Upstream Markup, Operating Leverage and Risk

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Abstract

This paper investigates markup charged by suppliers in the upstream of production network, contrasting with the focus on the markup that firms charge in product market. I build a partial equilibrium model that encompasses the production network and imperfect competition. From the model, I suggest a new variable, upstream markup, to measure the markup charged by direct and indirect suppliers. With labor rigidity and gross complementarity of variable inputs, model endogenously generates procyclical price of variable input, which decreases operating leverage. Moreover, higher upstream markup firms have more procyclical marginal cost, lower operating leverage, and less risk. I empirically document upstream markup increases cyclicality of marginal cost and decreases operating leverage. An equal-weighted HML portfolio sorted by upstream markup generates a significant negative return.

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1 Introduction

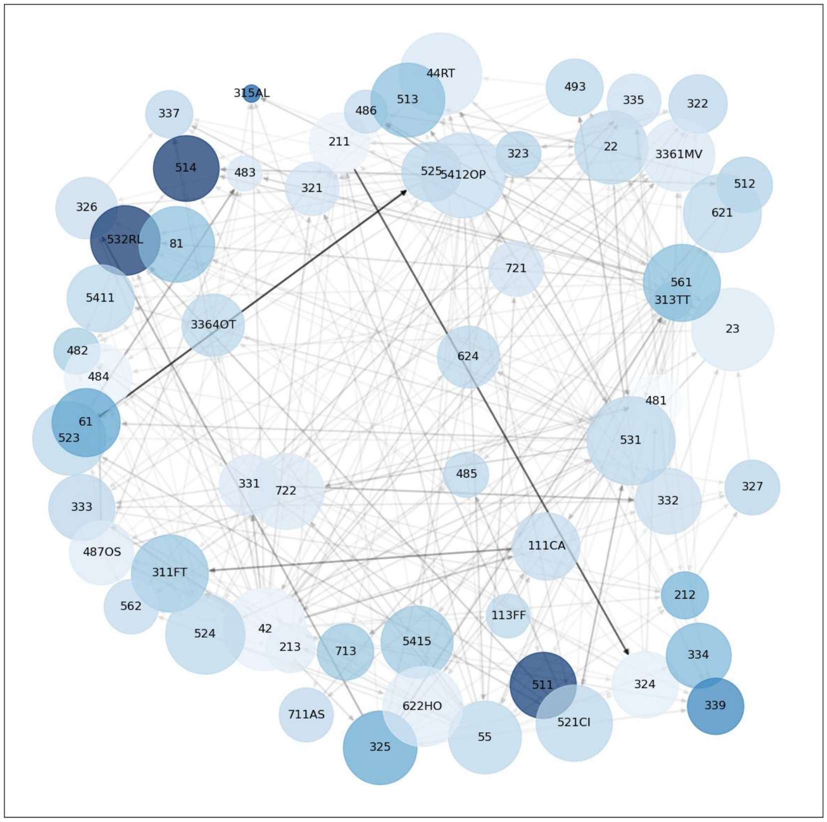
The steady increase in market power since the 1980s has been striking and has attracted significant attention from researchers. De Loecker et al. (2020) empirically documents that aggregate markup has risen from 21% to 61%, primarily driven by increasing market share of high markup firms. Autor et al. (2020) finds consistent results, showing that the increasing markup and rising superstar firms leads to fall of labor share, a phenomenon ubiquitous across OECD countries. This drastic and sweeping increase in market power has promopted researchers to investigate asset pricing implications of market power (Bustamante and Donangelo 2017; Corhay et al. 2020; Corhay 2017) and the influence of market power on firm decisions (MacKay and Phillips 2005; Xu 2012). This paper focuses on another important aspect of the markup. Rather than examining the markup that industries charge in the product market, this paper investigate the markup charged by suppliers in the upstream of production network.

Markup charged by suppliers, upstream markup, is substantial and interconnected within production network. By definition, markup is price over marginal cost of production. Marginal cost arises from variable inputs, which can be largely split into labor costs and intermediate input expenditures, which encompass raw materials, machinery parts, services, and software rentals. On average, US firms allocate 36% of their variable input costs to labor costs and 64% to intermediate input expenditures. However, previous research has largely overlooked the significance of these intermediate input costs and the associated charged markup. Moreover, intermediate input is produced within a complex product network. As illustrated in Figure 1, direct suppliers utilize intermediate input in production, which includes markup charged by indirect suppliers. Thus, it is crucial to consider not only markup of direct suppliers, but also that of indirect suppliers in 2nd, 3rd, and higher layers.

To analyze upstream markup, I develop a partial equilibrium model that captures the production network and imperfect competition. The economy consists of multiple industries with heterogenous and constant markup. Within each industry, firms hire labor and

Figure 1: Production Network in 2020

This figure shows the production network in 2020 from annual BEA input output data. The numbers inside circle is NAICS code of the industry. Size of the circle is proportional to the total production, darkness of the circle increases with markup and, darkness of the arrow increases with intermediate input expenditures.



purchase intermediate inputs from other industries for production, which takes form of a standard constant elasticity(CES) production function. While labor market is homogenous with perfect competition, suppliers charge markup on intermediate inputs. Aggregate demand shock drives the business cycle and wage is assumed to be procyclical. From the model, I demonstrate that operating leverage depends on the cyclicality of marginal cost, wages, and input prices. Assuming gross complementarity between variable inputs, the more procyclical the wage and input price are, the smaller the operating leverage is. In the benchmark model with full flexibility in labor, I show that cyclicality of marginal cost, wage, and input price are equal and operating leverage is zero.

In the presence of labor rigidity, operating leverage is not zero and cyclicality of marginal cost, wage, and input price differs. I consider an extreme case, where firms have fixed labor at the steady-state level and cannot adjust their labor force. This fixed labor naturally results in operating leverage, with firms with higher labor share experiencing greater operating leverage. When aggregate demand increases, firms must raise intermediate input expenditures to meet demand. Assuming gross complementarity between variable inputs, as input prices are higher than wage due to upstream markup, this results in higher cyclicality of input price than that of wage. As a result, higher cyclicality of marginal cost decreases the operating leverage, which is consistent with Kogan et al. (2023)[1].

Furthermore, since every firm depends more on intermediate input during expansionary periods, the marginal cost increases across the entire economy. The model endogenously generates higher cyclicality of input price than wages. Lastly, as firms with higher upstream markup experience higher input prices, they have more procycliacl mariginal cost, less operating leverage, and less risk.

Empirical analysis confirms the rigidity of labor and flexibility of intermediate input. I find that intermediate input expenditure is more than double sensitive to GDP growth and aggregate production growth. When GDP grows by 1%, labor cost increases by 1.05%, while input expenditure increases by 2.24%. Moreover, consistent with the model, input price is more sensitive than labor. 1% growth in GDP leads to 37 bps increase in input price, while wage increase by 15 bps (Donangelo et al. 2019). Lastly, due to labor rigidity and heterogeneous cyclicality of wages and input prices, variable costs are more volatile than sales and operating leverage is non-zero. Moreover, regression analysis of the interaction term reveals that upstream markup decreases operating leverage. Though there's no heterogeneity in cyclicality of labor costs and input quantity, industries with high upstream markup have more procyclical input expenditure and input prices. This results in less procyclical gross profit and lower operating leverage.

To examine the asset pricing implication of upstream markup, I conduct portfolio analysis

[1]Kogan et al. (2023) name this decrease in operating leverage from procyclical variable input prices as operating hedge.

sorted by upstream markup. Three different estimated markup methods were utilized: De Loecker et al. (2020) method, Lerner Index method, and BEA industry data. From quintile portfolio analysis, upstream markup decreases excess return, with High minus Low(HML) portfolio yielding lower than -3% annualized return. This pattern persists regardless of the markup estimation method employed. Even after controlling risk factors, HML portfolio generates a significant negative return. Moreover, the model suggests that firms with higher labor share benefit more from upstream markup, since high labor share generates high operating leverage. I find that negative relationship between upstream markup and return is more pronounced in firms with high labor share. Overall, portfolio analysis confirms that upstream markup decreases risk.

This paper contributes to the literature that study product market competition, asset pricing and capital structure. Early empirical work by Hou and Robinson (2006) documents that using HHI index from public firms in Compustat data, competition increases expected stock returns. In similar vain, Binsbergen (2016) argue that firms with higher deep habit have higher market power, lower operating leverage, and less expected returns. However, Bustamante and Donangelo (2017) use Census data which includes private firms and show competition decreases expected return. Corhay et al. (2020) introduce time-varying markup and markup increase expected return in both time-series and cross-section. While Xu (2012) shows competition lowers financial leverage, Corhay (2017) builds up model where competition increase credit spreads, decrease equity return, and lower financial leverage. Rather than product market, this paper study how markup charged by suppliers in production network relates to expected return,

Literature of production network and asset pricing is also extensive. Cohen et al. (2010) and Menzly and Ozbas (2010) first study information of firm and industry transmits to customers and suppliers in equity market. Sharifkhani and Simutin (2021) tries to explain momentum with product network so that feedback loop of information can explain the term structure of momentum return. While Ahern (2013) argues that firms central in product network have higher systematic risk, Herskovic (2018) show that change in network structure itself can be systematic risk. Gofman, Segal, et al. (2020) study that upstreamness increases expected return and Gofman and Wu (2022) investigate how upstreamness relates to trade credit and profitability. This paper is closely related to Baqaee and Farhi (2020), which consider production network with imperfect competition. While Baqaee and Farhi (2020) analyze how aggregate efficiency relates to product network and imperfection in time-series, this paper investigate how product network and imperfection have influence on firms' risk in cross-section.

This paper also relates to literature that connects operating leverage to asset pricing. Pioneering works of Carlson et al. (2004) and Zhang (2005) show how operating leverage can explain value spread in equity returns. Novy-Marx (2011) introduce empirical measure of operating leverage and empirically documents that operating leverage increase expected returns in cross-section. Danthine and Donaldson (2002) emphasize wage and labor rigidity, which can generate operating leverage and explain equity premium. Favilukis and Lin (2016) also stress wage rigidity and labor leverage in dynamic general equilibrium model to explain equity premium, time-varying equity volatility, and value premium. Donangelo et al. (2019) propose a labor share measure at the firm level, which increase labor leverage and expected returns. This paper is closely related to Kogan et al. (2023) that procyclical marginal cost results in less operating leverage. While Kogan et al. (2023) tries to explain profitability premium, this paper tries to endogenize procyclical marginal cost and investigate which industry benefit from procyclical marginal cost.

The remainder of the paper is organized as follows. Section 2 introduce a partial equilibrium model with production network and imperfect competition. I propose a method to measure upstream markup and In section3, I test the economic channel from the previous section and asset pricing implication with equity returns. Section 4 concludes.

2 Model

In this section, I build a partial equilibrium model to explain how to measure markup charged by suppliers in production network, upstream markup, and its influence on the operating leverage of firms. The economy consists of firms which use labor and intermediate inputs from other industries in production. In section 2.1, I introduce benchmark model where labor hiring is fully flexible. Then, I show the model with fixed-labor in section 2.2, where labor is fixed at the steady-state level and firms change intermediate inputs to meet demand.

2.1 Benchmark Model

Firms produce using labor l_{it} and intermediate inputs x_{iJt} from other firms. The production function for output y_{it} is a standard constant elasticity(CES) production function:

$$y_{it} = \left(\alpha_{IL}^{\frac{1}{\eta}} l_{it}^{\frac{\eta-1}{\eta}} + \sum_{J} \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}$$

,where $\alpha_{IL} + \sum_{J} \Omega_{IJ} = 1$ with constant returns to scale and η captures the elasticity of substitution between variable inputs. Firms operate in imperfect competition, where they have market power and are subject to an aggregate demand shock D_t. Aggregate demand shock D_t is an exogenous process, which follows an AR1 process, Aggregate wage W_t is also exogenously given by a function of aggregate demand shock D_t. Moreover, firms use homogenous labor with equal wage and the labor market is perfectly competitive.

$$\begin{aligned} D_{t+1} &= \rho_D D_t + \epsilon_t \\ \log W_t &= \log \bar{W} + \rho_W \log D_t \\ y_{it} &= Y_{It} p_{it}^{-\theta_I} D_t \end{aligned}$$

, where $\epsilon_t \sim N(0, \sigma_D^2)$ and θ_I captures the elasticity of demand the firms face in industry I. Higher the θ_I is, the more elastic demand curve is and the lower market power the firms have.

Firms choose optimal labor and intermediate inputs to maximize the profits π_{it} , given the aggregate demand shock and wage.

$$\begin{aligned}
\max_{l_{it}, x_{iJt}} \Pi_{it} &= p_{it} y_{it} - l_{it} W_t - \sum_J P_J x_{iJt} + \lambda_{it}^S \left(y_{it} - \left(\alpha_{IL}^{\frac{1}{\eta}} l_{it}^{\frac{\eta-1}{\eta}} + \sum_J \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \right) \\
&= Y_{It}^{-\frac{1}{\theta_I}} y_{it}^{\frac{\theta_I - 1}{\theta_I}} D_t^{-\frac{1}{\theta_I}} - l_{it} W_t - \sum_J P_J x_{iJt} + \lambda_{it}^S \left(y_{it} - \left(\alpha_{IL}^{\frac{1}{\eta}} l_{it}^{\frac{\eta-1}{\eta}} + \sum_J \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \right)
\end{aligned}$$

Solving the problem leads to firms' optimal pricing policy and factor demands for labor and intermediate inputs.

$$\begin{aligned}
p_{it} &= \frac{\theta_I}{\theta_I - 1} \lambda_{it}^S = \mu_I \lambda_{it}^S \\
l_{it} &= = \alpha_{IL} y_{it} \left(\frac{W_t}{\lambda_{it}^S} \right)^{-\eta} \\
x_{iJt} &= = \Omega_{IJ} y_{it} \left(\frac{P_{Jt}}{\lambda_{it}^S} \right)^{-\eta}
\end{aligned}$$

The Lagrangian multiplier λ_{it}^S captures the marginal cost of production and firms charge constant markup μ_I over the marginal cost. Factor demands increase with production and parameter α_{IL} and Ω_{IJ}, but decrease with the relative price of input $\frac{W_t}{\lambda_{it}^S}$ and $\frac{P_{Jt}}{\lambda_{it}^S}$. Rearranging the equation of factor demands and using Leontief inverse, marginal cost can be further split into labor compensation and markup charged by suppliers in production network.

In matrix form,

$$\begin{pmatrix} \vdots \\ \lambda_{It}^{S\ 1-\eta} \\ \vdots \end{pmatrix} = \underbrace{(I - \Omega\mathcal{M}^{1-\eta})^{-1} \begin{pmatrix} \vdots \\ \alpha_{IL} \\ \vdots \end{pmatrix}}_{\mu_I^U (Upstream\ Markup)} \times W_t^{1-\eta} \tag{1}$$

$$= \begin{pmatrix} \vdots \\ \alpha_{IL} \\ \vdots \end{pmatrix} \times W_t^{1-\eta} + \Omega\mathcal{M}^{1-\eta} \begin{pmatrix} \vdots \\ \alpha_{IL} \\ \vdots \end{pmatrix} \times W_t^{1-\eta} + \left(\Omega\mathcal{M}^{1-\eta}\right)^2 \begin{pmatrix} \vdots \\ \alpha_{IL} \\ \vdots \end{pmatrix} \times W_t^{1-\eta} + ...$$

, where $\mathcal{M}$ is a diagonal matrix with μ_I as its I-th element and power of matrix is the element-wise power.

In scalar form,

$$\begin{aligned} \lambda_{It}^{S\ 1-\eta} &= \alpha_{IL} W_t^{1-\eta} + \sum_J \Omega_{IJ}\alpha_{JL}\mu_J^{1-\eta} W_t^{1-\eta} + \sum_J \sum_K \Omega_{IJ}\alpha_{JL}\mu_J^{1-\eta}\Omega_{JK}\alpha_{KL}\mu_K^{1-\eta} W_t^{1-\eta} + ... \\ &= W_t^{1-\eta}(\alpha_{IL} + \sum_J \Omega_{IJ}\alpha_{JL}\mu_J^{1-\eta} + \sum_J \sum_K \Omega_{IJ}\alpha_{JL}\mu_J^{1-\eta}\Omega_{JK}\alpha_{KL}\mu_K^{1-\eta} + ...) \end{aligned}$$

The marginal cost is the harmonic average of wage and price charged by suppliers in production network. After expressing the term in matrix, marginal cost can be further split into wage and mark up from suppliers. The first term is the wage paid directly from hiring labor. Remaining terms capture both the wage and markup charged by the suppliers in production network. The second term captures the wage paid and the markup charged by direct suppliers in the first layer of production network. The next term is those of indirect suppliers in the second layer of production network, including the markup charged by the direct suppliers. Thus, in equation 1, Leontief inverse not only capture the markup from direct suppliers, but also markup from all the other indirect suppliers in production network.

$$(Upstream\ Markup)\ \mu_I^U \;=\; (I-\Omega\mathcal{M}^{1-\eta})^{-1}\begin{pmatrix}\vdots\\ \alpha_{IL}\\ \vdots\end{pmatrix}$$

I define the upstream markup as the constant term multiplied in front of wage in equation 1. Upstream markup is the Leontief inverse of product network Ω and mark up $\mathcal{M}^{1-\eta}$ charged by industries. Ultimately, it measures how much markup is charged in the upstream, between the industry and labor market. Upstream markup increases as industry rely more on intermediate inputs than labor and there are more layers in the upstream. Moreover, with $\eta < 1$, upstream markup increases as suppliers charge more markup in production network.

Proposition 1 *In benchmark case with flexible labor,*

$$\begin{aligned} Operating\ Leverage &\equiv \frac{\partial \log \pi_{it}}{\partial \log D_t} - \frac{\partial \log p_{it}y_{it}}{\partial \log D_t} \\ &= \frac{1-\eta}{\pi_{it}}\left[l_{it}W_t(\rho_\lambda^I - \rho_W) + \sum_J P_{Jt}x_{iJt}(\rho_\lambda^I - \rho_\lambda^J)\right] \end{aligned}$$

, where $\rho_\lambda^I \equiv \frac{\partial \lambda_{It}^S}{\partial \log D_t}$

Operating leverage depends on the cyclicality of marginal cost, wage, and the suppliers' marginal cost under the constant markup. $\eta < 1$ implies labor and intermediate inputs are gross complementary to each other. With gross complementarity, having procyclical wage and input price decreases the operating leverage. In the benchmark case, marginal cost of production of all indutries are to aggregate wage from equation 1 and operating leverage is zero.

Lemma 1 *In the benchmark case,* $\rho_W = \rho_\lambda^I$ *for all* I.

$$Operating\ Leverage = 0$$

2.2 Fixed Labor Model

To illustrate how labor friction interact with upstream markup, I build an extreme case where firms cannot adjust labor $\bar{l}_{it}$ from steady state level. When aggregate demand D_t changes, firms adjust intermediate inputs to meet demand. Since inputs are more expensive with markup charged by suppliers, cyclicality of costs differ and operating leverage arises.

$$\begin{aligned}\max_{x_{iJt}} \Pi_{it} &= p_{it}y_{it} - \bar{l}_{it}W_t - \sum_J P_J x_{iJt} + \lambda^S_{it}\left(y_{it} - \left(\alpha_{IL}^{\frac{1}{\eta}}\bar{l}_{it}^{\frac{\eta-1}{\eta}} + \sum_J \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}\right) \\ &= Y_{It}^{-\frac{1}{\theta_I}} y_{it}^{\frac{\theta_I-1}{\theta_I}} D_t^{-\frac{1}{\theta_I}} - \bar{l}_{it}W_t - \sum_J P_J x_{iJt} + \lambda^S_{it}\left(y_{it} - \left(\alpha_{IL}^{\frac{1}{\eta}}\bar{l}_{it}^{\frac{\eta-1}{\eta}} + \sum_J \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}\right)\end{aligned}$$

Profit maximization problem is the same with the benchmark case except fixed labor $\bar{l}_{it}$. With fixed labor, Optimal pricing decision and input decisions also remain the same, but the marginal cost differs. Marginal cost depends on intermediate input share and harmonic average of price charged by suppliers. In boom, firms rely more on intermediate input, which leads to increase in marginal cost. Moreover, as this happens in all firms, increase in λ^S_{Jt} leads to increase in P_{Jt}. With this network amplification effect, marginal cost increases furthermore. Overall, it generates procyclical marginal cost and price in the economy.

$$\begin{aligned}\lambda_{it}^{S\ 1-\eta} &= \frac{y_{it}^{\frac{\eta-1}{\eta}}}{y_{it}^{\frac{\eta-1}{\eta}} - \alpha_{IL}^{\frac{1}{\eta}}\bar{l}_{it}^{\frac{\eta-1}{\eta}}} \sum_J \Omega_{IJ} P_{Jt}^{1-\eta} \\ &= \underbrace{\frac{y_{it}^{\frac{\eta-1}{\eta}}}{\sum_J \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{\frac{\eta-1}{\eta}}}}_{Intermediate\ input\ share} \sum_J \Omega_{IJ} P_{Jt}^{1-\eta}\end{aligned}$$

Proposition 2 *In fixed labor case,*

$$
\begin{aligned}
Operating\ Leverage &\equiv \frac{\partial \log \pi_{it}}{\partial \log D_t} - \frac{\partial \log p_{it} y_{it}}{\partial \log D_t} \\
&= \frac{1}{\pi_{it}} \left[\bar{l}_{it} W_t (1 - (\epsilon - 1)\rho^I_\lambda - \rho_W) + (1-\eta) \sum_J P_{Jt} x_{iJt} (\rho^I_\lambda - \rho^J_\lambda) \right] \\
&= \frac{1}{\pi_{it}} \left[l_{it} W_t (1 - (\epsilon - 1)\rho^I_\lambda - \rho_W) + \frac{1-\eta}{\eta} \theta (1 - \epsilon \rho^I_\lambda) \times \sum_J P_{Jt} x_{iJt} \right]
\end{aligned}
$$

, *where* $\rho^I_\lambda \equiv \frac{\partial \lambda^S_{It}}{\partial \log D_t}$ *and* $\hat{\alpha}_{ILt} = \frac{\alpha_{IL}^{\frac{1}{\eta}} \bar{l}_{it}^{\frac{\eta-1}{\eta}}}{\sum_J \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{\frac{\eta-1}{\eta}}}$

Fixed labor naturally generates operating leverage, labor leverage, as shown in the first term of proposition 2. Consistent with Donangelo et al. (2019), labor leverage decreases as wage and marginal cost are more procyclical. The effect is stronger as industries have higher market competition θ_I.

Operating leverage from intermediate inputs also depends on the cyclicality of marginal cost between the firm and suppliers. This difference in cyclicality can be expressed with its own cyclicality of marginal cost. Similar to labor leverage, with $\eta < 1$, operating leverage decreases with cyclicality of marginal cost. The effect is stronger as industries rely more on labor $\hat{\alpha}_{ILt}$ in the steady state and have higher market competition θ_I.

Proposition 3 *In fixed labor case,*

$$
\begin{pmatrix} \vdots \\ \rho^I_\lambda {\lambda^S_{It}}^{1-\eta} \\ \vdots \end{pmatrix} = (I - \hat{\Omega} \mathcal{M}^{1-\eta})^{-1} \begin{pmatrix} \vdots \\ \frac{\hat{\alpha}_{ILt} It}{\eta + \epsilon \hat{\alpha}_{ILt} It} {\lambda^S_{It}}^{1-\eta} \\ \vdots \end{pmatrix}
$$

,*where* $\hat{\Omega}_{IJ} \equiv \frac{\eta(1+\hat{\alpha}_{ILt})}{\eta + \epsilon \hat{\alpha}_{ILt}} \Omega_{IJ}$

In scalar form,

$$\begin{aligned}\rho^I_\lambda &= \frac{\hat{\alpha}_{ILt}}{\eta+\epsilon\hat{\alpha}_{ILt}} + \sum_J \hat{\Omega}_{IJ}\mu_J^{1-\eta}\frac{\hat{\alpha}_{JLt}}{\eta+\epsilon\hat{\alpha}_{JLt}}\frac{\lambda_{Jt}^{S\ 1-\eta}}{\lambda_{It}^{S\ 1-\eta}} \\ &\quad + \sum_J\sum_K \hat{\Omega}_{IJ}\mu_J^{1-\eta}\hat{\Omega}_{JK}\mu_K^{1-\eta}\frac{\hat{\alpha}_{KLt}}{\eta+\epsilon\hat{\alpha}_{KLt}}\frac{\lambda_{Kt}^{S\ 1-\eta}}{\lambda_{It}^{S\ 1-\eta}} + \dots\end{aligned}$$

Cyclicality of marginal cost depends on adjusted labor share $\hat{\alpha}_{ILt}$, production network $\hat{\Omega}$, and markup $\mathcal{M}^{1-\eta}$ charged by industries. First of all, with higher labor share, firms face higher increase in marginal cost shown in the first term $\frac{\hat{\alpha}_{ILt}}{\eta+\epsilon\hat{\alpha}_{ILt}}$, since firms have to increase inputs relatively more than those with low labor share. Moreover, cyclicality of marginal cost increases as higher markup is charged by industries. Higher markup increases the price of intermediate input. In boom, when they buy more inputs, this makes the marginal cost more procyclical. Lastly, network amplifies this effect further more. In boom when labor share θ_{It} decreases due to fixed labor, $\hat{\Omega}$ increases. This further amplifies the effect coming markup.

3 Empirical Analysis

This section characterizes the data and quantitative results of the hypothesis from the model. Section 3.1 describes the data used and presents summary statistics. Then, section 3.2 documents the cyclicality of sales, costs, and profitability and how upstream markup changes the cyclicality. Lastly, section 3.3 tests the asset pricing implication of upstream markup in equity market.

3.1 Data and Upstream Markup

Production network data are obtained from the Bureau of Economic Analysis (BEA) Input-Output Accounts data. Following the literature, I used the input output data at the producer price before redefinition. The data are available in two frequencies: annual data with 61 industries from 1987 until 2022[2] and census data with over 300 industries from 1982 until 2017[3]. Though BEA provides census data prior to 1982, these data do not provide labor compensation, which is necessary in calculating upstream markup. I used the first data with higher frequency in evaluating the empirical channel in section 3.2 and the second data with granular cross-section in evaluating the asset pricing implication in section 3.3. The data provides the intermediate input expenditure between industries and labor compensation by industries. I also used Gross Domestic Product (GDP) growth from BEA. Lastly, BEA KLEMS data provides intermediate input index of price(IP_P) and quantity(IP_Q) by industry. This data is valuable in examining the channel, since it allows to see whether increase in input expenditure comes from price or quantity.

To calculate upstream markup, it requires three empirical counterparts[4]: industry level markup μ_I, production network Ω, and labor share α_{IL}. First, I use three different industry markup μ_I in empirical analysis. To begin with, two method measure markup at the firm level and industry level markup is a sales-weighted average of firm level markup[5]. Following De Loecker et al. (2020), firm level markup is product of the output elasticity of Cost of Goods Sold (COGS) and SALE-COGS ratio. Output elasticity θ_I is estimated at the NAICS summary level from BEA, using previous COGS as control variable. Despite estimation error, this measure tries to capture marginal cost from estimated elasticity. Next, I use simple definition of markup from Lerner Index. Markup is an inverse of Lerner Index, defined as SALE divided by operating income before depreciation(OIBDP) minus depreciation(DP). Though simple to use, this measure mainly rely on average cost to measure markup and may not accurately measure marginal cost. Lastly, I used the BEA industry level data and

[2]Data is available in two split sample from 1987-1996 and 1997-2021 with different granularity of industries. I grouped some industries so that the definition of industries are consistent.

[3]Census data before 1992 use SIC code, while data use NAICS code starting 1992. Also, the definition of industries partially changes each year. I grouped some industries so that the definition of industries remain consistent.

[4]I assumed $\eta = 0.8$ in the empirical analysis.

[5]When calculating industry average, I require annual data to have at least 5 firm-year observation and census data to have at least firm-year observation. For those industries with missing markup, I used sales-weighted average of non-missing markups to calculate upstream markup.

define markup as ratio of total production(TP) over total cost(TC). Though assuming firms are homogeneous and rely on average cost, this measure incorporate not only public firms, but also private firms.

$$\mu_{it}^{DEU} = \theta_I \times \frac{SALE_{it}}{COGS_{it}}$$
$$\mu_{it}^{LI} = \frac{SALE_{it}}{OIBDP_{it} - DP_{it}}$$
$$\mu_{It}^{BEA} = \frac{TP_{it}}{TC_{It}}$$

Production network Ω is a $N \times N$ matrix, whose $-ij$ th element is input expenditure from industry i to j over the sum of labor cost and total input expenditure of industry i. Similarly, labor share α_{IL} is labor cost divided by the sum of labor cost and total input expenditure.

$$\Omega_{IJt} = \frac{P_{Jt}X_{IJt}}{W_t L_{It} + \sum_J P_{Jt}X_{IJt}}$$
$$\alpha_{ILt} = \frac{W_t L_{It}}{W_t L_{It} + \sum_J P_{Jt}X_{IJt}}$$

Monthly stock return data are from Center for Research in Security Prices(CRSP) and accounting information is from Compustat database. The sample is from July 1985 to December 2022 and includes all common stocks (share code of 10 or 11) listed on NYSE, NASDAQ, and AMEX (exchange code of 1, 2, or 3) available from CRSP. The sample excludes firms with standard industry classification (SIC) code between 4000 and 4999 (regulated firms) or between 6000 and 6999 (financial firms). Following Fama and French (1993), I require each firm to have at least two years of data in Compustat before it is included in the sample and to have positive total asset (AT) and book equity.

Table 1 presents the summary statistics at the industry level. Total production(TP) is the sum of intermediate input produced and GDP. The labor share α_L is the ratio of

Table 1: Summary Statistics

This table reports the summary statistics of variables at the industry level. μ is estimated markup following De Loecker et al. (2020) and μ^U is upstream markup. Total production(TP) is the sum of intermediate input produced and GDP. Labor share α_L is the ratio of labor cost over sum of labor cost and total input expenditures from BEA input output data. Operating leverage is XSGA over SALE - COGS, asset growth $\Delta Asset$ measures the growth in the total asset(TA) and book leverage is ratio of book equity (BE) over total asset (AT) from Compustat.

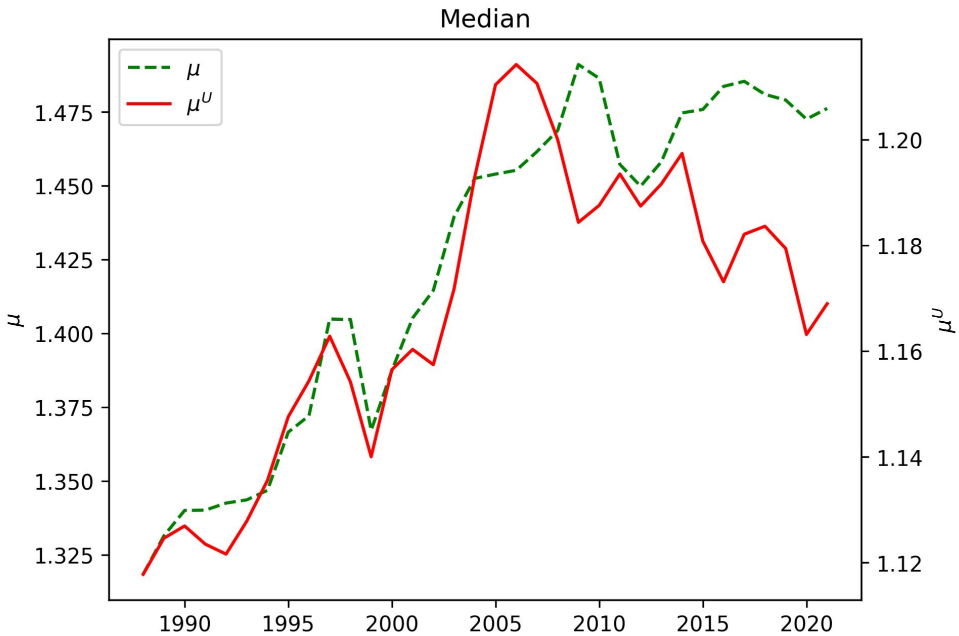
Panel A.	μ	μ^U	$\log TP$	Operating Leverage	$\Delta Asset$	Book Leverage	α_L
Mean	1.461	1.17	12.128	0.53	0.103	0.648	0.369
Std	0.369	0.063	1.098	0.167	0.113	0.119	0.163
Q1	1.245	1.126	11.293	0.452	0.045	0.583	0.249
Median	1.405	1.161	12.08	0.541	0.089	0.652	0.359
Q2	1.506	1.203	12.935	0.61	0.138	0.695	0.503
Nobs	2135	2135	2135	2135	2135	2135	2135
Panel B.	μ	μ^U	$\log TP$	Operating Leverage	$\Delta Asset$	Book Leverage	α_L
μ	1						
μ^U	0.104	1					
$\log TP$	0.056	0.161	1				
Operating Leverage	0.044	-0.278	0.067	1			
$\Delta Asset$	0.138	-0.153	-0.053	0.06	1		
Book Leverage	-0.199	-0.102	0.181	0.006	-0.107	1	
α_L	0.03	-0.793	0.01	0.239	0.135	0.044	1

labor cost over total variable cost, which is sum of labor cost and total intermediate input expenditure. The other variables are weighted average of firm level variables using either sales or asset depending on the denominator. Operating leverage is a flow-based measure calculates as the XSGA over SALE - COGS. Asset growth $\Delta Asset$ measures the growth in the total asset(TA) and Book leverage is ratio of book equity (BE) over total asset (AT).

Upstream markup has low correlation with production market markup about 10.4%. On the one hand, table B1 confirms this finding from the top and bottom 10 industries sorted by

Figure 2: Time-series of Markup and Upstream Markup (Median)

This figure plots the time-series of median markup estimated following De Loecker et al. (2020) and median upstream markup μ^U from 1987 until 2021.



upstream markup. Both top and bottom 10 industries include industries with high markup above 1.6 and low markup below 1.4. On the other hand, figure 2 shows strong correlation over time between markup and upstream markup. De Loecker et al. (2020) documents upward increasing trend in production markup. Consistent with the trend, upstream markup also seems to increase over time. However, after 2005, upstream markup start to diverge from markup and starts to decrease afterwards.

Moreover, upstream markup covaries negatively with operating leverage with correlation -27.8 %. It is consistent with the model, but could be driven by strong negative relation with labor share. Upstream markup covaries negatively with labor share with -79.3 %. As firms directly access labor market, there is less layers of suppliers in between the industry and labor market. In table B1, top 10 industries mostly have labor share less than 30%, while bottom 10 industries mostly have labor share higher than 50%. However, it is important to consider upstream markup, since panel regressions and portfolio analysis do not yield any meaningful results using labor share at the industry level.

Table 2: Cyclicality of Labor and Intermediate input cost

This table reports the panel regression of sales, cost, and gross profit growth on GDP growth and aggregate total production growth. Total production(TP) is sum of intermediate input revenue and GDP. Total input cost(TIC) is sum of all intermediate input expenditure. Total cost(TC) is sum of labor cost (LC) and TIC. Gross profit(GP) is TP minus TC. IP_P is price index of intermediate input and IP_Q is quantity index of intermediate input. The regression includes industry fixed effect and standardized errors are double clustered by industry and year. $^*p < .10$; $^{**}p < .05$; $^{***}p < .01$

Panel A.	TP Growth(%)	TC Growth(%)	GP Growth(%)	LC Growth(%)	TIC Growth(%)	IP_P Growth(%)	IP_Q Growth(%)
GDP Growth(%)	1.5170***	1.7782***	0.8556***	1.0285***	2.2393***	0.3735*	1.6723***
	(5.2987)	(4.7720)	(4.3498)	(4.7277)	(4.9184)	(1.7760)	(6.3044)
Nobs	1855	1855	1855	1855	1855	1855	1855
R-squared	0.1902	0.1698	0.0270	0.1578	0.1281	0.0428	0.1032
Industry Fixed	Y	Y	Y	Y	Y	Y	Y
Panel B.	**TP Growth(%)**	**TC Growth(%)**	**GP Growth(%)**	**LC Growth(%)**	**TIC Growth(%)**	**IP_P Growth(%)**	**IP_Q Growth(%)**
Agg TP Growth(%)	0.9095***	1.0918***	0.3903***	0.4944***	1.4221***	0.3561***	0.9312***
	(11.629)	(10.056)	(3.3095)	(4.6434)	(11.991)	(5.3540)	(10.503)
Nobs	1855	1855	1855	1855	1855	1855	1855
R-squared	0.2524	0.2364	0.0207	0.1346	0.1907	0.1437	0.1182
Industry Fixed	Y	Y	Y	Y	Y	Y	Y

3.2 Upstream Markup and Operating Leverage

This section presents empirical evidence supporting the channel proposed in the model[6]. Starting with the labor friction, I empirically document that industries depend on intermediate inputs rather than labor when adjusting sales in business cycle. Since intermediates are expensive with markup charged by suppliers, variable cost increase more rapid, which reduces the cyclicality of profit and business cycle. Moreover, this relationship is stronger for industries with higher upstream markup, since they face more expensive input.

To examine assumed labor friction on the model, I run panel regression of sales, cost,

[6]In this section, I present results with markup estimated following De Loecker et al. (2020). Results are consistent using other markup measures.

and index growth on GDP growth and aggregate TP growth. Total intermediate input cost(TIC) sums up all the input expenditure to other industries and total cost(TC) is sum of labor cost(LC) and TIC. Sales and cost variables are deflated with GDP deflator before calculating the growth. Moreover, growth of input price index is subtracted by the GDP deflator growth. All variables are winsorized at 1% and industries with negative gross profit in current and previous period are excluded. Moreover, since gross profit growth is volatile, data is truncated at 5% using gross profit growth.

Table 2 supports that industries have relatively sticky labor and change production using flexible intermediate inputs. In Panel A, when GDP grows by 1%, TIC increases more than 2%, while labor cost increases only by 1%. Since Donangelo et al. (2019) documents that wage on average increase by 15 bps when GDP grows by 1%, labor on average increase by 87 bps in quantity. In contrast, input price index increase by 37 bps and input quantity index increase by 1.67%. Both index increased more than double compared to those of labor. Consistent with Kogan et al. (2023), total cost increase more than total profit, which makes gross profit less procyclical. Results in panel B are largely consistent with panel A. Overall, this table documents that intermediate inputs are more flexible for industries and related cost, price, and quantity is more cyclical that those of labor.

To examine whether cyclicality differs by upstream markup, I run panel regression and interacted the upstream markup from previous period with GDP growth. Table 3 presents supporting evidence that operating leverage is lower for industries with high upstream markup. In panel A, gross profitability becomes less pro-cyclical as upstream markup increases. Though results in panel A lacks significance in other columns, panel B shows that industries with high upstream markup experience more procyclical TIP. This happens not from procyclical quantity, but from procyclical price. Moreover, there is no significant difference in cyclicality of labor cost due to upstream markup.

Table 3: Operation Hedging

This table reports the panel regression of cost and gross profit growth on GDP growth and aggregate total production growth. LC is labor cost and Total input cost(TIC) is sum of all intermediate input expenditure. Gross profit(GP) is total production minus total cost. IP_P is price index of intermediate input and IP_Q is quantity index of intermediate input. The regression includes industry fixed effect and standardized errors are double clustered by industry and year. $*p < .10$; $**p < .05$; $***p < .01$

Panel A.	GP Growth(%)	LC Growth(%)	TIC Growth(%)	IP_P Growth(%)	IP_Q Growth(%)
GDP Growth(%)	1.3914***	1.1812***	1.9636**	0.2341	1.5440***
	(3.6240)	(3.4360)	(2.0010)	(0.4966)	(3.0027)
GDP Growth(%) $\times\mu^U_{-1}$	-3.4650**	-0.6590	1.5781	1.3795	0.4739
	(-2.5125)	(-0.2684)	(0.1850)	(0.3369)	(0.1123)
μ^U_{-1}	0.0923	0.1169	-0.1041	0.1079	-0.1202
	(1.1483)	(1.2767)	(-0.4014)	(0.7759)	(-0.9065)
Nobs	1855	1855	1855	1855	1855
R-squared	0.0279	0.1629	0.1286	0.0643	0.1047
Industry Fixed	Y	Y	Y	Y	Y
Panel B.	**GP Growth(%)**	**LC Growth(%)**	**TIC Growth(%)**	**IP_P Growth(%)**	**IP_Q Growth(%)**
Agg TP Growth(%)	0.6463***	0.5429***	0.5641	-0.2259	0.7246**
	(2.5954)	(2.8271)	(1.2373)	(-1.5450)	(2.2367)
Agg TP Growth(%) $\times\mu^U_{-1}$	-1.6860	-0.2954	5.3010*	3.8204***	1.1279
	(-1.3509)	(-0.2176)	(1.6735)	(3.3847)	(0.5242)
μ^U_{-1}	-0.0196	0.0231	-0.3220**	0.0316	-0.2424**
	(-0.2093)	(0.2865)	(-2.5572)	(0.3877)	(-2.5439)
Nobs	1855	1855	1855	1855	1855
R-squared	0.0220	0.1348	0.1992	0.1970	0.1243
Industry Fixed	Y	Y	Y	Y	Y

3.3 Upstream Markup and Risk

Previous section documents that procyclical input expenditure lowers operating leverage and this is stronger for high upstream markup industries. This section examine whether industries with high upstream markup are less riskier due to lower operating leverage.

To test asset pricing implication of upstream markup, I conduct portfolio analysis sorted by upstream markup using census data. Annual data is not suitable for testing asset pricing implication, since data prior to 2003 was not published in timely manner. Moreover, census data gives more granular picture with more than 300 industries. Since census data is also released with 5 year lag, upstream markup data is matched with 5 year lag to prevent forward looking bias. At the start of every year, I sort industries into quintile portfolio by industry upstream markup and hold it for a year. In each panel, I use different markup to measure upstream markup.

Table 4 shows the annualized return of quintile portfolios sorted by upstream markup. In panel A, μ^{DEU} is used to measure upstream markup. In value-weighted portfolio, while excess return is decreasing with upstream markup, HML portfolio lacks significance. After controlling risk, the pattern is similar, where HML is negative, but lacks significance. However, In equal-weighted portfolio, excess return is decreasing with upstream markup and HML portfolio yields 3% return per year. HML portfolio still yields 3% after controlling market return and 3 factor return, but weakens after controlling 5 factor return. In panel B and C, I use μ^{LI} and μ^{BEA} to construct upstream markup. Results are similar to panel A in that HML portfolio is weak and lacks significance for value-weighted portfolio, but strong and significant for equal-weighted portfolio. Since this paper is not proposing anomaly strategy, but present economic channel driving the risk, it makes sense that upstream markup is able to explain equal-weighted portfolio. Also, large equities are likely to operate in more than one industry, which weakens the economic channel of upstream markup.

Table 4: Quintile Portfolio Returns

This table reports the annualized return of quintile portfolio sorted by upstream markup μ^U. Panel A, B, and C use μ^{DEU}, μ^{LI}, and μ^{BEA}, respectively, to calculate upstream markup. Excess return $r_t - r_f$ subtracts risk-free rate from return. α_{capm}, α_{ff3}, and α_{ff5} are constant obtained from regressing HML portfolio on market return, FF3 factors and FF5 factors, respectively. Newey-West t-statistics with 4 lags are reported in parentheses. *$p < .10$; **$p < .05$; ***$p < .01$

Panel A. μ^{DEU}	Value-weighted				Equal-weighted			
μ^U	$r_t - r_f$	α_{capm}	α_{ff3}	α_{ff5}	$r_t - r_f$	α_{capm}	α_{ff3}	α_{ff5}
L	10.71	1.83	1.84	-0.12	13.47	2.84	2.99	2.78
2	11.94	1.07	1.52	2.02	12.46	0.27	0.68	3.24
3	8.87	-0.97	-0.91	-2.38	11.3	-0.11	0.06	0.23
4	9.08	-1.13	-1.06	-1.72	12.32	0.24	0.78	2.28
H	8.46	0.34	0.09	-1.44	10.39	-0.34	-0.33	0.77
HML	-2.24	-1.49	-1.75	-1.33	-3.09**	-3.18**	-3.33**	-2.01
t-statistics	(-1.36)	(-0.82)	(-0.99)	(-0.76)	(-2.28)	(-2.27)	(-2.47)	(-1.45)

Panel B. μ^{LI}	Value-weighted				Equal-weighted			
μ^U	$r_t - r_f$	α_{capm}	α_{ff3}	α_{ff5}	$r_t - r_f$	α_{capm}	α_{ff3}	α_{ff5}
L	10.87	0.76	1.32	1.92	13.39	1.72	2.29	4.08
2	11.23	0.63	1.08	0.94	12.62	0.99	1.36	2.61
3	9.18	-2.13	-1.43	-0.09	12.37	0.67	1.05	1.72
4	11.21	2.06	1.78	-1.5	10.87	-0.6	-0.35	0.74
H	7.38	0.11	-0.28	-2.21	10.03	-0.43	-0.64	-0.3
HML	-3.49*	-0.65	-1.6	-4.14**	-3.36*	-2.15	-2.93*	-4.38**
t-statistics	(-1.66)	(-0.32)	(-0.97)	(-2.37)	(-1.85)	(-1.1)	(-1.82)	(-2.64)

Panel C. μ^{BEA}	Value-weighted				Equal-weighted			
μ^U	$r_t - r_f$	α_{capm}	α_{ff3}	α_{ff5}	$r_t - r_f$	α_{capm}	α_{ff3}	α_{ff5}
L	10.74	-0.05	0.71	2.13	13.51	1.79	2.53	4.96
2	10.29	0.22	0.42	-0.14	12.53	1.04	1.16	1.56
3	11.94	-0.05	0.73	2.52	12.92	0.84	1.25	2.27
4	9.21	0.8	0.68	-1.5	11.28	0.34	0.6	1.44
H	7.15	-0.34	-0.79	-2.79	9.87	-0.63	-0.85	0.02
HML	-3.59	-0.29	-1.5	-4.92***	-3.64*	-2.42	-3.37*	-4.93***
t-statistics	(-1.56)	(-0.13)	(-0.94)	(-2.9)	(-1.83)	(-1.11)	(-1.94)	(-2.68)

Table 5: Double Sort Excess Returns ($r_t - r_f$)

This table reports the annualized excess return of double sorted portfolio by upstream markup μ^U labor cost. Panel A, B, and C use μ^{DEU}, μ^{LI}, and μ^{BEA}, respectively, to calculate upstream markup. Firm level labor cost is calculated following Donangelo et al. (2019). Excess return $r_t - r_f$ subtracts risk-free rate from return. Newey-West t-statistics with 4 lags are reported in parentheses. *$p < .10$; **$p < .05$; ***$p < .01$

Panel A. μ^{DEU}	Value-weighted				Equal-weighted			
	μ^U				μ^U			
Labor Share	H	M	L	HML	H	M	L	HML
L	11.68	11.05	8.13	-3.54	15.17	13.1	14.51	-0.66
				(-1.55)				(-0.35)
M	11.55	9.29	10.33	-1.23	15.45	14.81	14.09	-1.36
				(-0.68)				(-0.8)
H	11.19	10.09	7.76	-3.43	16.81	16.45	13.4	-3.41**
				(-1.51)				(-2.08)
Panel B. μ^{LI}	**Value-weighted**				**Equal-weighted**			
	μ^U				μ^U			
Labor Share	H	M	L	HML	H	M	L	HML
L	10.86	11.87	8.4	-2.47	14.93	13.89	13.88	-1.06
				(-0.99)				(-0.49)
M	11.02	12.19	8.89	-2.13	15.26	16.49	11.82	-3.44*
				(-1.1)				(-1.85)
H	10.92	11.63	7.52	-3.4	16.88	16.97	12.09	-4.79**
				(-1.51)				(-2.37)
Panel C. μ^{BEA}	**Value-weighted**				**Equal-weighted**			
	μ^U				μ^U			
Labor Share	H	M	L	HML	H	M	L	HML
L	11.51	11.08	7.34	-4.17	116.44	13.41	12.22	-4.22*
				(-1.61)				(-1.91)
M	11.94	12.34	7.44	-4.5*	17.01	13.73	12.8	-4.21**
				(-1.78)				(-2.42)
H	11.45	9.67	7.52	-3.93	17.53	14.96	13.3	-4.23**
				(-1.47)				(-2.06)

The model propose that firms that relying more on labor are more exposed from upstream markup and have less risk. Since these firms have higher operating leverage, they benefit more from higher upstream markup. To examine this, I double sorted firms based on upstream markup and labor share from Donangelo et al. (2019). labor cost is calculated as industry average wage times the median of current and previous employees (EMP). Than, I divide the labor cost by sum if labor cost and OIBDP to obtain labor share. I used tercile so that portfolio does not end up with small samples.

$$\begin{aligned} Labor\ Cost_{it} &= Wage_{It} \times \frac{EMP_{it} + EMP_{it-1}}{2} \\ Labor\ Share_{it} &= \frac{Labor\ Cost_{it}}{Labor\ Cost_{it} + OIBDP_{it}} \end{aligned}$$

Table 5 shows the annualized return of double-sorted portfolio by upstream markup and labor cost. Consistent with table 4, value-weighted HML is small and mostly lacks significance in all panels and labor shares. However, equal-weighted HML return increase with labor share. While it lacks significance with low labor share, equal-weighted HML return yields more than 3% with significance in panel A and B. It confirms that upstream markup have more influence on firms with high labor share and high operating leverage.

4 Conclusion

This paper delves into crucial yet overlooked aspect of markup in the upstream of production network. I build a partial equilibrium model with imperfect competition and production network to understand and measure markup charged by suppliers in production network. With labor rigidity and gross complementarity between variable inputs, the model generates endogenous strong procylical price of variable input, which decrease operating leverage of firms. Firms with high upstream markup experience higher price of intermediate input, more procyclical price of variable input, and lower operating leverage.

The empirical results confirm the findings from the model. Intermediate input expenditures are more sensitive to aggregate business condition, surpassing that of labor costs and leading to non-zero operating leverage. Furthermore, the regression analysis illuminates how upstream markup impacts operating leverage, with industries characterized by higher markup exhibiting more procyclical input expenditures and prices, thus reducing operating leverage and associated risks. Portfolio analysis further corroborates these findings, indicating a negative relationship between upstream markup and excess returns, particularly affecting firms with higher labor shares.

In contributing to the existing literature on product market competition, asset pricing, and production network, this study offers novel insights into the intricate dynamics of market power within the production network. When regulating market power of firms and industries, regulators should not only consider impact in the product market, but also the influence on product network.

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A Proofs

A.1 Proof of Proposition 1

Optimization of firm problem is given as

$$\max_{l_{it},x_{it}} \Pi_{it} = y_{it}^{\frac{\theta_I-1}{\theta_I}} D_t^{-\frac{1}{\theta_I}} - l_{it}W_t - \sum_J P_J x_{iJt} + \lambda_{it}^S \left(y_{it} - \left(\alpha_{IL}^{\frac{1}{\eta}} l_{it}^{\frac{\eta-1}{\eta}} + \sum_J \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \right)$$

First order conditions are

1) FOC w.r.t. y_{it}

$$\begin{aligned} \lambda_{it}^S &= \frac{\theta_I - 1}{\theta_I} y_{it}^{-\frac{1}{\theta_I}} D_t^{-\frac{1}{\theta_I}} = \frac{\theta_{It}-1}{\theta_{It}} p_{it} \\ \Rightarrow p_{it} &= \frac{\epsilon_{It}}{\epsilon_I - 1} \lambda_{it}^S = \mu_I \lambda_{it}^S \end{aligned}$$

2) FOC w.r.t. l_{it}

$$\begin{aligned} W_t &= \lambda_{it}^S y_{it}^{\frac{1}{\eta}} \alpha_{IL}^{\frac{1}{\eta}} l_{it}^{-\frac{1}{\eta}} \\ \Rightarrow l_{it} &= = \alpha_{IL} y_{it} \left(\frac{W_t}{\lambda_{it}^S} \right)^{-\eta} \\ \Rightarrow \alpha_{IL}^{\frac{1}{\eta}} l_{it}^{\frac{\eta-1}{\eta}} &= = \alpha_{IL} y_{it}^{\frac{\eta-1}{\eta}} \left(\frac{W_t}{\lambda_{it}^S} \right)^{1-\eta} \end{aligned}$$

3) FOC w.r.t. x_{it}

$$\begin{aligned} P_{Jt} &= \lambda_{it}^S y_{it}^{\frac{1}{\eta}} \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{-\frac{1}{\eta}} \\ \Rightarrow x_{iJt} &= = \Omega_{IJ} y_{it} \left(\frac{P_{Jt}}{\lambda_{it}^S} \right)^{-\eta} \\ \Rightarrow \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{\frac{\eta-1}{\eta}} &= = \Omega_{IJ} y_{it}^{\frac{\eta-1}{\eta}} \left(\frac{P_{Jt}}{\lambda_{it}^S} \right)^{1-\eta} \\ \Rightarrow \sum_J \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{\frac{\eta-1}{\eta}} &= = y_{it}^{\frac{\eta-1}{\eta}} \sum_J \Omega_{IJ} \left(\frac{P_{Jt}}{\lambda_{it}^S} \right)^{1-\eta} \end{aligned}$$

Sum up the last equations from FOC 2) and 3).

$$\begin{aligned} y_{it}^{\frac{\eta-1}{\eta}} &= \alpha_{IL} y_{it}^{\frac{\eta-1}{\eta}} \left(\frac{W_t}{\lambda_{it}^S}\right)^{1-\eta} + y_{it}^{\frac{\eta-1}{\eta}} \sum_J \Omega_{IJ} \left(\frac{P_{Jt}}{\lambda_{it}^S}\right)^{1-\eta} \\ \Rightarrow \lambda_{it}^{S\ 1-\eta} &= \alpha_{IL} W_t^{1-\eta} + \sum_J \Omega_{IJ} P_{Jt}^{1-\eta} \end{aligned}$$

Assume other industries also charge constant markup over marginal cost ($P_{Jt} = \mu_J \lambda_{Jt}$)
Also, assume symmetric equilibrium

$$\Rightarrow \lambda_{It}^{S\ 1-\eta} = \alpha_{IL} W_t^{1-\eta} + \sum_J \Omega_{IJ} (\mu_J \lambda_{Jt})^{1-\eta}$$

Define $\mathcal{M}$ as $n \times n$ diagonal matrix, of which (i,i) element is μ_I and define power of matrix as element-wise exponential.
In matrix form,

$$\begin{aligned} \begin{pmatrix} \vdots \\ \lambda_{It}^{S\ 1-\eta} \\ \vdots \end{pmatrix} &= \begin{pmatrix} \vdots \\ \alpha_{IL} \\ \vdots \end{pmatrix} \times W_t^{1-\eta} + \Omega \mathcal{M}^{1-\eta} \begin{pmatrix} \vdots \\ \lambda_{It}^{S\ 1-\eta} \\ \vdots \end{pmatrix} \\ \Rightarrow \begin{pmatrix} \vdots \\ \lambda_{It}^{S\ 1-\eta} \\ \vdots \end{pmatrix} &= (I - \Omega \mathcal{M}^{1-\eta})^{-1} \begin{pmatrix} \vdots \\ \alpha_{IL} \\ \vdots \end{pmatrix} \times W_t^{1-\eta} \qquad (2) \\ &= \begin{pmatrix} \vdots \\ \alpha_{IL} \\ \vdots \end{pmatrix} \times W_t^{1-\eta} + \Omega \mathcal{M}^{1-\eta} \begin{pmatrix} \vdots \\ \alpha_{IL} \\ \vdots \end{pmatrix} \times W_t^{1-\eta} + \left(\Omega \mathcal{M}^{1-\eta}\right)^2 \begin{pmatrix} \vdots \\ \alpha_{IL} \\ \vdots \end{pmatrix} \times W_t^{1-\eta} + ... \end{aligned}$$

In scalar form,

$$\begin{aligned} \lambda_{It}^{S\ 1-\eta} &= \alpha_{IL} W_t^{1-\eta} + \sum_J \Omega_{IJ} \alpha_{JL} \mu_J^{1-\eta} W_t^{1-\eta} + \sum_J \sum_K \Omega_{IJ} \alpha_{JL} \mu_J^{1-\eta} \Omega_{JK} \alpha_{KL} \mu_K^{1-\eta} W_t^{1-\eta} + ... \\ &= W_t^{1-\eta} (\alpha_{IL} + \sum_J \Omega_{IJ} \alpha_{JL} \mu_J^{1-\eta} + \sum_J \sum_K \Omega_{IJ} \alpha_{JL} \mu_J^{1-\eta} \Omega_{JK} \alpha_{KL} \mu_K^{1-\eta} + ...) \qquad (3) \end{aligned}$$

Define $\frac{\partial \log p_{it}}{\partial \log D_t} \equiv \rho_p$, $\frac{\partial \log \lambda_{it}^S}{\partial \log D_t} \equiv \rho_\lambda^I$ and $\frac{\partial \log y_{it}}{\partial \log D_t} \equiv \rho_y$

1) Cyclicality of Sales ($p_{it} y_{it}$)

Since $p_{it} = \frac{\theta_I}{\theta_I - 1}\lambda_{it}^S$,

$$\begin{aligned} \log p_{it} &= \log \frac{\theta_I}{\theta_I - 1} + \log \lambda_{it}^S \\ \Rightarrow \rho_p &= \rho_\lambda^I \end{aligned}$$

Since $y_{it} = p_{it}^{-\theta_I} D_t$,

$$\begin{aligned} \log y_{it} &= -\theta_I \log p_{it} + \log D_t \\ \Rightarrow \rho_y &= -\theta_I \rho_\lambda^I + 1 \end{aligned}$$

Thus, the cyclicality of sales is

$$\begin{aligned} \frac{\partial \log p_{it} y_{it}}{\partial \log A_t} &= \rho_P + \rho_y \\ &= (1 - \theta_I)\rho_\lambda^I + 1 \end{aligned}$$

2) Cyclicality of Costs ($l_{it}W_t$, $x_{iJt}P_{Jt}$)
Define $\frac{\partial \log l_{it}}{\partial \log D_t} \equiv \rho_l$, $\frac{\partial \log W_t}{\partial \log D_t} \equiv \rho_W$, and $\frac{\partial \log x_{iJt}}{\partial \log D_t} \equiv \rho_{x_{IJ}}$
From FOC w.r.t. l_{it}, $W_t = \lambda_{it}^S y_{it}^{\frac{1}{\eta}} \alpha_{IL}^{\frac{1}{\eta}} l_{it}^{-\frac{1}{\eta}}$
In logs,

$$\begin{aligned} \log W_t &= \log \lambda_{it}^S + \frac{1}{\eta}\log y_{it} + \frac{1}{\eta}\log \alpha_{IL} - \frac{1}{\eta}\log l_{it} \\ \Rightarrow \rho_W &= \rho_\lambda^I + \frac{1}{\eta}\rho_y - \frac{1}{\eta}\rho_l \\ \Rightarrow \rho_l &= \eta\rho_\lambda^I + \rho_y - \eta\rho_W \\ &= 1 + (\eta - \theta_I)\rho_\lambda^I - \eta\rho_W \end{aligned}$$

Thus, the cyclicality of labor compensation is

$$\begin{aligned} \frac{\partial \log l_{it} W_t}{\partial \log A_t} &= \rho_W + \rho_l \\ &= 1 + (\eta - \theta_I)\rho_\lambda^I + (1 - \eta)\rho_W \end{aligned}$$

Similarly, from FOC w.r.t. x_{iJt}, $P_{Jt} = \lambda^S_{it} y_{it}^{\frac{1}{\eta}} \Omega_{IJ}^{\frac{1}{\eta}} x_{it}^{-\frac{1}{\eta}}$

$$\begin{aligned}
\Rightarrow \log P_{Jt} &= \log \lambda^S_{it} + \frac{1}{\eta}\log y_{it} + \frac{1}{\eta}\log \Omega_{IJ} - \frac{1}{\eta}\log x_{it} \\
\Rightarrow \rho^J_\lambda &= \rho^I_\lambda + \frac{1}{\eta}\rho_y - \frac{1}{\eta}\rho_{x_{IJ}} \\
\Rightarrow \rho_{x_{IJ}} &= \eta\rho^I_\lambda + \rho_y - \eta\rho^J_\lambda \\
&= 1 + (\eta - \theta_I)\rho^I_\lambda - \eta\rho^J_\lambda
\end{aligned}$$

Thus, the cyclicality of input expenditure is

$$\begin{aligned}
\frac{\partial \log P_{Jt} x_{iJt}}{\partial \log A_t} &= \rho_{x_{IJ}} + \rho^J_\lambda \\
&= 1 + (\eta - \theta_I)\rho^I_\lambda - (1-\eta)\rho^J_\lambda
\end{aligned}$$

3) Cyclicality of Marginal Costs ($\lambda^S w_{it}$)
From equation 2),

$$\rho^I_\lambda = \rho_w$$

4) Operating Leverage

$$\begin{aligned}
\frac{\partial \log \pi_{it}}{\partial \log A_t} - \frac{\partial \log p_{it} y_{it}}{\partial \log A_t} &= \frac{1}{\pi_{it}}[p_{it}y_{it}(1 + (1-\theta_I)\rho_\lambda) - l_{it}W_t(1 + (\eta-\theta_I)\rho_\lambda + (1-\eta)\rho_W) \\
&\quad - \sum_J P_{Jt}x_{iJt}[1 + (\eta - \theta_I)\rho_\lambda + (1-\eta)\rho^J_\lambda] - (1 + (1-\theta_I)\rho_\lambda) \\
&= \frac{1-\eta}{\pi_{it}}\left[l_{it}W_t(\rho^I_\lambda - \rho_W) + \sum_J P_{Jt}x_{iJt}(\rho^I_\lambda - \rho^J_\lambda) \right]
\end{aligned}$$

In benchmark case, cyclicality of price and cost are equal($\rho_p = \rho^I_\lambda = \rho^J_\lambda = \rho_W$).
Thus, operation leverage is zero.

A.2 Proof of Proposition 2

In fixed labor case, optimization problem is given as

$$\max_{l_{it},x_{it}} \Pi_{it} = y_{it}^{\frac{\theta_I-1}{\theta_I}} - \bar{l}_{it}W_t - \sum_J P_J x_{iJt} + \lambda_{it}^S \left(y_{it} - \left(\alpha_{IL}^{\frac{1}{\eta}} \bar{l}_{it}^{\frac{\eta-1}{\eta}} + \sum_J \Omega_{IJ}^{\frac{1}{\eta}} x_{iJt}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \right)$$

First order condtions are

1) FOC w.r.t. y_{it}

$$\begin{aligned} \lambda_{it}^S &= \frac{\theta_I - 1}{\theta_I} y_{it}^{-\frac{1}{\theta_I}} D_t^{-\frac{1}{\theta_I}} = \frac{\theta_I - 1}{\theta_I} p_{it} \\ \Rightarrow p_{it} &= \frac{\theta_I}{\theta_I - 1} \lambda_{it}^S = \mu_I \lambda_{it}^S \end{aligned}$$

2) FOC w.r.t. x_{it}

$$\begin{aligned} P_{Jt} &= \lambda_{it}^S y_{it}^{\frac{1}{\eta}} \Omega_{IJ}^{\frac{1}{\eta}} x_{it}^{-\frac{1}{\eta}} \\ \Rightarrow \Omega_{IJ}^{\frac{1}{\eta}} x_{it}^{\frac{\eta-1}{\eta}} &= \Omega_{IJ} y_{it}^{\frac{\eta-1}{\eta}} \left(\frac{\lambda_{it}^S}{P_{Jt}} \right)^{\eta-1} \\ \Rightarrow y_{it}^{\frac{\eta-1}{\eta}} &= \alpha_{IL}^{\frac{1}{\eta}} \bar{l}_{it}^{\frac{\eta-1}{\eta}} + y_{it}^{\frac{\eta-1}{\eta}} \sum_J \Omega_{IJ} \left(\frac{\lambda_{it}^S}{P_{Jt}} \right)^{\eta-1} \\ \Rightarrow {\lambda_{it}^S}^{1-\eta} \frac{y_{it}^{\frac{\eta-1}{\eta}} - \alpha_{IL}^{\frac{1}{\eta}} \bar{l}_{it}^{\frac{\eta-1}{\eta}}}{y_{it}^{\frac{\eta-1}{\eta}}} &= \sum_J \Omega_{IJ} P_{Jt}^{1-\eta} \end{aligned}$$

In logs,

$$(1-\eta)\log \lambda_{it} - \frac{\eta - 1}{\eta} \log y_{it} + \log(y_{it}^{\frac{\eta-1}{\eta}} - \alpha_{IL}^{\frac{1}{\eta}} \bar{l}_{it}^{\frac{\eta-1}{\eta}}) = \log \sum_J \Omega_{IJ} P_{Jt}^{1-\eta} \qquad (4)$$

Define $\frac{\partial \log p_{it}}{\partial \log D_t} \equiv \rho_p$, $\frac{\partial \log \lambda_{it}^S}{\partial \log D_t} \equiv \rho_\lambda^I$ and $\frac{\partial \log y_{it}}{\partial \log D_t} \equiv \rho_y$

1) Cyclicality of Sales ($p_{it} y_{it}$)
Since $p_{it} = \frac{\theta_I}{\theta_I - 1} \lambda_{it}^S$,

$$\begin{aligned} \log p_{it} &= \log \frac{\theta_I}{\theta_I - 1} + \log \lambda_{it}^S \\ \Rightarrow \rho_p &= \rho_\lambda^I \end{aligned}$$

Since $y_{it} = p_{it}^{-\theta_I} D_t$,

$$\begin{aligned} \log y_{it} &= -\theta_I \log p_{it} + \log D_t \\ \Rightarrow \rho_y &= -\theta_I \rho_\lambda^I + 1 \end{aligned}$$

Thus, the cyclicality of sales is

$$\begin{aligned} \frac{\partial \log p_{it} y_{it}}{\partial \log A_t} &= \rho_P + \rho_y \\ &= (1-\theta_I)\rho_\lambda^I + 1 \end{aligned}$$

2) Cyclicality of Costs ($l_{it}W_t$, $x_{iJt}P_{Jt}$)

Define $\frac{\partial \log W_t}{\partial \log D_t} \equiv \rho_W$ and $\frac{\partial \log x_{iJt}}{\partial \log D_t} \equiv \rho_{x_{IJ}}$

The cyclicality of labor compensation is

$$\frac{\partial \log l_{it} W_t}{\partial \log A_t} = \rho_W$$

From FOC w.r.t. x_{iJt}, $P_{Jt} = \lambda_{it}^S y_{it}^{\frac{1}{\eta}} \Omega_{IJ}^{\frac{1}{\eta}} x_{it}^{-\frac{1}{\eta}}$

$$\begin{aligned} \Rightarrow \log P_{Jt} &= \log \lambda_{it}^S + \frac{1}{\eta}\log y_{it} + \frac{1}{\eta}\log \Omega_{IJ} - \frac{1}{\eta}\log x_{iJt} \\ \Rightarrow \rho_\lambda^J &= \rho_\lambda^I + \frac{1}{\eta}\rho_y - \frac{1}{\eta}\rho_{x_{IJ}} \\ \Rightarrow \rho_{x_{IJ}} &= \eta\rho_\lambda^I + \rho_y - \eta\rho_\lambda^J \\ &= 1 + (\eta - \theta_I)\rho_\lambda^I - \eta\rho_\lambda^J \end{aligned}$$

Thus, the cyclicality of input expenditure is

$$\begin{aligned} \frac{\partial \log P_{Jt} x_{iJt}}{\partial \log A_t} &= \rho_{x_{IJ}} + \rho_\lambda^J \\ &= 1 + (\eta - \theta_I)\rho_\lambda^I - (1-\eta)\rho_\lambda^J \end{aligned}$$

3) Cyclicality of Marginal Costs ($\lambda^S w_{it}$)

From equation 3),

$$\begin{aligned}
(1-\eta)\log\lambda_{it} - \frac{\eta-1}{\eta}\log y_{it} + \log(y_{it}^{\frac{\eta-1}{\eta}} - \alpha_{IL}^{\frac{1}{\eta}}\bar{l}_{it}^{\frac{\eta-1}{\eta}}) &= \log\sum_J \Omega_{IJ}P_{Jt}^{1-\eta} \\
(1-\eta)\rho_\lambda^I - \frac{\eta-1}{\eta}\rho_y + \frac{\eta-1}{\eta}\frac{y_{it}^{\frac{\eta-1}{\eta}}\rho_y}{y_{it}^{\frac{\eta-1}{\eta}} - \alpha_{IL}^{\frac{1}{\eta}}\bar{l}_{it}^{\frac{\eta-1}{\eta}}} &= (1-\eta)\frac{\sum_J \Omega_{IJ}P_{Jt}^{1-\eta}\rho_\lambda^J}{\sum_J \Omega_{IJ}P_{Jt}^{1-\eta}} \\
\Rightarrow \rho_\lambda^I - \frac{1}{\eta}\frac{\alpha_{IL}^{\frac{1}{\eta}}\bar{l}_{it}^{\frac{\eta-1}{\eta}}}{y_{it}^{\frac{\eta-1}{\eta}} - \alpha_{IL}^{\frac{1}{\eta}}\bar{l}_{it}^{\frac{\eta-1}{\eta}}}(1-\theta_I\rho_\lambda^I) &= \frac{\sum_J \Omega_{IJ}P_{Jt}^{1-\eta}\rho_\lambda^J}{\sum_J \Omega_{IJ}P_{Jt}^{1-\eta}}
\end{aligned}$$

Define $\hat{\alpha}_{iLt} = \frac{\alpha_{IL}^{\frac{1}{\eta}}\bar{l}_{it}^{\frac{\eta-1}{\eta}}}{y_{it}^{\frac{\eta-1}{\eta}} - \alpha_{IL}^{\frac{1}{\eta}}\bar{l}_{it}^{\frac{\eta-1}{\eta}}}$,

$$\Rightarrow \rho_\lambda^I - \frac{\hat{\alpha}_{iLt}}{\eta}(1-\theta_I\rho_\lambda^I) = \frac{\sum_J \Omega_{IJ}P_{Jt}^{1-\eta}\rho_\lambda^J}{\sum_J \Omega_{IJ}P_{Jt}^{1-\eta}} \tag{5}$$

Note, from FOC, $\sum_J \Omega_{IJ}P_{Jt}^{1-\eta} = \frac{\lambda_{it}^{S\ 1-\eta}}{1+\hat{\alpha}_{iLt}}$

Assume all industries charge constant markup ($P_{Jt} = \mu_J\lambda_{Jt}^S$) and symmetric equilibrium with representative firm i in industry I.

$$\begin{aligned}
\rho_\lambda^I\frac{\eta+\theta_I\hat{\alpha}_{ILt}}{\eta} &= \frac{\hat{\alpha}_{ILt}}{\eta} + (1+\hat{\alpha}_{ILt})\frac{\sum_J \Omega_{IJ}\mu_J^{1-\eta}\lambda_{Jt}^{S\ 1-\eta}\rho_\lambda^J}{\lambda_{It}^{S\ 1-\eta}} \\
\Rightarrow \rho_\lambda^I\lambda_{It}^{S\ 1-\eta} &= \frac{\hat{\alpha}_{ILt}}{\eta+\theta_I\hat{\alpha}_{ILt}}\lambda_{It}^{S\ 1-\eta} + \frac{\eta(1+\hat{\alpha}_{ILt})}{\eta+\theta_I\hat{\alpha}_{ILt}}\sum_J \Omega_{IJ}\mu_J^{1-\eta}\lambda_{Jt}^{S\ 1-\eta}\rho_\lambda^J
\end{aligned}$$

Define $\hat{\Omega}_{IJ} \equiv \frac{\eta(1+\theta_{It})}{\eta+\epsilon\theta_{It}}\Omega_{IJ}$

$$\rho_\lambda^I\lambda_{It}^{S\ 1-\eta} = \frac{\hat{\alpha}_{ILt}}{\eta+\theta_I\hat{\alpha}_{ILt}}\lambda_{It}^{S\ 1-\eta} + \sum_J \hat{\Omega}_{IJ}\mu_J^{1-\eta}\lambda_{Jt}^{S\ 1-\eta}\rho_\lambda^J$$

In matrix form,

$$\begin{aligned}
\begin{pmatrix} \vdots \\ \rho_\lambda^I {\lambda_{It}^S}^{1-\eta} \\ \vdots \end{pmatrix} &= \begin{pmatrix} \vdots \\ \frac{\hat{\alpha}_{ILt}}{\eta+\theta_I\hat{\alpha}_{ILt}} {\lambda^S}^{1-\eta} \\ \vdots \end{pmatrix} + \hat{\Omega}\mathcal{M}^{1-\eta} \begin{pmatrix} \vdots \\ \rho_\lambda^I {\lambda_{It}^S}^{1-\eta} \\ \vdots \end{pmatrix} \\
\Rightarrow \begin{pmatrix} \vdots \\ \rho_\lambda^I {\lambda_{It}^S}^{1-\eta} \\ \vdots \end{pmatrix} &= (I - \hat{\Omega}\mathcal{M}^{1-\eta})^{-1} \begin{pmatrix} \vdots \\ \frac{\hat{\alpha}_{ILt}}{\eta+\theta_I\hat{\alpha}_{ILt}} {\lambda^S}^{1-\eta} \\ \vdots \end{pmatrix} \\
&= \begin{pmatrix} \vdots \\ \frac{\hat{\alpha}_{ILt}}{\eta+\theta_I\hat{\alpha}_{ILt}} {\lambda^S}^{1-\eta} \\ \vdots \end{pmatrix} + \hat{\Omega}\mathcal{M}^{1-\eta} \begin{pmatrix} \vdots \\ \frac{\hat{\alpha}_{ILt}}{\eta+\theta_I\hat{\alpha}_{ILt}} {\lambda^S}^{1-\eta} \\ \vdots \end{pmatrix} \\
&\quad + \left(\hat{\Omega}\mathcal{M}^{1-\eta}\right)^2 \begin{pmatrix} \vdots \\ \frac{\hat{\alpha}_{ILt}}{\eta+\theta_I\hat{\alpha}_{ILt}} {\lambda^S}^{1-\eta} \\ \vdots \end{pmatrix} + \ldots
\end{aligned}$$

4) Operating Leverage

$$\begin{aligned}
\frac{\partial \log \pi_{it}}{\partial \log A_t} - \frac{\partial \log p_{it} y_{it}}{\partial \log A_t} &= \frac{1}{\pi_{it}} \Big[p_{it} y_{it} (1 + (1-\theta_I)\rho_\lambda) - l_{it} W_t \rho_W \\
&\quad - \sum_J P_{Jt} x_{iJt} (1 + (\eta - \theta_I)\rho_\lambda + (1-\eta)\rho_\lambda^J) \Big] - (1 + (1-\theta_I)\rho_\lambda) \\
&= \frac{1}{\pi_{it}} \left[l_{it} W_t (1 - (\theta_I - 1)\rho_\lambda^I - \rho_W) + (1-\eta) \sum_J P_{Jt} x_{iJt} (\rho_\lambda^I - \rho_\lambda^J) \right]
\end{aligned}$$

From equation 4) and from FOC equation($P_{Jt} x_{it} = {\lambda_{it}^S}^{\eta} y_{it} \Omega_{IJ} P_{Jt}^{1-\eta}$)

$$\begin{aligned}
\rho_\lambda^I - \frac{\hat{\alpha}_{ILt}}{\eta}(1 - \theta_I \rho_\lambda^I) &= \frac{\sum_J P_{Jt} x_{it} \rho_\lambda^J}{\sum_J P_{Jt} x_{it}} \\
\Rightarrow \sum_J P_{Jt} x_{it} (\rho_\lambda^I - \rho_\lambda^J) &= \frac{\hat{\alpha}_{ILt}}{\eta}(1 - \theta_I \rho_\lambda^I) \times \sum_J P_{Jt} x_{it}
\end{aligned}$$

Thus, operating leverage becomes

$$\frac{\partial \log \pi_{it}}{\partial \log A_t} - \frac{\partial \log p_{it} y_{it}}{\partial \log A_t} = \frac{1}{\pi_{it}} \left[l_{it} W_t (1 - (\theta_I - 1)\rho_\lambda^I - \rho_W) + \frac{1-\eta}{\eta} \hat{\alpha}_{ILt} (1 - \theta_I \rho_\lambda^I) \times \sum_J P_{Jt} x_{iJt} \right]$$

B Tables

Table B1: Top & Bottom 10 Industries by Upstream Markup μ^U

NAICS	Industry Name	μ^U	μ	α^L
Panel A. Top 10 Industries				
324	Petroleum and coal products	1.3185	1.2	0.04
311FT	Food and beverage and tobacco products	1.2922	1.64	0.13
325	Chemical products	1.2876	1.64	0.18
111CA	Farms	1.286	1.39	0.1
326	Plastics and rubber products	1.2634	1.37	0.23
313TT	Textile mills and textile product mills	1.2568	1.38	0.24
211	Oil and gas extraction	1.2411	1.54	0.19
322	Paper products	1.2302	1.4	0.22
531	Housing and Real estate	1.2295	1.47	0.11
513	Broadcasting and telecommunications	1.2214	1.79	0.3
Panel B. Bottom 10 Industries				
514	Data processing, internet publishing, and other information services	1.1201	1.83	0.56
334	Computer and electronic products	1.1178	1.51	0.45
42	Wholesale trade	1.1154	1.06	0.54
61	Educational services	1.1146	1.68	0.61
561	Administrative and support services	1.1144	1.39	0.56
621	Ambulatory health care services	1.1135	1.39	0.6
55	Management of companies and enterprises	1.1123	1.47	0.6
5411	Legal services	1.112	1.47	0.58
493	Warehousing and storage	1.1118	1.47	0.62
5415	Computer systems design and related services	1.0903	1.37	0.66