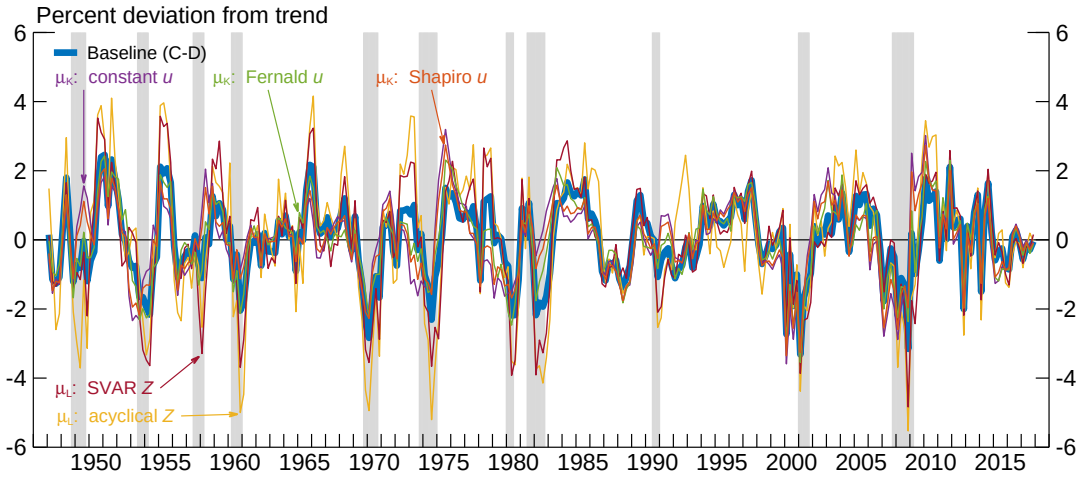
Returning to our markup measures, because some parts of labor compensation might be considered more a fixed cost per worker than a payment per hour, we also consider a measure of the labor share that includes only wages and salaries. As shown on line 2, the elasticity of this markup measure is 0.1, somewhat smaller than for compensation. In addition, although the baseline elasticity is statistically significant, we cannot reject that the elasticity of the markup based on wages and salaries is zero.

We next consider alternative measures of the markup that allows for overhead labor. Line 3 of table 1 shows the results for the markup using wages and salaries (e.g., line 2) for the sample starting in 1964 and line 4 shows the markup assuming all nonproduction and supervisory workers are overhead labor. Although the estimated elasticity declines, as expected, both estimates are small positive numbers that are not statistically different from zero. Thus, even after accounting for an estimate of overhead labor, we do not find evidence of a countercylical price markup.

20. See, Galí, Gertler and López-Salido (2007), Karabarbounis (2014), Bils, Klenow and Malin (2018).

21. The log wedge with Galí, Gertler and López-Salido's (2007) parameterization is defined to be ln(output per hour in private business) − ln(real nondurable plus services consumption) − ln(hours in private business).

Figure 4. Detrended Price-Cost Markup, CES Production Function



Source: Authors' calculations using data from the BEA, BLS, Fernald (2014), and Shapiro (1986); see section 4.3.

Notes: Series detrended using the HP filter. Shaded areas represent periods of business recession as determined by the NBER.

5.2 CES production function

The next generalization we consider is a CES production function and a lower elasticity of substitution between capital and labor. Figure 4 plots the cyclical components of the five measures of the markup based on a CES production function discussed in section 4.3, together with the baseline C-D markup for comparison. Focusing first on the markup measures based on the output-labor ratio (equation 15), denoted by μ_L, these measures have noticeably larger cyclical swings than the baseline C-D markup, the blue line. This is particularly true prior to the mid-1980s, when labor productivity switched from being procyclical to acyclical. Indeed, these measures move much more in line with the baseline after the mid-1980s. The other three measures, denoted by μ_K, are based on the output-capital ratio (equation 16). These measures of the markup tend to reach a cyclical peak just after a recession and reach a trough prior to or at the start of a recession.

The third panel of table 1 reports estimates of the unconditional cyclicality of the CES markup measures. Lines 5 and 6 show that the CES markups based on the output-labor ratio are more procyclical than the baseline, with estimated elasticities of 0.4 to 0.5. These measures end up being more procyclical than the baseline measure because

they add the log of detrended labor productivity, which is procyclical on average over the post-war period, to the baseline measure. Even when the labor productivity term is divided by the potentially procyclical labor-augmenting progress Z estimated using long-run restrictions, the CES–based markup is even more procyclical than the C-D markup. This result is surprising because diminishing returns to labor should make labor productivity countercyclical.

As shown by lines 7 through 9, CES markups based on the output-capital ratio are countercyclical or acyclical. When we assume constant capital utilization (line 7), the elasticity of the markup with respect to real GDP is -0.3. As seen in equation 16, a procyclical $\frac{Y_t}{u_t K_t}$ will make the markup less procyclical (or more countercyclical) than the C-D markup. Because capital stocks are slow to adjust, $\frac{Y_t}{K_t}$ has an elasticity near one with output. Line 8 shows that the markup based on the cyclicality of the workweek of capital is countercyclical (elasticity of -0.2), but less so than under the assumption of constant capital utilization. As shown on line 9, the markup based on Fernald's (2014) estimate of factor utilization is acyclical, with an estimated elasticity of zero. The relative cyclicality of these three measures lines up with what we would expect, given the differing cyclicality of the utilization measures.

Finally, lines 10 through 14 of table 1 show the results when we combine the two generalizations, allowing for both overhead labor and CES production functions. Not surprisingly, we find the markup to be somewhat more countercyclical than when we do not assume overhead labor.

To summarize our unconditional results, we find that the markup estimate based on C-D production functions are slightly procyclical or acyclical, even allowing for overhead labor. In contrast, the markup estimates based on a CES production function have estimated elasticites ranging from 0.5 to -0.5. Our preferred measure, based on the output-capital ratio and with capital utilization estimated from the workweek of capital, is modestly countercyclical, with an elasticity of -0.2 or -0.4, depending on whether we also allow for overhead labor.

5.3 Discussion

The results for our baseline measure should not be a surprise to anyone who has studied the cyclicality of the labor share. In fact, table 1 of Galí, Gertler and López-Salido (2007)

(GGLS) reports a correlation of the price-cost markup with GDP of 0.28 for their sample and data.

Our finding of an acyclical markup after accounting for overhead labor (line 4) is at odds with the countercyclicality found by GGLS, who followed Rotemberg and Woodford's (1999) method. To understand the source of the difference, first rewrite our equation 9 in terms of total labor share s rather than production worker share s':

$$\mathcal{M}^{\text{CD, OH}} = \frac{\alpha}{s} \cdot \frac{L}{L - \bar{L}}.$$

Recall that L is total labor and $L - \bar{L}$ is variable labor. All approaches start with this equation but differ in how they treat the last term. We use a direct measure of overhead labor to construct the series of variable labor input. Thus, our log markup allowing overhead labor is:

$$-\ln s_t - \ln\left(\frac{L_t - \bar{L}_t}{L_t}\right).$$

GGLS instead log-linearize the ratio around steady-state total hours and calibrate the ratio based on zero-profit assumptions. Their log markup is:

$$-\ln s_t - \delta \cdot \ln \tilde{L}_t,$$

where $\tilde{L}$ is the log deviation of total labor hours from trend.

GGLS calibrate δ, the steady-state ratio of overhead labor to variable labor, to 0.4. We estimate, however, that the average ratio of nonproduction labor to production labor is 0.22. When we create their markup using our data, we find that reducing the value of δ from 0.40 to 0.22 changes the estimated elasticity of their markup to output, β, from -0.27 to -0.08 (with a standard error of 0.1), much closer to our finding 0.04. Thus, the main source of the difference in cyclicality between their markup and our markup is the high value they assume for the overhead labor ratio.

In contrast, the GGLS approximation and calibration for the CES generalization is relatively close to our markup based on equation 16 with constant capital utilization. As reported on line 7 of our Table 1, the estimated β for this markup is -0.32. When we implement the GGLS approximation in our data, the estimated β is -0.27, so their markup is slightly less countercyclical than our estimate.[22]

22. We can exactly match the cyclicality of their markup if we use their value of capital share of 0.30 rather than our value of 0.32 to calibrate α_K in equation 16.

As shown by our table 1, the CES markup is less countercyclical after allowing for variable capital utilization. We believe it is important to allow for variable capital utilization in the markup measure both because it is important empirically and it is a key part of the leading medium scale NK models. For example, Christiano, Eichenbaum and Evans (2005) find that variable capital utilization is crucial for matching their data. In their model, the elasticity of capital utilization to a monetary policy shock is about 80 percent of the elasticity of output. Their empirical work, however, implies a higher elasticity of capital utilization. In particular, they find that two of their three empirical indicators of utilization imply that the elasticity of capital utilization with respect to a monetary policy shock is *greater* than the elasticity of output.

6 Conditional cyclicality of the markup

The unconditional cyclicality estimates presented in the last section are useful for describing the patterns in the data, but they are not useful for assessing how well the behavior of the markup fits the predictions of NK models. In both NK models with only sticky prices and in medium-scale models with both sticky prices and sticky wages, the cyclicality of the price markup depends crucially on the source of the shock. For example, demand shocks, such as monetary policy shocks and government spending shocks, should lead to countercyclical movements in the markup since an expansionary shock raises output and marginal cost, but firms cannot immediately adjust their prices. In the Smets and Wouters (2007) model, investment-specific technology (IST) shocks also lead to a countercyclical markup because these shocks do not raise productivity in the short run. Conversely, as pointed out by Galí (1999), a labor-augmenting or neutral technology shock should lead to procyclical movements in the markup since a positive technology shock raises output and reduces marginal cost, but prices do not adjust.

Estimated medium scale NK models identify parameters and shocks using data along with assumptions about the structure of the model and the time series process driving the unobserved shocks.[23] Virtually all of those models assume C-D production functions. Here we present independent evidence on the cyclicality of the markup based on our production function generalizations and on shocks identified using time series methods.

23. Smets and Wouters (2007).

6.1 Identification of shocks

We study the response of our markup measures to four types of shocks: monetary policy, government spending, TFP, and investment-specific technology (IST). We use standard SVARs to identify the shocks and estimate the responses. All four SVARs are estimated on quarterly data, include four lags, as well as a quadratic time trend. We plot bootstrapped standard errors.

The monetary SVAR includes log real GDP per capita, the log of the GDP price deflator, the log of commodity prices, the federal funds rate, and a measure of the log markup.[24] As in Christiano, Eichenbaum and Evans (1999), the monetary policy shock is identified as a shock to the federal funds rate using a Choleski decomposition. We order the federal funds rate second to last, with the markup being the last variable. We do not allow contemporaneous effects of the markup on the federal funds rate so that changes in the markup variable across specifications have little effect on the estimated federal funds shock.[25]

The government spending SVAR includes the updated version of Ramey's (2011) military news variable, divided by nominal GDP, along with log real GDP per capita, the log of the GDP price deflator, the three-month Treasury bill rate, and the log of the markup. Government spending news shocks are identified as the shocks to the military news variable, ordered first in the Choleski decomposition.

The TFP SVAR includes the log level of Fernald's (2014) utilization-adjusted measure of TFP, log real GDP per capita, log of the GDP price deflator, the three-month Treasury bill rate, and the log of the markup. TFP shocks are identified as the shocks to Fernald's TFP variable, ordered first in the Choleski decomposition.

Finally, to identify the IST shock we use Fisher's (2006) identifying assumption that only IST shocks can have a long-run effect on the relative price of investment goods. We first estimate the shock in a system with long-run restrictions. That system includes the log difference of the deflator for equipment investment relative to the deflator for consumption of nondurables plus services, log difference in real GDP per capita, log difference of the GDP price deflator (i.e. inflation), and the level of the three-month Treasury bill rate. We then incorporate that shock into an SVAR, ordered first, along

24. We use Krippner's (2013) estimate of the shadow federal funds rate in place of the actual funds rate from 2009:Q1 to 2016:Q3. We also estimated a version that ends estimation in 2008 and found very similar results.

25. As we show in the supplementary appendix, ordering the markup before the federal funds rate has little effect on the estimated impulse response functions.

with log real GDP per capita, log of the GDP price deflator, the three-month Treasury bill rate, and the log of the markup.

Because the federal funds rate only became available in 1954, the monetary SVAR is estimated from 1954:Q3 through 2017:Q4. The other three SVARs are estimated from 1947:Q1 through 2017:Q4.

6.2 Estimates of conditional cyclicality

Figure 5 shows the estimated impulse responses for log real GDP and the log of two measures of the markup in response to each of the four identified shocks. For ease of comparison, we consider expansionary shocks in all four cases. The baseline measure, in which production function is C-D, is the inverse of the labor share. The second measure is the markup assuming a CES production function, measured by the output-capital ratio, with variable capital utilization based on the workweek of capital.

Because we are interested in how the estimated conditional responses compare to NK models, we also plot simulations from the Smets and Wouters (2007) (SW) model, estimated using their data and sample.[26] We normalize the simulations so that the peak effect on output is the same as in our estimated SVARs.

Consider the effects of a monetary policy shock, shown in figure 5a. Output rises in both our SVAR estimates and in the simulation from the SW model, though the response of output occurs more quickly in the model. Both of our markup measures rise, meaning they are procyclical, whereas the SW simulations show a countercyclical response of their markup.[27]

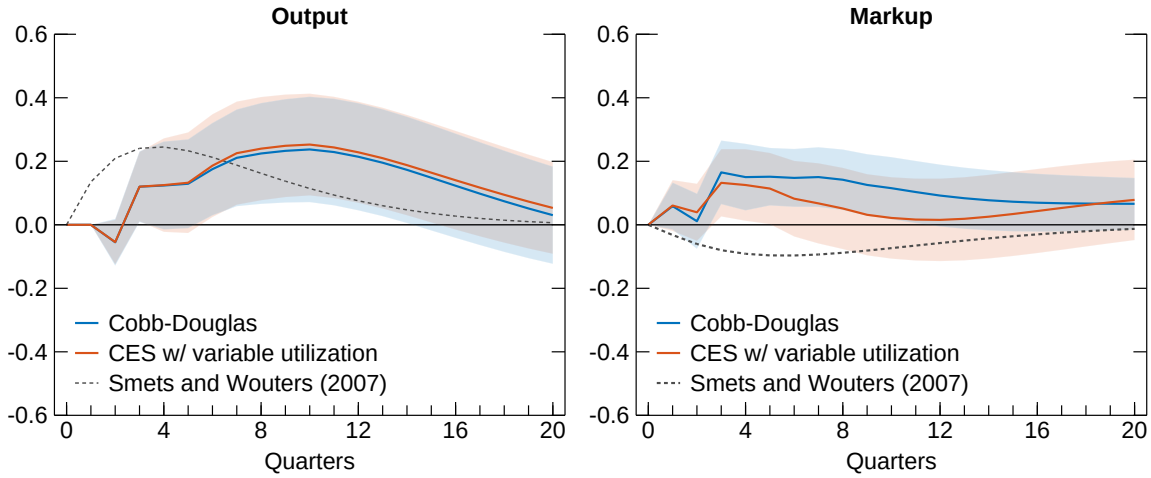
Figure 5b shows the responses to a positive government spending shock. Our SVAR estimates imply that output and the markup rise robustly in response. In contrast, the SW's simulations imply an increase in output but a small decline in the markup. It is important to note, though, that SW's government spending shock is actually a mix of shocks to government spending plus net exports, which mute the countercyclicality of the markup to this shock.

26. Recall that the SW model also has sticky wages, so they must rely less on the movement of the price markup than a NK model with just sticky prices. In those models, price markup movements are much more pronounced.

27. Smets and Wouters (2007) graph the log deviation of real marginal cost rather than the log deviation of the price markup. However, log real marginal cost is just the negative of the log of the price markup.

Figure 5. Conditional Cyclicality of the Price Markup

(a) Monetary Policy Shock



(b) Government Spending Shock

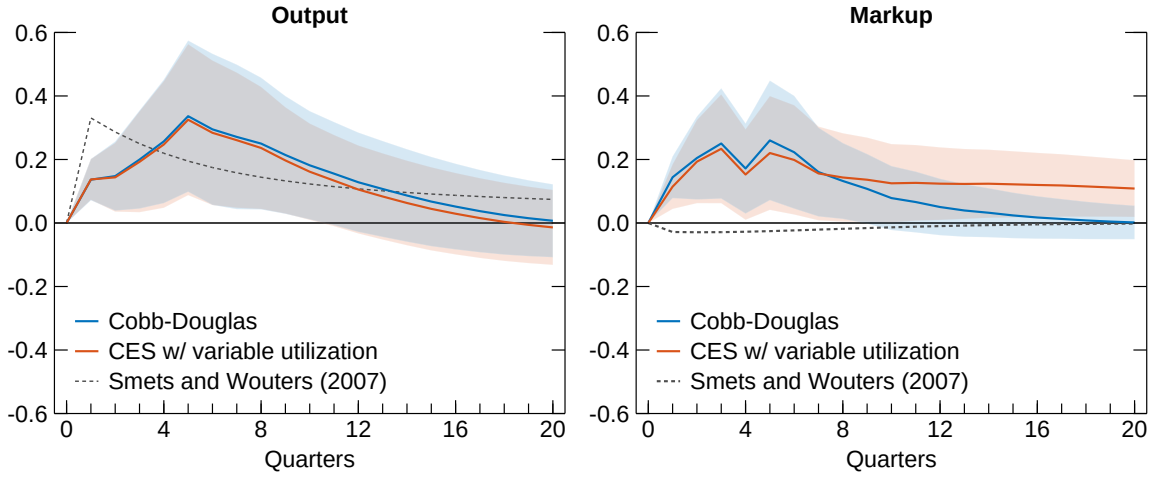


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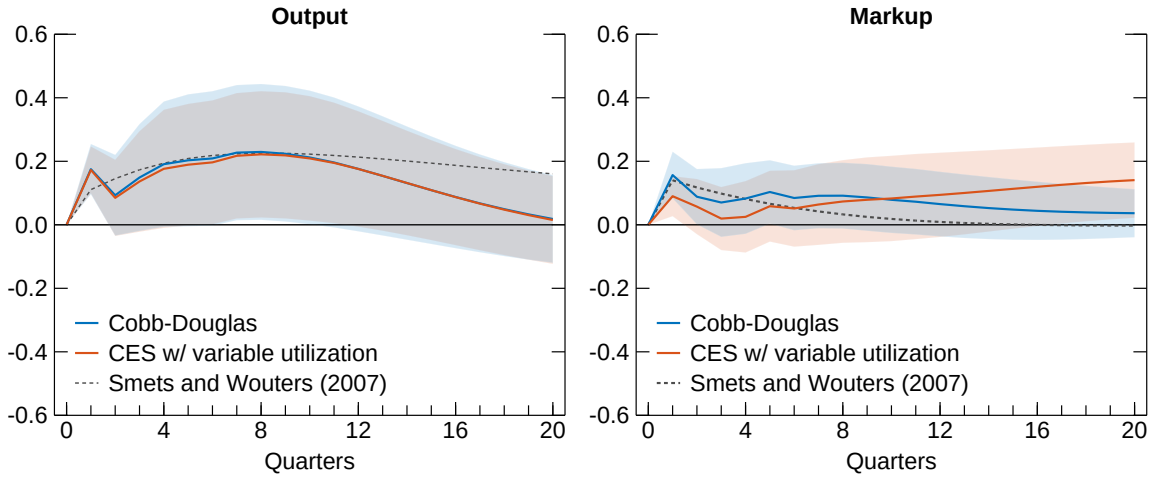
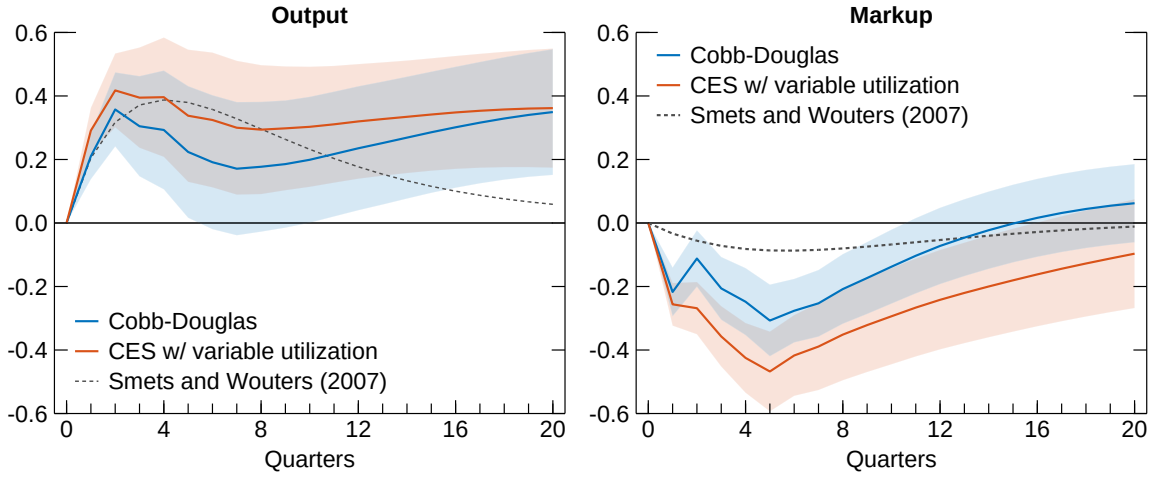
Figure 5. Conditional Cyclicality of the Price Markup (continued)

(c) Technology Shock



(d) Investment-Specific Technology Shock



Notes: Impulse response of log real GDP and log markup to a shock to variable indicated in heading; shaded areas indicate 90-percent confidence interval around estimate. CES markup measure based on output-capital ratio and workweek of capital. Estimation of monetary SVAR begins in 1954:Q3; all others start in 1947:Q1.

Thus, our SVARs estimates imply procyclical price markup movements in response to the two demand shocks we study. This result is at odds with SW's model estimates, as well as those of all other NK models with which we are familiar. Also interesting is that even our markup measures based on a CES production function, which ranged from procyclical to countercyclical in the unconditional analysis, are procyclical conditional on the demand shocks.

Figure 5c shows the responses to a positive TFP shock. In this case, the SVAR responses line up very well with the SW responses. All of the estimates show an increase in output and markups, all with quite similar dynamics.

At this point, the reader may wonder how we could have found countercyclicality of the CES–based markup in the unconditional analysis when we are finding procyclical CES–based markups in response to demand and TFP shocks. The answer to this apparent puzzle is provided in figure 5d, which shows the responses to a positive IST shock. Output rises in both of our SVAR specifications, as well as in SW's simulations. Our output responses are more persistent because we identify our shocks as those having permanent effects on the relative price of investment goods whereas SW assume stationary processes. In contrast to the responses to the three previous shocks, the markup response from our SVARs is significantly countercyclical. The estimated response from SW is also countercyclical but is muted compared to ours.

Table 2 summarizes these results as well as those for our other measures of the markup by calculating the implied elasticity with respect to real GDP. In order to summarize the entire dynamic pattern succinctly, we extend the method introduced in the government spending multiplier literature that calculates multipliers as ratios of integrals under IRFs.[28] In our case, we are interested in elasticities, which we calculate as the ratio of the cumulative IRF of the log markup (that is, the integral under the impulse response curve) over a 20-quarter horizon to the cumulative IRF of log output over the same horizon.

The main take-away from table 2 is that the estimated elasticities are positive for the monetary policy shock, the government spending shock, and the TFP shock and negative for the IST shock. Moreover, as can be seen by looking down the columns, our estimates have the same sign across almost all measures of the markups we consider. This stands in contrast to the unconditional elasticities, where some measures were procyclical while others were countercyclical.

28. See, for example, Ramey (2016), pp. 116 and 119.

Table 2. Conditional Cyclicality of the Price-Cost Markup

Measure	*Monetary policy*	*Govt. spending*	*TFP*	*IST*
CD production function, 1947–2017				
1. Labor compensation	.72	.67	.49	−.42
2. Wages and salaries	.92	.66	1.05	−.57
CD production function, overhead labor, 1964–2017				
3. All worker wages and salaries	1.12	.18	.51	−.82
4. Prod. worker wages and salaries	.94	.30	.47	−.84
CES production function, 1947–2017				
5. μ_L, naive technology trend	1.11	1.24	2.74	−.29
6. μ_L, SVAR technology trend	.77	.55	.48	−.36
7. μ_K, constant capital utilization	.24	.87	.43	−.77
8. μ_K, variable utilization (Shapiro)	.38	1.08	.62	−.78
9. μ_K, variable utilization (Fernald)	.54	.99	.25	−.77
CES production function, overhead labor, 1964–2017				
10. μ_L, naive technology trend	1.28	2.04	2.27	−1.41
11. μ_L, SVAR technology trend	1.01	.10	.46	−.84
12. μ_K, constant capital utilization	.50	.59	.32	−1.08
13. μ_K, variable utilization (Shapiro)	.64	.69	.51	−1.09
14. μ_K, variable utilization (Fernald)	.89	−.08	.17	−1.16
Memo:				
15. Smets and Wouters (2007)	−.51	−.10	.18	−.25

Notes: Implied elasticity of markup with respect to real GDP based on ratio of cumulative impulse response functions (IRFs) over 20-quarter horizon. For CES production function, elasticity of substitution between capital and labor $\sigma = 0.5$. See section 4.3 for a description of the CES markup measures. Smets and Wouters (2007) results are from our calculations.

Finally, on line 15 we report the comparable elasticities from the SW model. Their model estimates imply markups decrease in response to monetary policy and government spending shocks, which is not consistent with our findings. The responses in their model to the TFP shock and the IST shock are qualitatively consistent with our estimates.

6.3 Discussion

These conditional results shed light on the cyclical behavior of the markup and how well NK models can capture that behavior. An important finding is that all of our measures of the markup are procyclical or acyclical in response to a monetary policy shock. In complementary work, Cantore, Ferroni and León-Ledesma (2019) find that the labor share responds countercyclically to monetary policy shocks in the five countries they study. Since our baseline markup is the inverse of the labor share, our results are similar.

While our four estimated shocks do not exhaust the list of possible shocks, they nonetheless provide some insight into the unconditional cyclicality we estimated in the previous section. Recall that some of our CES–based markup measures suggested that the markup is mildly countercyclical. The unconditional elasticities depend on both the individual elasticities to each shock and on the variance of each shock in the sample. Interestingly, a large literature, surveyed in Ramey (2016), finds that IST shocks are some of the most important shocks driving output and hours at business cycle frequencies. Thus, even if the markup is procyclical in response to monetary policy, government spending, and TFP, the markup can, in principle, be countercyclical overall if IST shocks are the dominant shocks driving business cycles.

It is also interesting to note that long-run trends in investment-specific technological change also play a central role in Karabarbounis and Neiman's (2014) explanation for the global decline in the labor share. In particular, they argue that labor shares declined globally since 1980 because of the acceleration of the pace of investment-specific technological change coupled with an elasticity of substitution between capital and labor above 1. We also find a central role for IST shocks as the only one of our measured shocks that produces a countercyclical markup. However, the shock appears to be so important that it leads the unconditional estimate of the markup to be countercyclical for some of the CES–based measures. Recall that our results are based both on the C-D specification and the CES specification assuming an elasticity of substitution between

capital and labor of 0.5. Further results (not shown) indicate that the unconditional cyclicality of the CES–based markup becomes procyclical if we measure the markup using Karabarbounis and Neiman's (2014) value of the elasticity of 1.25. The response of the CES–based markup using their assumed elasticity continues to be countercyclical conditional on IST shocks, but noticeably less so than when we use our assumption of an elasticity of 0.5.

Finally, we note that our findings in aggregate data also appear in detailed industry-level data in manufacturing. In earlier versions of this paper, Nekarda and Ramey (2009, 2013) we presented results for the unconditional and conditional cyclicality of markups in an annual panel of four-digit manufacturing industries. The estimated elasticity for our baseline markup measure was 0.27, very close to our estimated aggregate elasticity. To estimate conditional elasticities, we used government spending shocks, based on instruments developed in Nekarda and Ramey (2011), as well as new industry-specific measures of monetary shocks and TFP shocks.[29] In all cases, we found that the various measures of markups were either procyclical or acyclical. Thus, estimates from the detailed industry data are very similar to those from the aggregate data, suggesting that our aggregate results are not being driven by industry composition effects.

7 Conclusion

This paper has presented new evidence on the cyclicality of aggregate price markup, and in particular on the cyclicality conditional on leading macroeconomic shocks. We began by arguing that the labor input margin continues to be the best way to measure the markup, citing new evidence that measured wages are a good indication of the marginal cost of an extra of hour of labor. Even focusing on that measure, though, we derived a range of measures of the markup by varying assumptions about elasticities of substitution between capital and labor, whether there is overhead labor, and how key inputs are measured.

Our analysis of the elasticity of the markup with respect to output, both filtered to focus on variation at business-cycle frequencies, yields a range of estimates from procyclical to countercyclical, depending on the measure. The baseline C-D measure

29. We did not consider IST shocks because it was not clear how to develop an industry-level instrument for those types of shocks.

is procyclical, and remains so after we account for overhead labor. Some measures of the markup based on a CES production function are procyclical whereas others are countercyclical.

Turning to the conditional analysis, we identify four macroeconomic shocks using standard time-series methods from the literature: monetary policy shocks, government spending shocks, TFP shocks, and IST shocks. The markup increases in response expansionary monetary policy, government spending, and TFP shocks. In contrast, the markup decreases in response to the IST shock. These findings for the conditional cyclicality hold for all measures of the markup that we considered.

We compare our results to those from the Smets and Wouters (2007) model. We find that the responses of our various measures of the markup are qualitatively consistent with those from the SW model for the two technology shocks we analyze. In contrast, we find that the responses of the markup to monetary policy and government spending shocks are inconsistent with the simulations from the SW model. In particular, we find that the markup increases in response to expansionary demand shocks whereas the SW model predicts a decrease. Because this key sticky-price transmission mechanism for monetary policy and government spending shocks is at odds with the data, our results suggest that NK models might benefit from a renewed focus on wage rigidities rather than price rigidities.

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Data appendix

Table A1. Sources

Data series	*N-R mnemonic*	*Source and mnemonic*	
Real Gross Domestic Product	rgdp	FRED	GDPC1
Gross Domestic Product: Implicit Price Deflator	pgdp	FRED	GDPDEF
Gross Domestic Product	ngdp	FRED	GDP
Real Government Consumption Expenditures and Gross Investment	rgov	FRED	GCEC1
Real Federal Consumption Expenditures and Gross Investment	rfed	FRED	FGCEC1
Output, [sector]	output_[sector]	BLS	See notes
Implicit price deflator, [sector]	pd_[sector]	BLS	See notes
Hours worked, [sector]	hours_[sector]	BLS	See notes
Employment, [sector]	emp_[sector]	BLS	See notes
Average weekly hours worked, [sector]	ww_[sector]	BLS	See notes
Compensation, [sector]	comp_[sector]	BLS	See notes
Compensation per hour, [sector]	cph_[sector]	BLS	See notes
Wages and salaries, private business	ws_bus	FRED	A132RC1Q027SBEA
Population	pop	FRED	B230RC0Q173SBEA
Average weekly hours, all employees	ww_priv	FRED	AWHAET
Average weekly hours, production and nonsupervisory workers	ww_priv_prod	FRED	AWHNONAG
Employment, all employees	emp_priv	FRED	USPRIV
Employment, production and nonsupervisory workers	emp_priv_prod	FRED	CES0500000006
Business sector TFP growth	dtfp	Fernald (2014)	dtfp
Utilization of capital and labor	dutil_jf	Fernald (2014)	dutil_jf
Business sector TFP growth, adjusted for utilization	dtfp_util	Fernald (2014)	dtfp_util
Real gross private domestic investment: Fixed investment	rinvest_priv_fixed	FRED	A007RA3Q086SBEA
Capital share of factor payments, average	cap_share_avg	BLS	See notes

Continued.

Data series	*N-R mnemonic*	*Source and mnemonic*	
Quantity index, fixed assets and consumer durable goods: Private	realk_privfixed	BEA	Table 1.2, line 3
Workweek of capital, manufacturing	n.a.	Shapiro (1986)	Table III
Plant hours per week, manufacturing	n.a.	GS (2011)	phw_adj_K4
Index of industrial production, manufacturing	jqi_mfg	FRED	IPMANSICS
Capacity utilization, manufacturing	rku_mfg	FRED	CUMFNS
Effective federal funds rate	rff	FRED	FEDFUNDS
3-month Treasury bill rate	tb3	FRED	TB3MS
Krippner shadow short rate	ssr	Krippner (2013)	ssr
Present value of change in expected defense spending due to political events	pdvmil	Ramey (2011)	n.a.
KR-CRB Spot Commodity Price Index: All Commodities	pzall	CRB	n.a.
Personal Consumption Expenditures: Nondurable Goods	pcend	FRED	PCND
Personal Consumption Expenditures: Services	pcesv	FRED	PCESV
Quantity index, real personal consumption expenditures: Nondurable goods	qrpcend	FRED	DNDGRA3Q086SBEA
Quantity index, real personal consumption expenditures: Services	qrpcesv	FRED	DSERRA3Q086SBEA
Price index, personal consumption expenditures: Services	ppcesv	FRED	DNDGRG3Q086SBEA
Price index, personal consumption expenditures: Nondurable goods	ppcend	FRED	DNDGRG3Q086SBEA
Price index, nonresidential investment: Equipment	pequip	FRED	Y033RD3Q086SBEA

Notes: Data from FRED can be accessed at https://fred.stlouisfed.org/. Unpublished BLS data can be downloaded from https://www.bls.gov/lpc/#tables. CRB stands for Commodity Research Bureau. GS stands for Gorodnichenko and Shapiro (2011); see http://www.umich.edu/~shapiro/data/SPC/.

Markups

We construct the baseline measure of the price-cost markup as the inverse of the labor share, which is value added divided by labor compensation in the private business sector. Both series are measured in current dollars. Measures of the markup that allow for overhead labor are measured as value added divided by labor compensation paid to variable labor. Variable labor hours are calculated by multiplying total hours worked in the private business sector by the fraction of production workers in total private employment.[30] Compensation paid to variable labor is computed as average hourly earnings for all workers in the private business sector times variable labor hours. In addition to excluding hours worked by overhead labor, this measure omits benefits paid by employers, such as contributions to pensions and insurance, some of which are paid regardless of the number of hours worked by employees. Additional adjustments to the markup measures are described in section 4.3.

Capital stock

The measure of the real productive capital stock for private business is computed as follows. We begin with annual data on the real stock of private fixed capital, from line 3 of Fixed Asset Table 1.2 from the BEA. The annual data are interpolated to quarterly frequency using the Denton method, with quarterly real private fixed investment as our indicator series.[31] The resulting index level of the capital stock was normalized to the value of real productive capital stock in 2012 taken from the BLS's MFP program.[32]

Relative price of equipment investment

The investment-specific technology shock identification is based on the relative price of equipment investment. This relative price is measured as the ratio of the implicit price deflator for gross private domestic investment in equipment divided by the implicit price deflator for personal consumption expenditures on nondurable goods plus services. The latter is constructed from the series on each component separately using Whelan's (2002) method for aggregating chain weighted series.

30. We use the fraction of employment rather than fraction of total hours because the data needed to compute hours worked by all employees begin only in 2006.

31. Baum and Hirstakeva (2014).

32. `https://www.bls.gov/mfp/special_requests/capital.xlsx`; sheet PG, cell B290.