Price-Cost Markup Cyclicality: New Evidence and Implications*

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Abstract

Existing empirical evidence on price-cost markup cyclicality is mixed. This paper proposes a new method to estimate markups that neither assumes a CES production function nor makes commonly used assumptions on labor input. I apply this method to estimate time-varying, industry-specific markups and assess their cyclicality. I find that markups are procyclical unconditionally, procyclical conditional on demand shock and product exiting, and countercyclical conditional on financial shock and price rigidity. These results suggest that much of the cyclicality in markups arises from input complementarity, rather than nominal rigidity, and the economy behaves as if it has increasing returns to scale.

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1 Introduction

Price-cost markup countercyclicality is a first-order building block in many sub-fields of macroeconomics. In the context of models of nominal rigidity, countercyclical markups conditional on demand change are necessary to explain both procyclical wages and countercyclical unemployment (Rotemberg and Woodford 1991, Rotemberg 2013). In the study of monetary policy, many New Keynesian models suggest that central banks should target constant average markup for price stability (Goodfriend and King 1997). In scholarship on price dynamics, countercyclical markups conditional on financial distortion explain missing disinflation during the Great Recession (Gilchrist et al. 2014). In turn, models predict countercyclical markups as a result of increases in marginal cost and rigid prices (Smets and Wouters 2003, 2007, Christiano et al. 2005), imperfect competition (Rotemberg and Woodford 1992), firm entry and exit (Jaimovich and Floetotto 2008, Bilbiie et al. 2012), and deep habits (Ravn et al. 2006). Finally, Bils et al. (2014) argues that (unconditional) countercyclical markups play an important role in cyclicality of the labor wedge.

Despite the importance of markup cyclicality, existing empirical evidence on the topic is mixed. Some studies find that markups are countercyclical (Bils 1987, Rotemberg and Woodford 1991, 1999, Chevalier and Scharfstein 1996, Gali et al. 2007, Bils et al. 2013, 2014, Gilchrist et al. 2014), while others find that markups are either procyclical or acyclical (Hall 2013, Nekarda and Ramey 2013, Stroebel and Vavra 2015). This paper finds that markups are procyclical based on a new method that neither relies on a CES production functional form assumption nor makes commonly used assumptions on labor input. In particular, I focus on firms' first order condition of energy input with a general production functional form assumption to estimate markups and assess their cyclicality.

The first contribution of this paper is to focus on energy input as a firm's choice variable. The cost minimization of a firm gives a first order condition that the marginal product of input equals the real input price under the perfectly competitive market. Once we relax the assumption on market structure, the markup arises as wedge between the marginal product of input and the real input price. Most papers that study markup cyclicality use labor input as a firm's choice variable to derive the first-order condition. Hence, they must deal with the labor overhead, labor adjustment cost, labor input quality and marginal wage schedule (or monopsony power) in the labor market since all four different forces generate a wedge on equalization of the marginal product of input (labor) and the real input price (wage). In contrast, I use energy input as a firm's choice variable to abstract away from these four issues, as energy input likely has less overhead components, more flexibility, more homogeneous input quality, and fewer monoposony effects compared to labor input. I present markup estimates based on labor input along with my markup measures.[1]

The second contribution of this paper is to use a general production function with a flexible substitution pattern across inputs to estimate markups. In the context of cost-minimization, I first need to estimate the marginal product of input (energy) to recover markups as they are a wedge between the marginal product of input (energy) and the real input (energy) price. Since the marginal product of energy heavily depends on the substitution pattern of inputs and the underlying production functional form assumption, it is crucial to assume a general production function to estimate markups. I allow both first-order and second-order flexible polynomial on output elasticity with respect to energy, which is a unit-free measure of the marginal product of energy. This specification allows a flexible substitution among energy and other inputs, similar to a Translog production function. Moreover, I allow for conventional Cobb-Douglas and a CES production functions with respect to energy, but these specifications are strongly rejected in the data. Notice that I only need to specify a part of the production function that is associated with energy input to recover the marginal product of energy, and being fully flexible on the other part of the production function.

The third contribution of this paper is to apply panel data techniques on disaggregated data to estimate time-varying, industry-specific markups and assess markup cyclically. These

[1] I also show markup estimates based on material input and discuss the result.

markups are estimated without making assumptions about the demand system or market structure by utilizing input prices as instrumental variables. Estimated industry-specific, time-varying markups allow me to use panel data techniques to assess markup cyclicality, and I find that markups are strongly procyclical. Finally, I assess conditional markup cyclicality with a difference-in-difference technique, and find that markups are procyclical conditional on demand shock and exit of products, and countercyclical conditional on financial shock and price rigidity. These results confirm the prediction of models with firm dynamics (Jaimovich and Floetotto 2008), financial friction (Gilchrist et al. 2014), and price rigidity, but are inconsistent with countercyclical desired markups with respect to demand shock.

There are two novel implications of estimated markups and their cyclicality. First, the estimation result for output elasticity with respect to energy with a flexible substitution pattern of inputs shows that there is a strong complementarity between production worker and energy. This strong input complementarity can explain both a procyclical (or acyclical) real wage and countercyclical unemployment conditional on demand change *without* incorporating countercyclical markups.[2] Input complementarity leads to a procyclical markups shown in this paper without integrating wage rigidity and without contradicting price rigidity. Notice that the input complementarity in this paper is less restrictive compared to what is in a Leontief production function, which restricts returns to scale (between energy and other inputs) to be constant.

Second, estimated markups inform that there is a strong *procyclical* returns to scale in the United States production.[3] When firms employ more of different inputs such as labor, capital, energy and material in expansion, the complementarity among these inputs leads to large returns to scale, and when firms employ less of different inputs in a recession,

[2] A markup countercyclicality is known to be necessary to explain procyclical (or acyclical) real wages and countercyclical unemployment conditional on demand change (Rotemberg and Woodford 1999, Rotemberg 2013).

[3] Returns to scale is constant under a conventional Cobb-Douglas or a CES production function, but it depends on inputs once we allow a more flexible production function, such as a Translog production function. Since inputs are varying across time, returns to scale can vary across time.

the complementarity among these inputs leads to small returns to scale. This is a novel channel on explaining the procyclical productivity, in addition to other channels such as an exogeneous productivity change, increasing returns to scale, resource reallocations and cyclical factor utilization. One striking implication of procyclical returns to scale is that the U.S. economy behaves as if it has increasing returns to scale even though it has constant returns to scale on average.

My approach is in the spirit of Bils (1987) and Hall (1986). First, as in Bils (1987) and many papers that follow (Rotemberg and Woodford 1991, 1999, Gali et al. 2007, Bils et al. 2013, 2014, Nekarda and Ramey 2013), I utilize a firm's first order condition to derive the markup expression. However, unlike this approach, my analysis uses energy input as a firm's choice variable rather than labor or material. More importantly, I allow for a more general substitution pattern across inputs that leads to strong markup procyclicality, and also estimate markups rather than calibrate markups as in this literature. Second, the estimation techniques I used in this paper resembles Hall (1986) and many papers that follow (Hall 1988, Haskel et al. 1995, Klette 1999, Konings et al. 2005, De Loecker and Warzynski 2012, Gandhi et al. 2013, De Loecker et al. 2014). However, previous literature uses labor or material as a firm's choice variable, and further assumes Hicks-neutral production function along with other assumptions that are not assumed in this paper.[4] Furthermore, most papers that use this type of markup estimation technique answer questions related with trade liberalization, rather than markup cyclicality. I am not aware of any paper that assesses the markup cyclicality by using the recent development of this estimation technique.

The rest of this paper is structured as follows. Section 2 presents the theoretical framework and the empirical specification to estimate markups. Section 3 compares and contrasts the method in this paper with those used in previous literature. Section 4 discusses data, section 5 presents the estimated markups, and section 6 shows the result on the

[4]For example, Gandhi et al. (2013) assumes markups are not varying across entities, and De Loecker and Warzynski (2012) need to use productivity estimation technique to recover markups, which require assumptions such as timing of input choice and strict monotonicity on the investment demand function.

markup cyclicality. Section 7 discusses the implication of the result in this paper. Section 8 concludes.

2 Markup Estimation: Theory & Empiric

2.1 Theoretical Framework

I need to put a structure on firms in the economy to recover markups since markups are not directly observed in the data. A firm in my model has the following three components to produce output:[5]

$$\textbf{Cost Function: } \sum_{k=1}^{K} \left[W_{jt}^{k}(V_{jt}^{k}) + \phi_k(V_{jt}^{k}/V_{j,t-1}^{k})\right] V_{jt}^{k}$$

$$\textbf{Production Function: } Q_{jt} = F(V_{jt}^{1}, ..., V_{jt}^{K}, A_{jt})$$

$$\textbf{Quality Aggregator: } V_{jt}^{k} = G_k(V_{jt,1}^{k}, ..., V_{jt,N}^{k}), \forall k$$

a firm j uses K different inputs, such as labor and capital, at time t to produce good Q_{jt}. V_{jt}^{k} denotes each input indexed by k, W_{jt}^{k} is an input price corresponding to input V_{jt}^{k}. W_{jt}^{k} depends on V_{jt}^{k} in the cost function as a firm affects input price by purchasing different amount of input V_{jt}^{k} (monopsony effect). $\phi_k(V_{jt}^{k}/V_{j,t-1}^{k})$ denotes adjustment costs a firm must pay to change input V_{jt}^{k}. A_{jt} is a firm's productivity and $F(\cdot)$ is a continuous and twice differentiable production function with $F_1(\cdot) > 0$. $V_{jt,n}^{k}$ denotes quality of input V_{jt}^{k} indexed by n, and $G_k(\cdot)$ aggregates different quality of inputs for each input V_{jt}^{k}.

Notice that this is a markedly general setup. I will only make assumptions on energy input to simplify a firm's production decision based on the three equations above. Assume that V_{jt}^{1} is an energy input. The approach in this paper has to do with following assumptions:[6]

[5] In Appendix A.1, I present the simple version of the theoretical framework that leads markups to be equal to the inverse of labor share. The inverse of labor share has been used to measure markups in previous studies (e.g. Gali et al. 2007, Bils et al. 2013). Section 3 compares and contrasts with previous works and section 5 presents the result along with the inverse of labor share.

[6] These assumptions are more plausible compared to labor input or material input. Comparing the

Assumption 1: Cost-Minimization. A firm is minimizing cost expenditure subject to output constraint by choosing energy input.

Assumption 2: $\phi_1(V^1_{jt}/V^k_{j,t-1}) = 0$. The energy input is fully flexible.

Assumption 3: $W^1_{jt}(V^1_{jt}) = W^1_{jt}$. An individual firm does not affect energy price.

Assumption 4: $V^1_{jt} = V^1_{jt,1}$. The energy input has homogeneous quality.

Note that these assumptions only apply to V^1_{jt}, not to other inputs that are used to produce good Q_{jt}. Under the four assumptions listed above, all firms in the economy solve the following cost-minimization problem by choosing V^1_{jt}:

$$\begin{aligned} \min_{V^1_{jt}} \ & W^1_{jt}V^1_{jt} + \sum_{k=2}^{K}[W^k_{jt}(V^k_{jt}) + \phi_k(V^k_{jt}/V^k_{j,t-1})]V^k_{jt} \\ \text{s.t.} \ & F(V^1_{jt}, ...) = \bar{Q} \end{aligned}$$

Forming Lagrangian function, taking derivatives with respect to energy input, and dividing output price on both sides to get the following first order condition.

$$\frac{W^1_{jt}}{P_{jt}} = \frac{\lambda_{jt}}{P_{jt}}F_1(V^1_{jt}, ...)$$

λ_{jt} is a Lagrangian multiplier, and it is also the marginal cost of firm j at time t as it denotes how much the cost changes with respect to the marginal increase in output quantity. Define the markup $\mu_{jt} \equiv \frac{P_{jt}}{\lambda_{jt}}$. Then the markup is a wedge between real input price and

estimation result based on energy input in section 5 and based on labor or material input in Appendix C suggests that energy input is more plausible for these assumptions. Moreover, even these assumptions are violated for the energy input, the main result will not change unless factors that arise from relaxing these assumptions are strongly cyclical in a particular way to change the direction of the markup cyclicality.

marginal product of input. Multiply $\frac{V_{jt}^1}{Q_{jt}}$ on both sides to get

$$\underbrace{\frac{W_{jt}^1 V_{jt}^1}{P_{jt} Q_{jt}}}_{\equiv s_{jt}^e} = \underbrace{\frac{\lambda_{jt}}{P_{jt}}}_{\equiv \frac{1}{\mu_{jt}}} \underbrace{\frac{F_1(V_{jt}^1, ...)V_{jt}^1}{F(V_{jt}^1, ...)}}_{\equiv \theta_{jt}^e(V_{jt}^1, ...)}$$

Rearranging terms, we have

$$\mu_{jt} = \frac{\theta_{jt}^e(V_{jt}^1, ..., V_{jt}^K, A_{jt})}{s_{jt}^e} \tag{2.1}$$

The left hand side of the equation (2.1) is the markup, μ_{jt}, and the right hand side is the ratio of θ_{jt}^e, the output elasticity with respect to the energy input, and s_{jt}^e, the energy input share. As one can see, under the four assumptions discussed earlier, the markup is a simple ratio of output elasticity with respect to energy and energy input share.

There are three other commonly discussed concerns in measuring markups in addition to the labor input flexibility, monopsony effect or marginal wage schedule, and labor input quality: labor overhead, labor hoarding, and variable capital utilization. The overhead component of the energy input is less likely to exist and less likely to be cyclical compared to the labor input. Moreover, allowing aggregate time-varying overhead components for all inputs does not change the main result in this paper. I discuss this in Appendix A.2. Allowing labor hoarding is likely to generate more countercyclical markups in previous work (Rotemberg and Woodford 1999), but it is likely to generate more procyclical markups with equation (2.1). I discuss this in Appendix A.3. Variable capital utilization is likely to be unrelated since θ_{jt}^e does not depend on capital input as shown in section 5.1.

2.2 Empirical Specification

Since s_{jt}^e is typically observed in the data, we can recover markups once we estimate θ_{jt}^e. The estimation requires one more assumption:

Assumption 5: $\theta^e_{jt}(V^1_{jt}, ..., V^K_{jt}, A_{jt}) = \theta^e_{jt}(V^1_{jt}, ..., V^K_{jt})$. The output elasticity with respect to energy does not depend on productivity.

This assumption states that there is no firm-specific energy-augmenting technology. Notice that this assumption is more general than the conventional approach. Consider two specific cases. First, suppose a researcher only allows labor and capital in production function with value-added measure of output, hence implicitly assuming separable energy: $\ln(Q_{jt}) = \ln(H_1(V^1_{jt})) + \ln(H_2(A_{jt}, ...))$. In this case, $\theta^e_{jt} = \frac{\partial \ln(Q_{jt})}{\partial \ln(V^1_{jt})}$ does not depend on A_{jt}. Second, suppose a researcher assumes Hick-neutral productivity as in the Solow-residual method: $\ln(Q_{jt}) = \ln(A_{jt}) + \ln(G(V^1_{jt}, ...))$. In this case, $\theta^e_{jt} = \frac{\partial \ln(Q_{jt})}{\partial \ln(V^1_{jt})}$ does not depend on A_{jt}. Assumption 5 allows a labor-augmenting or capital-augmenting technology.

Taking logs of equation (2.1) under the assumption 5, we have:

$$\ln(s^e_{jt}) = \ln(\theta^e_{jt}(V^1_{jt}, ..., V^K_{jt})) - \ln(\mu_{jt}) \tag{2.2}$$

The idea of estimating elasticity $\ln(\theta^e_{jt})$ is to run regression with instruments based on equation (2.2) by specifying a flexible functional form on $\ln(\theta^e_{jt})$ and treating the markup $\ln(\mu_{jt})$ as residual. I assume the following specification on $\ln(\theta^e_{jt})$, which nests a Cobb-Douglas production function assumption with respect to energy input: $\ln(\theta^e_{jt}) = \beta_0 + \sum_{k=1}^{K} \beta_k \ln(V^k_{jt})$. This is a first-order approximation on output elasticity, which corresponds to the flexible production function that allows input complementarity among inputs.[7] Allowing second-order terms on $\ln(\theta^e_{jt})$ makes all the results in this paper stronger, and I report this specification and result in Appendix D.1. In addition, I discuss two other commonly used testable specifications in section 2.4 and report results in section 5 and 6.

[7]This is very similar to a Translog production function with respect to energy, which leads to the following specification on output elasticity with respect to energy: $\ln(\theta^e_{jt}) = \ln\left[\beta_0 + \sum_{k=1}^{K} \beta_k ln(V^k_{jt})\right]$. One can think of a first-order approximation specification as a linear-approximation of a Translog production function.

With a first-order approximation on $\ln(\theta^e_{jt})$, equation (2.2) becomes the following equation:

$$\ln(s^e_{jt}) = \beta_0 + \sum_{k=1}^{K} \beta_k \ln(V^k_{jt}) - \ln(\mu_{jt}) \tag{2.3}$$

2.3 Markup Estimation and Identification

Estimating (2.3) directly with OLS regression suffers from the endogeneity problem from the theoretical point of view. Based on equation (2.2), firms change markups whenever they change inputs if we do not make further assumptions on demand system or market structure. IV regression, however, can identify elasticity and markup if there are exogenous variations that make firms to change their inputs but not their markups. While this imposes restrictive assumption on firms' behavior, I conduct several empirical tests and find that this assumption does not necessarily violate many leading models of variable markups. I illustrate in detail on the following paragraphs.

I first double-demean equation (2.3) across entities and across time in order to eliminate entity-specific and aggregate components of markups.[8] This addresses the omitted variable bias arising from the correlation between entity-specific markups or aggregate time-varying markups and input usage of firms. By double-demeaning across time t and entity j in equation (2.3), we have

$$\ln(\ddddot{s}^e_{jt}) = \sum_{k=1}^{K} \beta_k \ln(\ddddot{V}^k_{jt}) - \ln(\ddddot{\mu}_{jt}) \tag{2.4}$$

where $\ddddot{X}_{jt} = \ddot{X}_{jt} - \bar{\ddot{X}}_t$, $\ddot{X}_{jt} = X_{jt} - \bar{X}_j$ for variable X. By running the OLS regression of the equation (2.4), one can estimate unbiased $\beta's$ by assuming $E[\ln(\ddddot{\mu}_{jt})|\ln(\ddddot{V}^1_{jt}), ..., \ln(\ddddot{V}^K_{jt})] = 0$.

However, there are two problems with double-demeaning regression based on equation (2.4). First, since the energy input share (s^e_{jt}) has energy on the numerator, it generates a mechanically positive correlation of V^1_{jt}. Second, the assumption $E[\ln(\ddddot{\mu}_{jt})|\ln(\ddddot{V}^1_{jt}), ..., \ln(\ddddot{V}^K_{jt})] =$

[8] Double-demeaning works the same as putting both time fixed effects and industry fixed effects in the regression. Double-demeaning also eliminates all overhead inputs that might be fixed across entities or fixed across time.

0 is restrictive. This assumption holds under a CES demand with monopolistic competition in a static setting[9], but does not hold without the CES demand system or in a dynamic setup. Suppose a demand elasticity change with respect to the business cycle in a way discussed by Stroebel and Vavra (2015). That is, suppose demand elasticity faced by a firm declines during a boom due to higher wealth that decreases search efforts of households.[10] Decrease in demand elasticity leads to an increase in a firm's desired markups. According to equation (2.1), a cost-minimizing firm must either decrease s^e_{jt} (energy share) or increase θ^e_{jt} (output elasticity with respect to energy) by choosing different inputs V^k_{jt}. This violates $E[\ln(\ddddot{\mu}_{jt})|\ln(\ddddot{V}^1_{jt}), ..., \ln(\ddddot{V}^K_{jt})] = 0$.[11]

Due to the two problems in OLS regression discussed above, I use double-demeaned lagged input prices, $\ln(\ddddot{W}^k_{j,t-1})$ and $\ln(\ddddot{W}^k_{j,t-2})$, as instrumental variables. First, it prevents mechanical correlation discussed in OLS regression.[12] Second, instruments solve issues related with the demand shock discussed above. Consider again the demand shock that shifts demand elasticity, markups, and firms' input usage. If we assume firms take the input prices given, demand shock does not change input prices, hence input prices would generate exogenous variation that is not correlated with demand shock. But if we believe each firm has monoposony power, the demand shock will lead to a change in input prices through a change in input demand. Thus, I use lagged input prices, because idiosyncratic demand shock would not likely to change the previous year's input prices.

To be more concrete, consider the relevance and the exogeneity condition of instruments.

[9] Consider a monopolist's profit maximization problem, instead of cost-minimization problem. Solving a monopolist's static profit maximization with respect to V^1_{jt} yields a first order condition analogous to equation (2.2): $\ln(s^e_{jt}) = \ln(\theta^e_{jt}) + \ln(1 - \frac{1}{\epsilon_{jt}})$, where ϵ_{jt} is a demand elasticity. One can see that $(1 - \frac{1}{\epsilon_{jt}}) = \frac{1}{\mu_{jt}}$ under the monopolistic competition. If we further assume a CES demand system, μ_{jt} must be constant and $\ln(\ddddot{\mu}_{jt})$ disappears.

[10] Notice that this is different from the standard channel discussed in rigid price models with constant elasticity. In standard rigid price models, markups decrease in booms due to sticky price and an increase in marginal cost.

[11] If one assumes that firms only change the energy share s^e_{jt} with respect to demand shock and does not change $\theta^e_{jt}(V^1_{jt}, ...)$, there is no bias. However, it is very unlikely that firms change inputs such that $\theta^e_{jt}(V^1_{jt}, ...)$ does not change.

[12] Using the contemporaneous input prices, $\ln(\ddddot{W}^k_{j,t})$, still generates a mechanical correlation.

As illustrated in figure 1a, the assumption is that variation in the previous year's double-demeaned input prices are strong enough to affect double-demeaned inputs this year (relevance), but not strong enough to affect double-demeaned markups this year (exogeneity). The relevance condition is $Corr[\ln(\ddddot{V}_{jt}^k), \ln(\ddddot{W}_{j,t-1}^k)] \neq 0, \forall k$ and $Corr[\ln(\ddddot{V}_{jt}^k), \ln(\ddddot{W}_{j,t-2}^k)] \neq 0, \forall k$, and it works through the autocorrelation of input prices, or input price rigidity, as in figure 1b. I show that F-statistics from this regression is well above 10 in Appendix B.

The exogeneity condition is $Corr[\ln(\ddddot{\mu}_{jt}), \ln(\ddddot{W}_{j,t-1}^k)] = 0, \forall k$ and $Corr[\ln(\ddddot{\mu}_{jt}), \ln(\ddddot{W}_{j,t-2}^k)] = 0, \forall k$. Intuitively, when a firm faces idiosyncratic high input prices in the previous year compared to other firms, I assume that this firm does not set idiosyncratically high markups in the following year. I acknowledge that there are effects that generate time persistency in markups, such as price rigidity, product durability, and consumer habits that could potentially violate the exogeniety assumption as shown in figure 1c. For example, if there is an increase in government spending in period t-1 that affects different industries' markups and input prices differentially, and if markups are persistent over time due to price rigidity, the exogeneity assumption would be violated.

To address this concern, I conduct two different analysis. First, I control the double-demeaned previous year's output price in my regression as all time-persistent markup channels work through lagged output prices, and I find that coefficients do not change due to this control. Intuitively, think of decomposing lagged input prices into two parts: a *related* part that is used when firms set the output price last year, and an *unrelated* part that is not used when firms set the output price last year. By controlling the lagged output price, I only assume that the *unrelated* part of variation in lagged input prices is also *unrelated* with the current markup. In this setup, I allow firms to set markups based on its last year's price, its expectation on future economic condition, and current economic condition including input price shock, but not based on the *unrelated* part of lagged input prices. Second, I control for price rigidity index, product durability index and necessities index in Bils et al. (2013) in my regression, and I find that coefficients are robust with these controls. If any of these channels violate the exogeneity assumption, controlling these indexes must change coefficients. I report this result in Appendix D.2.

In addition to the persistence-markup effect, inventory adjustment and investment decision can potentially violate the exogeneity assumption.[13] I address these two concerns by controlling double-demeaned inventories and investment for both last year and this year, and find that coefficients do not change with controls as reported in Appendix D.2. I confirm my analysis by conducting three more robustness checks. First, I find that Hansen's J-test cannot reject the validity of these instruments.[14] Second, I use two-year and three-year lagged double-demeaned input prices as instrumental variables, and coefficients remain the same with these instruments as reported in Appendix D.3. First-state F-statistics are still well above 10 and Hansen's J-test cannot reject the validity of instruments. Finally, I estimate θ^e_{jt} separately from the production function estimation to recover markups as in De Loecker and Warzynski (2012) and markups are still unconditionally procyclical, and procyclical or acyclical conditional on demand shock.[15] I report this specification and result in Appendix D.4.

It is useful to discuss identification with equation (2.4) to understand what variation in the data identifies θ^e_{jt}. Ideally, we need random variation in inputs that affects share of energy. If the share of energy increases (decreases) with an exogenous increase (decrease) in input V^k_{jt}, I can interpret this as an increase (decrease) in energy efficiency (θ^e_{jt}) due

[13]markups and inventories are known to be closely related (Bils and Kahn 2000, Kryvtsov and Midrigan 2013). For example, suppose input prices are exogeneous to firms and input price is low in the previous year but high in the coming year. Then forward-looking firms might have incentive to accumulate inventories in the previous year and sell those inventories this year with low output price, potentially generating a correlation between last year's input prices and this year's markups. Adjustment in investment might violate the exogeneity assumption due to a similar reason.

[14]Hansen's J-test should reject the validity of instruments if one of assumptions 1-6 is violated and the new term appears from relaxing the assumption is correlated with input prices. In Appendix C, I show that Hansen's J-statistics are large when markups are estimated based on labor or material input, implying that the assumptions 1-6 are more plausible for energy input compared to other inputs.

[15]Markups are acyclical conditional on various shock in this method due to a less variation in output elasticity with respect to energy. I assume a restricted Translog production function to recover $\ln(\theta^e_{jt})$ with Hicks-netrual technology. It seems crucial to allow labor-augmenting technology to capture the strong input complementarity between labor and energy, which is not allowed in this type of production function estimation technique.

to the increase (decrease) in V_{jt}^k under the assumption 1-5. In this case, energy and V_{jt}^k are complements (substitute) and the coefficient β_k captures this complementarity. The exogenous variation in inputs are coming from lagged input prices, and with assumption 1-5 and double-demeaning technique, I only need to assume that last year's idiosyncratic input prices are uncorrelated with the idiosyncratic markup this year to identify θ_{jt}^e. Notice that I do not make any assumption on demand system or the market structure in estimating θ_{jt}^e and markups.

Once I estimate $\beta's$ consistently, I can recover markups by subtracting $\ln(s_{jt}^e)$ from $\widehat{\ln(\theta_{jt}^e)}$:

$$\widehat{\ln(\mu_{jt})} = \sum_{k=1}^{K} \hat{\beta}_k \ln(V_{jt}^k) - \ln(s_{jt}^e) + C \tag{2.5}$$

where $C = \beta_0 + \sum_{k=2}^{K} \hat{\beta}_k \ln(\bar{V}^k)$. This estimation technique identifies markups up to constant.

2.4 Two Special Cases

This section discusses two special testable specifications on $\ln(\theta_{jt}^e)$ as a part of my analysis. The first specification is a constant θ_{jt}^e, or $\theta_{jt}^e = c$ where c is an arbitrary constant. This assumption corresponds to a Cobb-Douglas production functional form assumption with respect to energy input. To be explicit, consider a production function $\ln(Q_{jt}) = c\ln(V_{jt}^1) + g(V_{jt}^2, ..., V_{jt}^K, A_{jt})$ with arbitrary function $g(\cdot)$. Then it is easy to see that $\theta_{jt}^e = \frac{\partial \ln(Q_{jt})}{\partial \ln(V_{jt}^1)} = c$. Under this assumption, equation (2.2) becomes

$$\ln(s_{jt}^e) = \ln(c) - \ln(\mu_{jt})$$

One advantage of this assumption is that no regression is required to recover markups up to constant. We can directly observe a variation in markups in the data as s_{jt}^e is typically observed in the data. This simple assumption is nested in equation (2.3), so this assumption is testable. I show that the estimated $\beta's$ in equation (2.3) are statistically different from zero in section 5, hence rejecting $\theta^e_{jt} = c$.

The second specification is $\theta^e_{jt} = \frac{\partial Q_{jt}}{\partial V^1_{jt}} \frac{V^1_{jt}}{Q_{jt}} = c(\frac{Q_{jt}}{V^1_{jt}})^{-\rho}$. This assumption corresponds to a CES production functional form assumption with respect to energy input, which is a conventional generalization of a Cobb-Douglas production function. That is, suppose we have $Q_{jt} = (c(V^1_{jt})^\rho + g(V^2_{jt}, ..., V^K_{jt}, A_{jt}))^{\frac{1}{\rho}}$, where $g(\cdot)$ is an arbitrary function of other inputs and productivity components. This leads to $\theta^e_{jt} = \frac{\partial Q_{jt}}{\partial V^1_{jt}} \frac{V^1_{jt}}{Q_{jt}} = c(\frac{Q_{jt}}{V^1_{jt}})^{-\rho}$. With this specification, the equation (2.2) becomes

$$\ln(s^e_{jt}) = \ln(c) - \rho \ln(Q_{jt}) + \rho \ln(V^1_{jt}) - \ln(\mu_{jt})$$

Double-demeaning the above regression equation leads to

$$\ddddot{\ln(s^e_{jt})} = -\rho \ddddot{\ln(Q_{jt})} + \rho \ddddot{\ln(V^1_{jt})} - \ddddot{\ln(\mu_{jt})} \tag{2.6}$$

Based on this equation, we can run regression and estimate ρ's with instruments. In particular, I use three instruments: lagged and double-demeaned input prices for energy, labor (total payroll) and capital (price of investment). Then I recover markups by subtracting the estimated $\ln(\theta^e_{jt})$ from $\ln(s^e_{jt})$. Notice that this regression specification allows a researcher to test the CES production functional form assumption with respect to energy. If we reject the hypothesis that the coefficient of energy is equal to the negative coefficient of output, the data rejects CES production functional form assumption with respect to energy input. In section 5, I show that this specification is strongly rejected in the data.

3 Comparison to the Previous Literature

This section discusses how the approach in this paper differs from other works on measuring price-cost markup cyclicality. In particular, I compare and contrast the approach in this paper with the input margin method originated from Bils (1987) and the Solow-residual approach originated from Hall (1986).[16] Both approaches adapt a cost-minimization framework, but with different assumptions and empirical specifications from this paper.

3.1 Approach 1

Suppose we have the four assumptions discussed in section 2 on input V_{jt}^k. Then one can derive a very similar expression as in equation (2.1) from a firm's cost minimization condition:

$$\mu_{jt} = \frac{\theta_{jt}^k}{s_{jt}^k} \tag{3.1}$$

where μ_{jt} is the markup, θ_{jt}^k is an output elasticity with respect to input V_{jt}^k, and s_{jt}^k is the input share for input V_{jt}^k.

The input margin method (Rotemberg and Woodford 1999, Nekarda and Ramey 2013) uses labor input or labor hours input instead of energy input as a choice variable of a firm to derive equation (3.1). That is, V_{jt}^k is labor or labor hours input. This method assumes a Cobb-Douglas production function with respect to labor input. Then equation (3.1) becomes

$$\mu_{jt} = \frac{c}{s_{jt}^k} \tag{3.2}$$

where c is an arbitrary constant. One can identify markups up to constant by looking at the inverse of the labor share. This method is the same as what's discussed in section 2.4., except using labor input instead of energy input. Bils et al. (2014) adapts this method by using material input as a choice variable, hence using the inverse of material input share to assess markup cyclicality. I present and discuss the result based on the inverse of labor

[16] As discussed in Nekarda and Ramey (2013), there are two other direct approaches and two other indirect approaches to access markup cyclicality. Also, there are other ways to recover markups in industrial organization and international trade literature. Atkin et al. (2015) discusses three common approaches in these literature, including Solow-residual approach.

input share and the inverse of material input share in section 5.

Then this method generalizes assumptions one by one. Suppose one assumes a CES production function on labor, rather than Cobb-Douglas production function. Then the equation (3.2) becomes

$$\mu_{jt} = \frac{c}{s_{jt}^{k}}\Big(\frac{Q_{jt}}{V_{jt}^{k}}\Big)^{-\rho}$$

where c is an arbitrary constant. One can recover the markup by calibrating ρ from this expression. This method is similar to what is discussed in section 2.4, except using labor input instead of energy input, and calibrating ρ instead of estimating ρ.

Instead of a CES production functional form assumption, suppose we relax overhead labor assumption. Then the equation (3.2) becomes:

$$\mu_{jt} = \frac{c}{\bar{s}_{jt}^{k}}$$

where $\bar{s}_{jt}^{k} = \frac{W_{jt}^{k}(V_{jt}^{k} - \bar{V}_{jt}^{k})}{P_{jt}Q_{jt}}$. Then one can calibrate the markup by calibrating the labor overhead component. Similarly, this method relaxes no monopsony power assumption in the labor market and allows wages to change with respect to labor input demand by making a specific structural assumption on the marginal wage schedule and calibrating the corresponding parameters. This method also relaxes no labor adjustment cost assumption by specifying the adjustment cost explicitly.[17]

3.2 Approach 2

Consider the Solow-residual approach originated from Hall (1986). This approach uses either labor input or material input as a choice variable, and makes the four assumptions discussed in section 2 to derive the equation (3.1). Then it estimates θ_{jt}^{k} from the techniques used in productivity literature with the control function (Olley and Pakes 1996, Levinsohn

[17] Please see Rotemberg and Woodford (1999) and Nekarda and Ramey (2013) for a full treatment of this approach.

and Petrin 2003, Ackerberg et al. 2006) and recovers markups with the observed input share s^k_{jt} from equation (3.1) (De Loecker and Warzynski 2012, De Loecker et al. 2014).[18]

In particular, the estimation technique in this paper is similar to the approach discussed in Gandhi et al. (2013). They also derive equation (2.2) and propose to estimate aggregate markups by allowing time fixed effects and running partial linear regressions with the flexible functional form on $\ln(\theta^e_{jt})$. In this way, estimated fixed effects are time-varying aggregate average markups. This method suffers from the same two problems in the OLS regression I discussed in section 2.3. In addition, when I follow this methodology, I find that time fixed effects are not precisely estimated with my database. Many fixed effects have p-value higher than 0.5 when I test a hypothesis that the coefficient is equal to zero.

4 Data

This paper uses annual six-digit NAICS industry-level data from NBER-CES Manufacturing Industries Database. Industry-level database has two advantages over aggregate database. First, it allows me to use panel data techniques to estimate markups by exploiting both cross-sectional and time-series variation. Second, once I obtain time-varying, industry-specific markups, I can assess both unconditional and conditional markup cyclicality by using the panel data techniques.

This database records detailed information on 473 manufacturing industries from 1958 to 2009. It is compiled from the Annual Survey of Manufacturers and the Census of Manufactures. The variables in this database include gross output (value of shipment), value added, 5-factor inputs (production worker, non-production worker, capital, material and energy) for each industry over time. This data also records deflators for output, material, energy, investment, and wage bills for production workers and total employees. I report

[18]There are papers that use this framework to study markup cyclicality such as Haskel et al. (1995), but they require stronger assumptions compared to the recent development of this technique and what are assumed in this paper. For example, they assume a change in productivity is not correlated with a change in inputs, and assume 1-5 in section 2 on every inputs firms are using. De Loecker (2011) discusses limitation of previous works and its development.

summary statistics in Appendix B.1, and more detailed explanation of this database can be found in Bartelsman et al. (2000). I supplement this database with GDP data from Bureau of Economic Analysis.[19]

5 Estimation Result

In this section, I present the estimation result based on the approach in section 2. First, I show the estimate of $\ln(\theta^e_{jt})$ based on equation (2.4) and how instruments fix the potential bias in the OLS regression. Then I present the estimate of $\ln(\theta^e_{jt})$ with a CES production functional form assumption with respect to energy, and show that the data rejects this specification. Second, I show the distribution of markups across industry and time. I find that previous markup measures based on inverse of input share underestimates dispersion of markups across time and across industry.

5.1 Elasticity Estimation

Table 1 presents the estimated $\ln(\theta^e_{jt})$ based on equation (2.4). Based on column (1), I find that energy input follows the law of diminishing returns and most other inputs, especially production worker, are complement to energy. First, the coefficient in front of energy, β_1, is negative. This states that the energy input becomes less efficient as a firm uses more energy, hence capturing the law of diminishing returns to energy.[20] Second, coefficients

[19] One might argue that firm-level database is necessary to estimate markups. One advantage of firm-level database is that a researcher can allow a more flexible functional form on output elasticity with respect to energy due to a more variation in the data. However, using firm-level database is not a panacea. A typical firm-level database, including confidential U.S. census database, does not have the output price and input price at firm-level. This prevents adapting the methodology used in this paper and generates the famous output price and input price bias that potentially change a direction of markup cyclicality when Solow-residual method is used (Gorodnichenko 2012, De Loecker and Goldberg 2014). Moreover, a typical firm-level database suffers from the external validity concern due to both its narrow industry and short time period coverage, hence it might not be adequate to study the cyclical pattern of markups over the business cycle.

[20] Notice that this is different from the conventional law of diminishing returns with a Cobb-Douglas production function. A Cobb-Douglas production function leads to a constant θ^e_{jt}, whereas a more general production function, such as a Translog production function, leads θ^e_{jt} to depends on inputs.

in front of other inputs except non-production workers are positive, implying that energy becomes more efficient as a firm uses more of these inputs. This states that these inputs are complement to energy. In particular, the coefficient in front of production worker is economically and statistically significant, implying that it is strong complement to energy input.[21] Non-production worker is a substitute since the coefficient of non-production worker is negative, but the result is not very statistically significant with a t-statistics 1.73. I use results in column (1) to recover markups.

I find that the OLS regression results are polar opposite to the IV regression result. The coefficient of energy input is positive and the coefficient of other inputs are negative in column (4). This difference arises due to the two problems in OLS regression discussed in section 2.3. First, there is a mechanical correlation of energy input that appears in both left-hand side and right-hand side of the equation (2.4). This leads to a positive estimated coefficient of energy input. Second, coefficients are likely to be biased due to the demand shock discussed in section 2.3. The direction of bias can be assessed by treating a markup as an omitted variable. Consider $\text{plim}(\hat{\beta}_k^{ols}) = \beta_k - \frac{Cov(\ln(\tilde{V}_{jt}^k), \mu_{jt})}{Var(\ln(\tilde{V}_{jt}^k))}$. The direction of bias depends on the correlation of the markup and input for each coefficient. The correlation can be assessed with the first order condition: $\mu = \frac{F_1(V_{jt}^1, ...)}{(W_{jt}^1/P_{jt})}$. Under the law of diminishing returns, a firm must decrease energy input to increase marginal product of energy ($F_1(V_{jt}^1, ...)$) and markups. This leads to upward bias in a coefficient of energy input. Similarly, a firm must increase the complements of energy and decrease the substitutes of energy to increase $F_1(V_{jt}^1, ...)$ and markup, leading to downward bias for the coefficients of complements and upward bias for the coefficients of substitutes as shown in Table 1.

Controlling the lagged output price does not change the result as shown in column (3). In particular, the coefficient in front of the lagged output price is negligible and not statistically significant, implying that persistence in markups is not likely to cause

[21]If I only allow labor input instead of both production worker and non-production worker, I find that labor input is strong complement to energy input.

inconsistency in my estimates.[22] I report Hansen's J-statistics to test the exogeneity condition of instruments for regression (1), (2), and (3), and the p-values are well above 0.1. Column (2) and (5) include capital in the regression, but the estimated coefficient of capital is not economically or statistically significant. It only makes other coefficients less statistically significant, implying that capital and energy are neither substitutes nor complements holding all other inputs constant. Finally, notice that all coefficients are statistically significant except the capital input coefficient. This result implies that we reject constant θ^e_{jt}, or a Cobb-Douglas production functional form assumption with respect to energy.

The alternative production function discussed in section 2.4 is a CES production function. Table 2 presents the estimate of $\ln(\theta^e_{jt})$ under a CES production functional form assumption based on equation (2.6). Based on column (1), I conclude that the data rejects a CES production functional form assumption with respect to energy. If the CES production functional form assumption holds, the coefficient of energy must be equal to the negative coefficient of output. I strongly reject this hypothesis with small p-value, 0.0052, and with $\chi^2 = 7.82$. This implies that the CES production functional form assumption with respect to energy input suffers from a misspecification problem. If I restrict the coefficient of energy to be equal to the negative coefficient of output in estimation, energy and output seem to be substitute with $\rho = 0.23$ as shown in column (3).[23] This result is misleading and in contrast with the result in table 1. Notice that I also reject both Leontief and linear production functions with respect to energy since a CES production function nests these production functions as a special (or limiting) case.

Column (2) reports the OLS result, but they suffer from mechanical correlation and omitted variable bias as discussed with the first-order polynomial specification on $\ln(\theta^e_{jt})$. I also report Hansen's J-statistics to test the exogeneity condition of instruments and p-value

[22] I treat lagged output price as control in my regression, but making lagged output price endogenous and using lagged input prices as instruments do not change the result.

[23] ρ should be equal to one for a linear production function, and ρ should approach negative infinity for a Leontief production function.

is well above 0.1.[24]

From now on, I use my benchmark result to estimate $\ln(\theta_{jt})$, which is the column (1) of table 1. I recover markups by subtracting $\ln(s^e_{jt})$ from $\widehat{\ln(\theta^e_{jt})}$ as in equation (2.5). Markups are identified up to constant since I double-demean variables to estimate coefficients.

5.2 Markups

I find that there is a greater variation of markups across time and across industries compared to previously known markups measures. A distribution of estimated markups and other conventional measure of markups across time and industries are presented in table 3. Column (1) is based on estimated markups, and other columns are based on the inverse of input shares.[25]

The dispersion in estimated markups across time is greater than the inverse of any input shares. Standard error is 0.34 with the estimated markups, but it is 0.16 for the inverse of energy share. 75-25 ratio is 0.58 for markups, but 0.35 for the inverse of labor shares. In particular, the inverse of material share seems to have the minimum variation across time. Its standard error is only 0.02 and 75-25 ratio is only 0.03. Similarly, a dispersion in the estimated markups across industries is greater than the inverse of any input share, and the inverse of material share has a minimum variation across industries.

6 Markup Cyclicality

In this section, I present results on markup cyclicality. I first assess unconditional markup cyclicality with graph and regression analysis. Then I show how markups move with respect to demand shock, product entry and exit, financial shock and price rigidity by using a difference-in-difference technique.

[24]In Appendix B, I report the first stage F-statistics for regression based on equation (2.4) and (2.6), and all of them are well above 10 for all inputs. This result holds if I regress each input on one input's price only

[25]As shown in equation (3.2), the inverse of input share is equal to markups up to constant under the assumptions discussed in section 2 and 3.

6.1 Unconditional Markup Cyclicality

To assess markup cyclicality, I take the simple average of $\ln(\mu_{jt})$ across industries, linearly detrend the measures, and plot with linear-detrended $\ln(GDP_t)$ on figure 2.[26] Figure 2 shows a strong procyclical pattern of markups. This procyclicality is driven by either procyclicality of $-\ln(s^e_{jt})$ or procyclicality of $\ln(\theta^e_{jt})$. I plot the linear-detrended simple averages of $-\ln(s^e_{jt})$ to decompose the cyclical pattern of markups, and find that $-\ln(s^e_{jt})$ is weakly procyclical. This result implies that the variation in $\ln(\theta^e_{jt})$ explains the procyclicality of markups.

The procyclicality of $\ln(\theta^e_{jt})$ is driven by a strong input complmentarity as shown in section 5.1. $\ln(\theta^e_{jt})$ depends positively on the production worker and material, and negatively on the energy and non-production worker. Given that all inputs are procyclical, the procyclicality of $\ln(\theta^e_{jt})$ must be driven by the procyclicality of complementary inputs, particularly due to production worker that is a strong complement to energy input. This result suggests that using a flexible production functional form that allows input complementarity is extremely important to assess markup cyclicality.

To be more concrete, I conduct the regression analysis based on industry-specific, time-varying markups and value of shipment measure in NBER-CES database. I allow both time and industry fixed effects to precisely pin down the cyclical pattern. Consider the following regression.

$$\Delta \ln(\mu_{jt}) = \lambda_j + \lambda_t + \gamma_1 \Delta \ln(vship_{jt}) + \epsilon_{jt} \tag{6.1}$$

$\widehat{\ln(\mu_{jt})}$ is the estimated log of markups, $\ln(vship_{jt})$ is the log of value of shipment, and λ is the fixed effect.[27] Table 4 reports the result based on equation (6.1).

[26] Using Hodrick-Prescott filter or Baxter-King filter illustrates the same pattern. Please see Appendix D.5 for the result based on different filters.

[27] Notice that this specification allows markups to be identified up to not only constant, but also time-varying or industry-specific parameters to assess markup cyclicality. For example, allowing the time-varying or industry-specific overhead components of inputs except energy input will identify markups up to time-varying or industry-specific parameter, but this will not change the result as these will be absorbed in fixed

There are three main observations in table 4. First, markups are strongly procyclical as shown in column 1. An increase in 1 % of value of shipment leads to an increase in 1.18 % of the markup. Second, all other measures of markups show procyclical pattern except material share.[28] An increase in 1 % of value of shipment leads to an increase in 0.50 % of markup with the energy share, increase in 0.39 % of markup with the labor share, and increase in 0.41 % of the markup with the CES production functional form specification. Although the markup measure based on the material share is negative, it is not economically significant. In addition, the 95% confidence interval of regression coefficient based on the material share includes zero, suggesting that it is hard to conclude markups are countercyclical even based on the material share. The material input is likely to suffer from a monopsony effect and heterogeneous input quality issue that can change the direction of markup cyclicality.[29] Third, although procyclical, a conventional CES production functional form specification leads to more countercyclical markups compared to other specifications. However, this specification is strongly rejected in the data. Markup cyclicality results based on a correlation of $\Delta \ln(\mu_{jt})$ and $\Delta \ln(vship_{jt})$ are consistent with results in the regression analysis.

From the figure and the table, I conclude that markups are unconditionally procyclical.[30]

effects.

[28]The direction of cyclicality does not change by using more flexible production functional form than Cobb-Douglas production function when labor input or material input is used to construct markups. In Appendix C, I construct markups and assess its cyclicality based on both labor and material with flexible production functions.

[29]In Appendix C.4, I discuss why the inverse of material share is more countercyclical compared to other measures in detail.

[30]Using different weights on industries in regression analysis does not change the result. I used two different weights, the share of value of shipment and the share of value added, for robustness check and present the result in Appendix D.6.

6.2 Conditional Markup Cyclicality

In this section, I present how markups change with respect to demand shock, product entry and exit, financial shock and price rigidity. I utilize estimated industry-specific, time-varying markups and use a difference-in-difference technique to exploit both cross-sectional and time-series variations. The construction of shocks relies heavily on previous literature.

The regression specification is following:

$$\Delta\widehat{\ln(\mu_{jt})} = \lambda_j + \lambda_t + \alpha(\Delta Z_t * X_j) + \epsilon_{jt} \tag{6.2}$$

where X_j stands for seven different industry-specific variables: $X_j = \{\bar{\theta}_j,\ X_j^{dur},\ X_j^{engel},\ X_j^{pfreq},\ X_j^{fin},\ X_j^{entry},\ X_j^{entry}\}$. $\bar{\theta}_j$ measures industry-specific sensitivity to government spending, which comes from Nekarda and Ramey (2011).[31] X_j^{dur} stands for durability index, X_j^{engel} stands for slope of engel curve or luxuriousness index, X_j^{pfreq} stands for price frequency. All three measures come from Bils et al. (2013). X_j^{fin} is a Rajan and Zingales (1998) 4-digit NAICS financial constrained index.[32] X_j^{entry} measures product entry rate and X_j^{exit} measures product exit rate, and both measures come from Bernard et al. (2010).[33] Z_t stands for two different time-specific aggregate variables: $Z_t = \{\ln(GDP_t), \ln(G_t)\}$. $\ln(GDP_t)$ is the log of GDP. $\ln(G_t)$ is the government defense spending.[34] $\Delta\widehat{\ln(\mu_{jt})}$ is the estimated change in log of markups and λ denotes the fixed effect.

I assess all conditional markup cyclicality with this regression. First, markup cyclicality conditional on demand change is assessed with $\ln(G_t) * \bar{\theta}_j$, $X_j^{dur} * \ln(GDP_t)$ and $X_j^{engel} *$

[31] $\bar{\theta}_j$ is constructed by taking the average of value of shipment to government across time for each 4-digit NAICs industry. Using the initial value of shipments to government for $\bar{\theta}_j$ does not change the result.

[32] This measure is constructed with Compustat database by first building up financial dependence index at industry level: Financial Dependence$_{ij}$ = $\frac{\sum_t CapitalExp_{ijt} - CashFlow_{ijt}}{\sum_t CapitalExp_{ijt}}$. i denotes firm, j denotes industry, and t denotes time. Then I take the median of Financial Dependence$_{ij}$ within 4-digit NAICs to construct X_j^{fin}.

[33] Product entry (exit) rate is defined by the number of firms adding (dropping) the product between census years divided by the average number of firms producing the product in both years.

[34] Results in this paper do not change when the whole government spending is used instead of the defense spending.

$\ln(GDP_t)$ as in Nekarda and Ramey (2013) and Bils et al. (2013). With $\ln(G_t) * \bar{\theta}_j$, α tells us how much the markup of a government-spending-sensitive industry goes up more compared to the markup of a government-spending-insensitive industry when government demand increases. Government defense spending has been argued to vary due to political reason instead of economic reason (Barro 1981, Nekarda and Ramey 2011). With $X_j^{dur} * \ln(GDP_t)$ and $X_j^{engel} * \ln(GDP_t)$, α tells us how much a demand-sensitive industry's markup goes up more than that of a demand-insensitive industry in expansion. According to Bils et al. (2013), a durability index is a strong predictor of the demand shock. A consumer must increase N% expenditure to increase 1% stock on product that last N years, so his or her consumption for a durable product must be more sensitive to the business cycle.[35] Similarly, X_j^{engel} captures the relative demand sensitivity as luxury goods are more likely to be sensitive to demand shock. In this setup, I interpret $\alpha > 0$ as procyclical markups conditional on demand change.

Table 5 presents the result. The regression results support that markups are procyclical with respect to demand shock and product exiting, and countercyclical with respect to financial shock and price rigidity. 95% confidence intervals do not include 0, suggesting that these results are statistically significant. For product entry, the coefficient is negative but not statistically significant. These results confirm the prediction of models with firm entry and exit (Jaimovich and Floetotto 2008, Bilbiie et al. 2012), with financial friction (Chevalier and Scharfstein 1996, Gilchrist et al. 2014), with price rigidity, but in contrast with countercyclical desired markups conditional on demand shock. This is consistent with Nekarda and Ramey (2013) who find that markups are either procyclical or acyclical with respect to demand shock, but inconsistent with Bils et al. (2013) who finds that markups are countercyclical with respect to demand shock. They use a similar identification strategy but construct markups based on the inverse of labor share.

[35] For the detailed argument, please see Bils and Klenow (1998) and Bils et al. (2013).

7 Implications

7.1 Input Complementarity vs. Markup Countercyclicality

One striking implication of the result in this paper is that the strong input complementarity can explain both procyclical (or acyclical) wages and countercyclical unemployment conditional on demand change without incorporating markup countercyclicality. In fact, the input complementarity explains why markups are procyclical. Figure 3 shows how both traditional countercyclical markup and input complementarity explain an increase in wage and labor when firms face a positive demand shock.

Figure 3a shows the labor market under the perfect competition. Since the production function only depends on labor, capital and productivity, the marginal product of labor only depends on labor, capital and productivity. When firms experience a positive demand shock, they can only adjust labor input since capital input is a predetermined variable and productivity is not correlated with positive demand shock. That is, they cannot shift the labor demand schedule but the labor supply schedule must shift to the right to increase employment.[36] But then this effect leads to a decrease in wages and an increase in labor input due to positive demand shock, which cannot be reconciled with empirical evidence.[37] Markup countercyclicality has been proposed to reconcile this seemingly contradictory prediction as in figure 3b. In models with nominal price rigidity, markups fall when firms face positive demand shock due to rigid price and the increases in marginal cost. Decrease in markups allows the labor demand schedule to shift to the right, hence capturing both increase in labor and increase in wages (or constant wages) at the equilibrium.

Input complementarity, however, can also shift the labor demand schedule when firms

[36]The labor supply shifts to the right with respect to demand shock due to various different reasons (Rotemberg and Woodford 1991). For example, the labor supply can shift to the right due to an increase in the marginal utility of wealth as a result of an increase in government spending.

[37]Real wage procyclicality with respect to demand change is following the argument in Rotemberg and Woodford (1991, 1992). There are evidences on weakly countercyclical real wages conditional on government spending (Nekarda and Ramey 2011), but I am not aware of any paper that finds strong countercyclical real wages conditional on demand change predicted by conventional models with the perfectly competitive market

face positive demand shock as shown in figure 3c. If we allow other inputs such as energy and material in the production function, then the marginal product of labor not only depends on labor, capital, and productivity, but also depends on energy and material. When flexible inputs are complementary to the labor input, the increase in these inputs due to positive demand shock must shift the labor demand schedule to the right just like countercyclical markups. Given that there is a strong complementarity of energy and production worker as shown in section 5 and that markups are procyclical with respect to demand shock as shown in section 6, input complementarity is a better explanation for countercyclical unemployment and procyclical (or acyclical) wages than countercyclical markups. Notice that if input complementarity is strong enough, we can allow procyclical markups and still explain procyclical (or acyclical) wages and countercyclical unemployment.

To see how the markup cyclicality is driven by the input complementarity and other types of friction such as nominal rigidity, I rewrite the equation (3.1):

$$\mu_{jt} = \frac{P_{jt}}{MC_{jt}} = \frac{\theta^k_{jt}}{s^k_{jt}} = \theta^k_{jt} \frac{Q_{jt}}{V^k_{jt}} \frac{P_{jt}}{W^k_{jt}} \tag{7.1}$$

If we assume $\frac{Q_{jt}}{V^k_{jt}}$ is acyclical[38] and θ^k_{jt} is a constant by assuming Cobb-Douglas production function, all that matter for markup cyclicality is a relative strength of rigidity in output price and input price. A standard price rigidity model predicts that markups are countercyclical with respect to demand shock due to output price rigidity. Studies that find markup procycality or acyclicality either emphasize wage rigidity (Nekarda and Ramey 2013) or desired markup effect that lead to change in output price (Stroebel and Vavra 2015) to justify their analysis.

In addition to output and input price rigidity, I allow a flexible functional form on θ^k_{jt} and let this vary across time. As shown in section 5, this estimated θ^k_{jt} explains a large part of variation in the procyclical pattern of markups, suggesting that the markup cyclicality is

[38] Output and input are both procyclical, which is likely to cause $\frac{Q_{jt}}{V^k_{jt}}$ acyclical .

driven by the input complementarity, rather than nominal rigidity. Notice that this result does not necessarily contradict with the empirical evidences on price rigidity (Bils and Klenow 2004, Nakamura and Steinsson 2008). Output price can be sticky with procyclical markups due to countercyclical marginal costs that arise from the input complementarity.

7.2 Returns to Scale Procyclicality

The estimated markups and its cyclicality inform that returns to scale is strongly procyclical in the United States production. Procyclical markups imply countercyclical real marginal cost by the definition ($\mu = \frac{P}{MC}$). That is, real marginal cost is decreasing with output, and this movement in real marginal cost should inform on returns to scale.[39]

Formally, returns to scale is defined as following:

$$\gamma(V_{jt}^1, ..., V_{jt}^K) \equiv \frac{\partial \ln(Q(\lambda V_{jt}^1, ..., \lambda V_{jt}^K))}{\partial \ln(\lambda)}\bigg|_{\lambda=1}$$
$$= \sum_k \theta^k(V_{jt}^1, ..., V_{jt}^K)\big(= \sum_k \frac{\partial Q_{jt}}{\partial V_{jt}^k}\frac{V_{jt}^k}{Q_{jt}}\big)$$

$\gamma(V_{jt}^1, ..., V_{jt}^K)$ measures the percentage increase in output from one percent increase in all inputs. Under the conventional Cobb-Douglas production function, γ_{jt} is constant. If we assume $\ln(Q_{jt}) = \ln(A_{jt}) + \alpha \ln(L_{jt}) + \beta \ln(K_{jt})$, we have $\gamma = \alpha + \beta$. In this case, $\gamma > 1$ refers to increasing returns to scale, $\gamma = 1$ refers to constant returns to scale, and $\gamma < 1$ refers to decreasing returns to scale. Once we allow a more flexible production function such as a Translog production function, γ_{jt} is not constant but it depends on inputs. Consider a restricted version of Translog production function that allows input complementarity: $\ln(Q_{jt}) = \ln(A_{jt}) + \alpha \ln(L_{jt}) + \beta \ln(K_{jt}) + \psi[\ln(L_{jt}) * \ln(K_{jt})]$. The only difference from Cobb-Douglas production function is an interaction term. In this case,

[39] For example, with auxiliary assumptions, the constant marginal cost with positive fixed cost leads to the increasing returns to scale, and the increasing marginal cost with one input and zero fixed cost leads to the decreasing returns to scale.

$\gamma_{jt} = \gamma(l_{jt}, k_{jt}) = \alpha + \beta + \psi[l_{jt} + k_{jt}]$. Since γ_{jt} depends on inputs, it varies across time and industries.

The insight from Hall (1990) and Basu and Fernald (1997) allows markups to inform on a returns to scale parameter. Suppose we make four assumptions listed in section 5 for every input. Then equation (2.1) holds for every input: $\theta^k_{jt} = \mu_{jt}(s^k_{jt}), \ \forall k$. Summing up across k, we have $\gamma_{jt} = \sum_k \theta^k_{jt} = \mu_{jt} \sum_k s^k_{jt}$. Since $\sum_k s^k_{jt}$ is observed in the data and $\ln(\mu_{jt})$ is estimated up to constant, I can assess the cyclicality of γ_{jt} with the same specification as in equation (6.1).[40] Table 6 presents the regression result based on $\Delta \widehat{\ln(\gamma_{jt})} = \lambda_j + \lambda_t + \gamma_1 \Delta \ln(vship_{jt}) + \epsilon_{jt}$.

Column (1) presents regression result based on γ_{jt} recovered from markups estimated in section 5. The coefficient is positive, and it is both economically and statistically significant, implying that returns to scale is strongly procyclical. Other measures of markups underestimate the procyclicality of returns to scale.[41]

Procyclical returns to scale is a novel channel on explaining the procyclical productivity in addition to exogenous productivity change, increasing returns to scale, resource reallocations and cyclical factor utilization. A restrictive production function that does not allow flexible substitution across inputs, such as a Cobb-Douglas production function, cannot capture the cyclicality of returns to scale in explaining procyclical productivity. Factor utilization is known to be the most important driving force of procyclical productivity (Basu 1996), but this result would be overstated without incorporating a flexible production function.

This result has a striking implication that the economy behaves as if it has increasing returns to scale even though it has constant returns to scale on average. Under the constant γ assumption with a Cobb-Douglas production function, some studies find that there is

[40] I can only assess the cyclicality γ_{jt} and cannot recover γ_{jt} parameters because markups are only identified up to constant.

[41] In fact, a CES production function has constant returns to scale, so it must not vary across time. The procyclicality is likely to come from the inconsistent estimation due to the misspecification of a production function.

constant returns to scale (Basu and Fernald 1997) and others find that there is increasing returns to scale (Hall 1990, Domowitz et al. 1988) in the U.S. economy. Suppose the economy has constant returns to scale on average with procyclical γ_{jt}. Then in expansion when firms employ more inputs, firms can produce even more outputs due to increasing returns to scale, but in recession when firms employ less inputs, firms can only produce even less outputs due to the decreasing returns to scale. This is consistent with the assumption of increasing returns to scale in the study of business cycles.

8 Conclusion

In this paper, I find that markups are procyclical using a new method that does not rely on a CES production funtional form assumption. I look at the first order condition for energy input to avoid assumptions and calibrations on the overhead components, adjustment cost, monopsony power, and input quality with labor input. I apply panel data techniques to recover time-varying, industry-specific markups with a flexible production function. Finally, I find that markups are procyclical unconditionally, procyclical with respect to demand shock and product exiting, and countercyclial with respect to financial shock and price rigidity.

This result has a novel implication that input complementarity can explain both procyclical (or acyclical) wages and countercyclical unemployment without relying on countercyclical markups. Also, it turns out that returns to scale is strongly procyclical, rather than invariant across time. These results do not necessarily contradict with evidence on price rigidity, but they call for a reevaluation of business cycle models that generate countercyclical markups with a restrictive production function. Models that incorporate markup procyclicality with a flexible production functional form would better explain the business cycle facts and help to pin down how monetary and fiscal policy affect the real economy.

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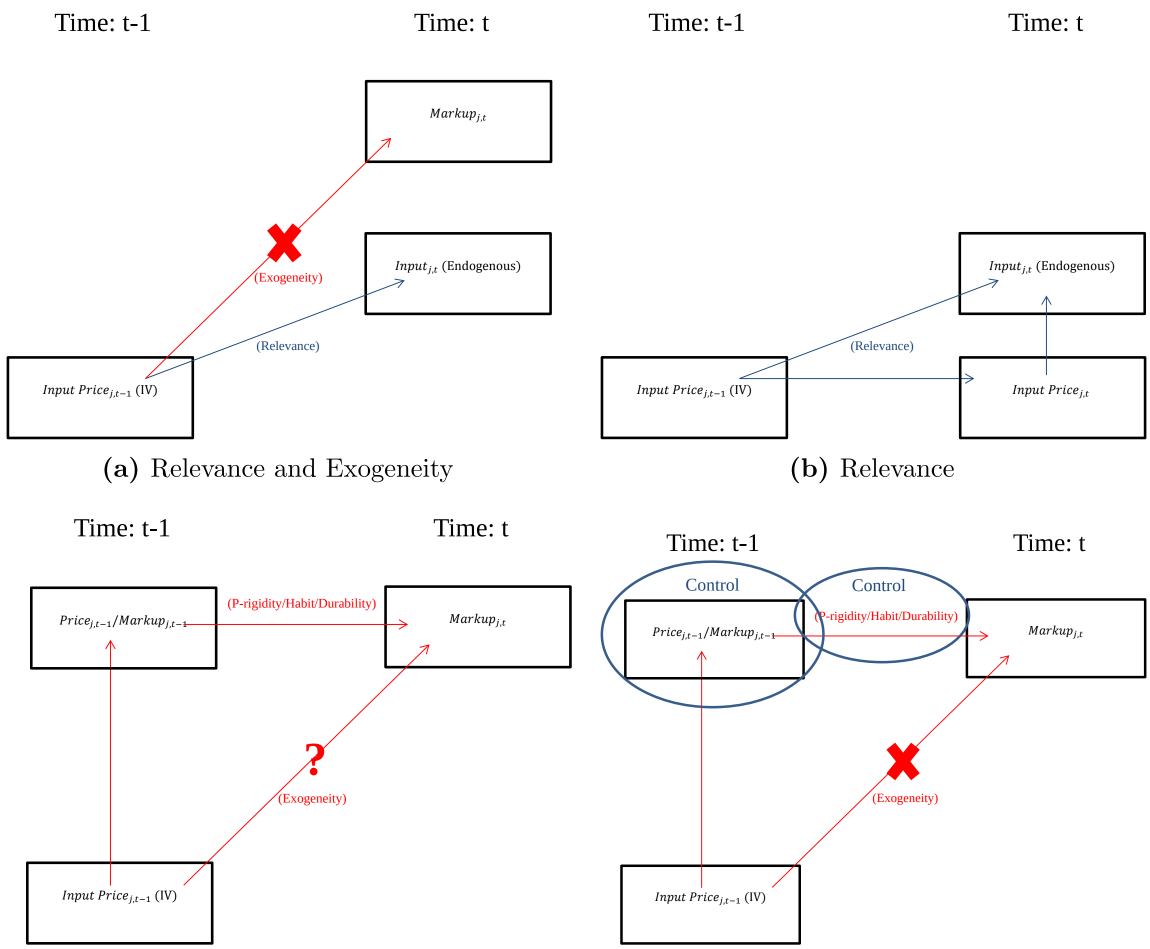
Figure 1: Instrument: Identification



(a) Relevance and Exogeneity

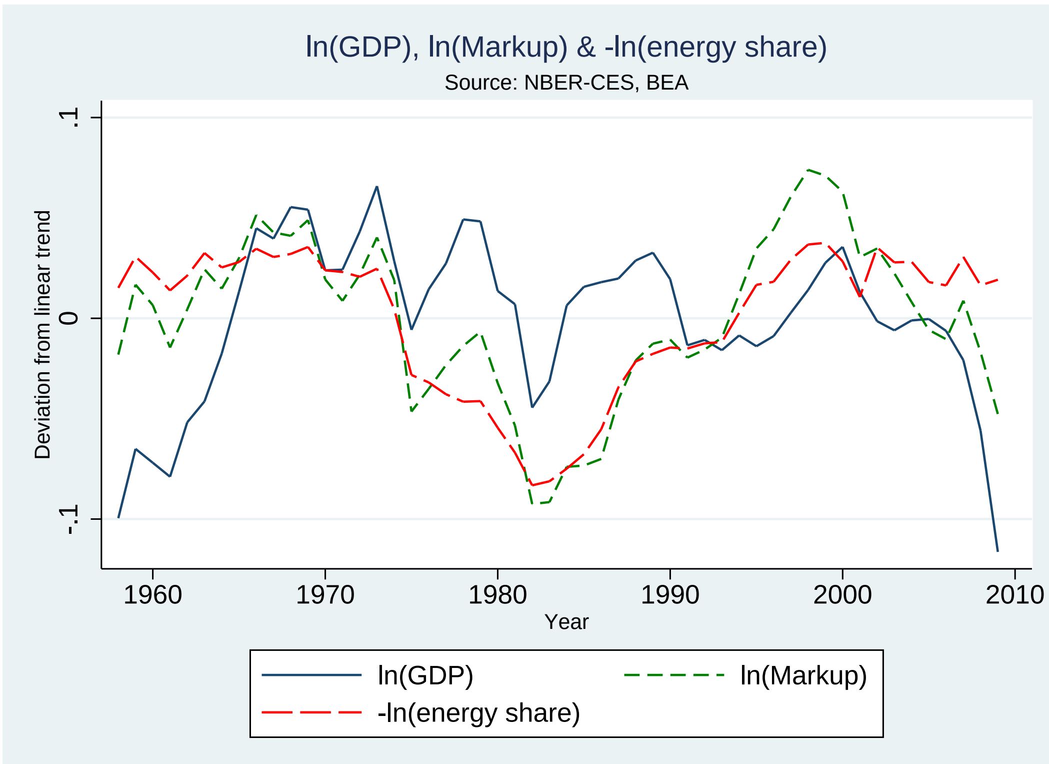
(b) Relevance

(c) Concern on Exogeneity

(d) Control for Exogeneity

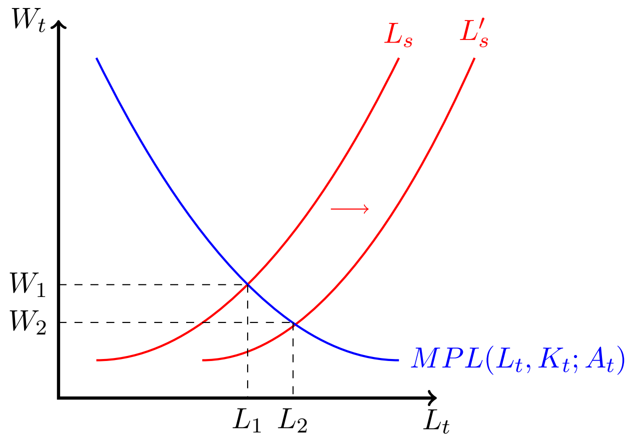
Note. (a) shows relevance and exogeneity conditions of instruments. (b) shows that the relevance condition works through the autocorrleation of input prices. (c) shows concern on the exogeneity condition due to the factors that make markups persistent. (d) shows how controls address concerns on the exogeneity condition.

Figure 2: Average Markup Cyclicality

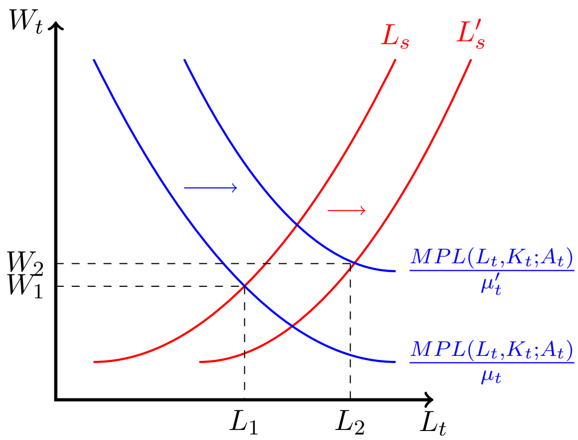


Note. Y-axis is a deviation from linear trend, and x-axis is year from 1958 to 2009. Estimated markups, $\ln(\mu_{jt})$, are constructed by assuming 1st-order polynomial specification on $\ln(\theta^e_{jt})$. Estimated markups and $-\ln(s^e_{jt})$ are averaged across industries within each time period, and also detrended from the linear trend. Both measures are then divided by 5 to compare with the detrended GDP on the graph. GDP database is supplemented from Bureau of Economic Analysis.

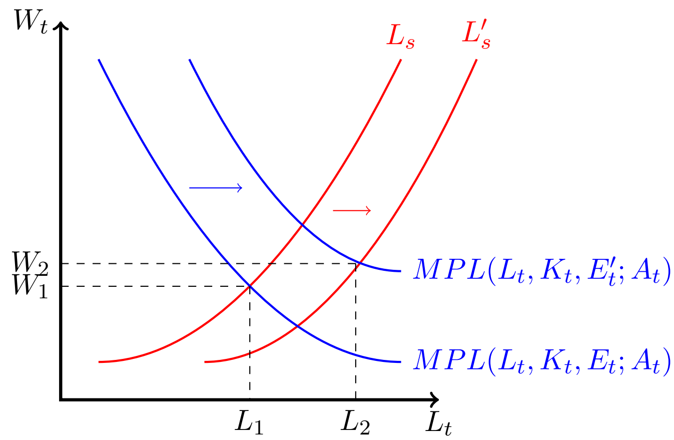
Figure 3: Labor Market: Input Complementarity vs. Markup Countercyclicality



(a) Perfect Competition



(b) Markup Countercyclicality



(c) Input Complementarity

Note. Y-axis is real wage and x-axis is labor. The figures show how labor market reacts to positive demand shock (a) under the perfect competition, (b) with markup countercyclicality, and (c) with input complementarity.

Table 1: Elasticity (θ^e_{jt}) estimation based on equation (2.4)

	(1)	(2)	(3)	(4)	(5)
			$\ln(\ddddot{s}^e_{jt})$		
	IV ($\ddddot{W}^k_{j,t-1}, \ddddot{W}^k_{j,t-2}$)			OLS	
energy	$-0.4^{\star\star}$	$-0.56^{\star\star}$	$-0.4^{\star\star}$	$0.85^{\star\star\star}$	$0.85^{\star\star\star}$
	(0.16)	(0.23)	(0.16)	(0.03)	(0.03)
material	$0.32^{\star\star}$	0.17	$0.29^{\star}$	$-0.42^{\star\star\star}$	$-0.41^{\star\star\star}$
(- energy)	(0.15)	(0.22)	(0.16)	(0.03)	(0.03)
labor (p)	$1.41^{\star\star\star}$	$1.69^{\star\star\star}$	$1.33^{\star\star\star}$	$-0.33^{\star\star\star}$	$-0.33^{\star\star\star}$
	(0.31)	(0.45)	(0.29)	(0.03)	(0.03)
labor (np)	$-0.45^{\star}$	$-0.59^{\star}$	-0.39	$-0.12^{\star\star\star}$	$-0.12^{\star\star\star}$
	(0.26)	(0.33)	(0.26)	(0.02)	(0.02)
capital		0.51			-0.03
		(0.44)			(0.02)
output price			-0.03		
(lagged)			(0.1)		
obs	23,220	23,220	23,220	24,166	24,166
J-test	6.76	6.04	8.73		
(p-value)	(0.34)	(0.3)	(0.19)		

Note. The regression result based on the equation (2.4): $\ln(\ddddot{s}^e_{jt}) = \sum_{k=1}^{K} \beta_k \ln(\ddddot{V}^k_{jt}) - \ln(\ddddot{\mu}_{jt})$. Column (1), (2) and (3) show the regression result with instrumental variables, and (4) and (5) show the OLS result. Five different inputs are used in this regression: energy, material that exclude energy, non-production worker, production worker, and capital. All inputs and lagged input prices are logged and then double-demeaned across industries and across time. Standard errors in parentheses are clustered on the NAICS industry code. J-test refers to Hansen's J-statistics for overidentifying restriction. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 2: Elasticity (θ^e_{jt}) estimation based on equation (2.6)

	(1)	(2)	(3)	(4)
	$\ln(\ddddot{s}^e_{jt})$			
	Unconstrained ($\beta_e \neq -\beta_q$)		Constrained ($\beta_e = -\beta_q$)	
	IV ($\ddddot{W}^k_{j,t-1}$)	OLS	IV ($\ddddot{W}^k_{j,t-1}$)	OLS
energy	0.06	0.58	0.23***	0.50***
	(0.12)	(0.05)	(0.01)	(0.07)
output	−0.37***	−0.45***	−0.23***	−0.50***
	(0.1)	(0.07)	(0.01)	(0.07)
obs	23,694	24,167	23,694	24,167
J-test	0.1			
(p-value)	(0.75)			

Note. The regression result based on the equation (2.6):
$\ln(\ddddot{s}^e_{jt}) = -\rho\ln(\ddddot{Q}_{jt}) + \rho\ln(\ddddot{V}^1_{jt}) - \ln(\ddddot{\mu}_{jt})$. Column (1) and (2) present the result based on unconstrained regression, and column (3) and (4) present the result based on constrained regression such that the coefficient of the energy input is equal to the negative coefficient of the output. Column (1) and (3) show the regression result with instrumental variables and column (2) and (4) show the OLS result. Output, energy and corresponding lagged input prices are logged and double-demeaned across industries and across time. Energy price deflator, total payroll, and price of investment are used to instrument endogenous variables. Standard errors in parentheses are clustered on the NAICS industry code. J-test refers to Hansen's J-statistics for overidentifying restriction. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 3: Markup distribution across time and industries

	(1) $\widehat{\ln(\mu_t)}$	(2) NR (2013) $-\ln(s_t^l)$	(3) BKM (2014) $-\ln(s_t^m)$	(4) $-\ln(s_t^e)$
$\ln(\theta_{jt})$	1st order poly	constant	constant	constant
V_{jt}^1	energy	labor	material	energy
	markup distribution across time (averaged across industry)			
min	-0.71	-0.40	-0.04	-0.24
p10	-0.42	-0.30	-0.03	-0.21
p50	-0.04	-0.02	-0.00	0.00
p90	0.49	0.28	0.03	0.20
max	0.58	0.34	0.05	0.30
mean	0.00	0.00	0.00	0.00
sd	0.34	0.21	0.02	0.16
p75-p25	0.58	0.35	0.03	0.31
obs	52	52	52	52
	markup distribution across industry (averaged across time)			
min	-5.54	-2.79	-0.58	-1.05
p10	-1.86	-1.08	-0.28	-0.49
p50	0.16	0.18	-0.00	-0.11
p90	1.74	0.77	0.30	0.58
max	3.37	1.43	0.80	2.21
mean	0.00	0.00	0.00	-0.00
sd	1.45	0.74	0.23	0.47
p75-p25	1.59	0.85	0.30	0.53
obs	473	473	473	473

Note. Markups are averaged across industries to construct the aggregate time-varying markups and averaged across time to construct industry-specific markups. Column (1) shows the result based on markup measures in this paper. Column (2) shows the result based on the labor share as in Nekarda and Ramey (2013), column (3) shows the result based on the material share as in Bils et al. (2014), and column (4) shows the result based on the energy share. Since markups are only identified up to constant, all markup measures are centered at 0 to facilitate the comparison.

Table 4: Unconditional Markup Cyclicality

	(1) $\widehat{\ln(\mu_{jt})}$	(2) NR (2013) $-\ln(s^l_{jt})$	(3) BKM (2014) $-\ln(s^m_{jt})$	(4) -ln(s^e_{jt})	(5) $\ln(\widehat{\mu^{CES}_{jt}})$
$ln(\theta_{jt})$	1st order poly	constant	constant	constant	CES
V^1_{jt}	energy	labor	material	energy	energy
$\Delta\ln(vship_{jt})$	1.18	0.39	-0.01	0.50	0.41
	[1.12, 1.24]	[0.37, 0.42]	[-0.03, 0.01]	[0.47, 0.54]	[0.38, 0.44]
industry FE	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes
R^2	.3632	.4033	.0570	.2310	.2699
obs	23,693	23,694	23,694	23,694	23,694
$\rho_{\mu,y}$	0.52	0.58	-0.07	0.32	0.31
	[0.49, 0.55]	[0.56, 0.61]	[-0.1, -0.04]	[0.29, 0.35]	[0.28, 0.34]

Note. The regression result based on the equation (6.1):
$\Delta\ln(\mu_{jt}) = \lambda_j + \lambda_t + \gamma_1\Delta\ln(vship_{jt}) + \epsilon_{jt}$. Column (1) shows the regression result based on estimated markups. Column (2) shows the result based on the inverse labor share as in Nekarda and Ramey (2013). Column (3) shows the result based on the inverse material share as in Bils et al. (2014). Column (4) shows the result based on the inverse energy share and column (5) shows the result based on estimated markup by assuming a CES production function. The markups for the CES production function is estimated using constrained regression and double-demeaning techniques with lagged double-demeaned input prices as instruments. The 95% confidence intervals are constructed with the standard errors that are cluster bootstrapped based on industry with 5000 repetitions. $\rho_{\mu,y} = Corr(\Delta\ln(\mu_{jt}), \Delta\ln(vship_{jt}))$ is reported separately. Column (1) misses one number of observation compare to other columns since there is one observation with 0 non-production worker in the data.

Table 5: Conditional Markup Cyclicality

	$\widehat{\Delta\ln(\mu_{jt})}$			
	(1)	(2)	(3)	(4)
$\Delta\ln(G_t) * \bar{\theta}_j$	3.76			
	[1.12, 6.40]			
$\Delta\ln(GDP_t) * X_j^{dur}$		1.17		
		[0.99, 1.35]		
$\Delta\ln(GDP_t) * X_j^{engel}$			4.07	
			[3.05, 5.09]	
$\Delta\ln(GDP_t)$				3.35
				[3.12, 3.58]
industry FE	Yes	Yes	Yes	No
year FE	Yes	Yes	Yes	No
R^2	.1408	.1400	.1346	.0682
obs	14,832	18,569	18,569	23,693
	(5)	(6)	(7)	(8)
$\Delta\ln(GDP_t) * X_j^{entry}$	-0.12			
	[-0.57, 0.33]			
$\Delta\ln(GDP_t) * X_j^{exit}$	0.52			
	[0.07, 0.97]			
$\Delta\ln(GDP_t) * X_j^{fin}$		-0.27		
		[-0.50, -0.03]		
$\Delta\ln(GDP_t) * X_j^{pfreq}$			1.31	
			[0.20, 2.41]	
$\Delta\ln(vship_{jt})$				1.18
				[1.12, 1.24]
industry FE	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes
R^2	.1310	.1363	.1303	.3632
obs	23,673	23,693	18,569	23,693

Note. The regression result based on the equation (6.3):
$\widehat{\Delta\ln(\mu_{jt})} = \lambda_j + \lambda_t + \alpha(\Delta Z_t * X_j) + \epsilon_{jt}$. Each column uses different $\Delta Z_t * X_j$ to assess conditional markup cyclicality. Column (4) reports the overall relationship between GDP and average markups, and Column (8) assesses unconditional markup cyclicality. The 95% confidence intervals are constructed with the standard errors that are cluster bootstrapped based on the NAICS industry code with 5000 repetitions.

Table 6: Returns to Scale Cyclicality

	(1)	(2) NR (2013)	(3) BKM (2014)	(4)	(5)
			$\widehat{\ln(\gamma_{jt})}$		
$\ln(\theta_{jt})$	1st order poly	constant	constant	constant	CES
V^1_{jt}	energy	labor	material	energy	energy
$\Delta\ln(vship_{jt})$	1.08	0.29	-0.11	0.40	0.31
	[1.01, 1.14]	[0.26, 0.31]	[-0.13, -0.10]	[0.36, 0.43]	[0.28, 0.33]
industry FE	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes
R^2	.3238	.3157	.1629	.1813	.2021
obs	23,693	23,694	23,694	23,694	23,694
$\rho_{\gamma,y}$	0.49	0.49	-0.35	0.26	0.24
	[0.46, 0.51]	[0.47, 0.52]	[-0.38, -0.32]	[0.24, 0.29]	[0.22, 0.27]

Note. The regression result based on the following equation: $\Delta\widehat{\ln(\gamma_{jt})} = \lambda_j + \lambda_t + \gamma_1\Delta\ln(vship_{jt}) + \epsilon_{jt}$. Column (1) shows the regression result based on γ_{jt} constructed from the estimated markups. Column (2) recovers γ_{jt} by assuming that the markups are equal to the inverse labor shares as in Nekarda and Ramey (2013). Column (3) recovers γ_{jt} by assuming that the markups are equal to the inverse material share as in Bils et al. (2014). Column (4) shows the result based on the markups equal to the inverse energy shares assumption and column (5) shows the result based on the estimated markup with a CES production function assumption. The markups based on the CES production function are estimated using constrained regression and double-demeaning techniques with lagged double-demeaned input prices as instruments. The 95% confidence intervals are constructed with the standard errors that are cluster bootstrapped based on industry with 5000 repetitions. $\rho_{\gamma,y} = Corr(\Delta\widehat{\ln(\gamma_{jt})}, \Delta\ln(vship_{jt}))$ is reported seperately.