Online Appendix of Accounting Analysis for Labor Share: The Tug of War Between Automation and Emerging New Tasks

Seungjin Baek and Deokjae Jeong

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1 Superstar Hypothesis

In this Online Appendix, we discuss why the Superstar-firm hypothesis proposed by Autor et al. (2020) cannot fully account for the ‘global’ labor share decline.

Autor et al. (2020) present seven stylized facts, which can be summarized into the following narratives. Story I: The markups of the top 10 firms are significantly larger than those of other firms. Story II: The increase in concentration—defined as the revenue of the top 10 firms divided by the revenue of all firms in each sector—leads to an increase in markup in each sector. Story III: An increase in markup within each sector results in a decline in labor share for that sector. Story IV: Consequently, the increase in concentration contributes to the decline in labor share.

For the Superstar hypothesis to be valid, all four stories outlined above must be true. The next section demonstrates that, in the case of the EU, while Stories I and III hold true, the remaining narratives are not supported. Moreover, our analysis reveals that overall concentration in the EU has declined even as labor share has decreased.

In essence, Autor et al. (2020)'s hypothesis can be divided into two parts: (Part A) increasing concentration leads to increasing markup, and (Part B) increasing markup results in a declining labor share. Our findings for EU countries indicate that while Part B is true, Part A is not supported.

There is a reason we chose to evaluate the Superstar hypothesis separately without incorporating it into our main model. Although our model includes markup as one of the explanations for the decline in labor share (Part B), we did not incorporate Part A into the model. Since our separate analysis revealed that Part A is not valid, there was no need to include it in our primary model.

2 A Detailed Analysis

In this section, we will analyze CompNet data, which collects firm-level information and generates various group-level variables based on sector, country, and year. CompNet provides a wealth of statistics, including the number of observations, mean, quantile values, and standard errors, allowing us to extract valuable insights as if we had access to the firm-level variables themselves.

One exception is markup value. Due to confidentiality concerns, CompNet researchers calculated different versions of firm-level markups and released the information only at the group-level. Consequently, users cannot obtain firm-level markup values.

As standard, 'markup' is defined as the price-to-marginal cost ratio:

$$\mu \equiv \frac{P}{c}. \tag{1}$$

Various methods exist for estimating markup, with a detailed discussion provided by De Loecker et al. (2020). In this section, we will use two versions of markups: Accounting markup and Production markup.

1) Accounting markup: This straightforward method can be easily computed from CompNet data. We define the total cost as the sum of labor cost and capital cost, primarily to avoid double counting issues when aggregating costs for firms at the group-level. For example, one firm's material cost might be another firm's intermediate cost. The cleanest approach is to only use labor and capital costs when aggregating. A similar issue arises when aggregating firm-level revenues, so we use "value added" instead of "revenue" for group-level analysis. Note that De Loecker et al. (2020) included material cost, intermediate cost, and selling, general, and administrative expenses (SG&A) in the total cost, and directly used "value added" due to their focus on firm-level calculations.

Given our definitions, Accounting markup can be expressed as follows:

$$\begin{aligned}\mu &\equiv \frac{P}{c} \\ &= \frac{PQ}{cQ} \qquad (2) \\ &= \frac{\text{Value added}}{\text{Labor cost} + \text{Captial cost}} \qquad (3)\end{aligned}$$

Since labor share is defined as $\frac{\text{Labor cost}}{\text{Value added}}$, we get:

$$S_L = \frac{1}{\mu}\left(\frac{\text{Labor cost}}{\text{Labor cost} + \text{Captial cost}}\right) \qquad (4)$$

, where S_L is labor share.

The Accounting markup method relies on strong assumptions: constant returns to scale production functions for all firms, no fixed costs, and perfect substitutability between factors of production. To mitigate these limitations, we will also use the 2) Production markup method, which is appreciated for its weaker assumptions and ease of computation using basic variables. For each firm, its cost minimization solution leads to the following condition, as shown in Equation 7 of De Loecker et al. (2020):

$$\mu = \theta^V \cdot \frac{PQ}{P_V V} \tag{DL7}$$

, where θ^V is the output (Q) elasticity of an input (V), P is the price for the output, and P_V is the price for input. Depending on data availability, either labor, capital, or intermediate input can be used for V. If labor is used for V, Equation DL7 becomes:

$$\begin{aligned} \mu &= \theta^L \cdot \frac{PQ}{WL} \\ \Leftrightarrow S_L &= \frac{1}{\mu} \cdot \theta^L \end{aligned} \tag{5}$$

, where θ^L is the output (Q) elasticity of labor input (L). A crucial aspect of estimating Production markup is properly estimating θ^L, the elasticity that varies by time and group. This estimation requires firm-level data, which we cannot replicate in this paper. De Loecker et al. (2020) suggests using their proposed "two-stage control function approach," and CompNet provides markup values based on this approach (Specification 4 of CompNet). However, this estimation version has too many missing observations compared to a less complicated version (Specification 3 of CompNet). Therefore, we use Specification 3.

Specification 3 assumes a Cobb-Douglas production function (without assuming constant returns to scale) and estimates elasticity using a year-fixed effect OLS to ensure that elasticity varies by time. We acknowledge that Specification 3 relies on stronger assumptions than Specification 4, and when using the former, the advantage of Production markup over Accounting markup significantly decreases. If we had access to firm-level datasets (Amadeus for the EU and Orbis for the world), we could have conducted a more granular analysis, such as deriving firm-level markups. Given our data constraints, using Specification 3 is the best option.

In the following subsection, we evaluate the four stories posited by Autor et al. (2020). If all four stories are valid, their hypothesis offers a strong explanation for the decline in labor share in EU countries; otherwise, it does not.

Two quick notes: (1) we use value-added instead of revenue to avoid double-counting. Although not shown in figures or tables, all results in this section remain unchanged even when using revenue instead of value-added; and (2) we use the entire industrial sectors. Again, although not shown in figures or tables, all results in this section remain unchanged even when focusing on manufacturing sectors.

2.1 Story I

The statement of Story I, ”Markups of the top 10 firms are significantly larger than markups of other firms,” is indeed true in the EU. As CompNet does not provide the ”markup of top 10 firms,” we cannot use Production markup for Story 1. Instead, we will employ Accounting markup, which we derived from CompNet data. CompNet offers data on revenue (Rev), value-added (VA), labor compensation (WL), and capital compensation (RK) for each group. Additionally, for each variable, CompNet provides the ratio of the top ten firms to all firms in the group. For example, CR12 is $(\mathrm{WL}_{\mathrm{ten}})/(\mathrm{WL}_{\mathrm{entire}})$. This information allows us to calculate $\mathrm{WL}_{\mathrm{ten}}$. Using these variables, we can compute the Accounting markup for each group as:

$$\mu_{\mathrm{ten}} = \frac{\mathrm{VA}_{\mathrm{ten}}}{\mathrm{WL}_{\mathrm{ten}} + \mathrm{RK}_{\mathrm{ten}}}. \tag{6}$$

For each group, we define ’markup-ratio’ as the markup of the top 10 firms divided by the markup of that group (i.e., $\mu_{\mathrm{ten}}/\mu_{\mathrm{entire}}$). If Story 1 is accurate, the ’markup-ratio’ will be greater than one. Figure 1 displays this metric by country, with most countries exhibiting a value larger than one. A more detailed analysis is possible when the observation is at the group-level. The estimated coefficient for the constant term is 0.07 with significance under the 0.001 level for the following OLS:

$$\begin{aligned} &\text{markup-ratio} = 1 \\ \Rightarrow\ &(\text{markup-ratio} - 1)_{ijt} = \text{constant} + \varepsilon_{ijt} \end{aligned}$$

, where i, j, and t represent industry, country, and year, respectively. This result implies that the markup of the top 10 firms is seven percent larger than the markup of all firms in the group.

2.2 Story II

Story II states that "In each group, an increase in concentration leads to an increase in the markup." Concentration is defined as the revenue of the top 10 firms divided by the revenue of all the firms in that group, consistent with the definition used by Autor et al. (2020). To make each concentration and markup variable comparable across different groups, we regress each variable on industry and country dummies only and obtain the error term. Since we are interested in long-run trends, we use the 10-year growth rate of the error term. Define grX_{ijt10} as:

$$grX_{ijt10} = \frac{X_{ijt10} - X_{ijt1}}{X_{ijt1}} \tag{7}$$

, where t10 is 10 years after t1. The horizontal orange lines in Figure 2 display the regression results without constant terms, clustered by industry and country to account for serial correlations. The estimated coefficients are all insignificant. The figure suggests that Autor et al. (2020)'s Story II is not supported. Approximately half of the groups exhibit opposite movements (dots in the second and fourth quadrants). For example, when concentration increased for 10 years, markup decreased for 10 years. If Story II were valid, the figure would resemble Figure 4.

De Loecker et al. (2020) emphasized that Production markups below the 90th quantile were time-stable, while only those above the 90th quantile increased rapidly over time (their Figure III(B)). This observation suggests that top firms drove the increase in average markup. Taking their argument into account, we alternatively choose the 90th quantile of the Production markup. Nonetheless, the results do not change significantly.

2.3 Story III

Story III states that "In each group, an increase in the markup leads to a decline in the labor share." If we use Accounting markup, this story holds true. Equation 4 expresses the inverse relationship between the markup and labor share at the *group-level*. We have constructed both variables by strictly adhering to the definition in Equation 4. From Equation 4, it follows that:

$$d\ln(S_L) = -d\ln(\mu) + d\ln\Big(\frac{\text{Labor cost}}{\text{Labor cost} + \text{Captial cost}}\Big) \tag{8}$$

, where 'd' represents the time difference by a year.

$$d\ln(S_L) = \alpha \cdot d\ln(\mu) + \beta \cdot d\ln\Big(\frac{\text{Labor cost}}{\text{Labor cost} + \text{Captial cost}}\Big) + \varepsilon \tag{9}$$

$$d\ln(S_L) = \alpha \cdot d\ln(\mu) + \epsilon \tag{10}$$

If we regress Equation 9, the coefficient, α, will be exactly -1 (If we regress Equation 10, the coefficient will be slightly larger than -1 due to an upward bias from the unobserved error term).

We perform the same analysis using Production markup instead. Similar to the case of Accounting markup, Equation 5 shows the inverse relationship between labor share and the Production markup. Note that this inverse relationship would be strictly true if we had firm-level markups. However, CompNet releases their data after aggregating it to the group-level. Therefore, our regression in this case will be much noisier.

Table 1 presents the relevant regression results (using Equation 10). As expected, -0.756 is close to -1 for Accounting markup, and -0.112 is not close to -1 for Production markup. Overall, Story III is true by definitions and constructions.

2.4 Story IV

Story IV states that "An increase in concentration leads to a decline in labor share." To verify this, we reproduce the same analysis as in Story II, with the variables changed accordingly. Figure 3 presents the regression result, where the line represents a coefficient that is insignificant at the 0.05 level. The same story as in Story II applies: about half of the groups exhibit a positive correlation (dots in the first and third quadrants).

It is worth noting that Autor et al. (2020) already conducted a similar analysis to what we have presented here. In their Table A.8, they presented regression results at the country level (regressing the 10-year change in labor share on the 10-year change in concentration). The table shows that 64% of countries were either insignificant or even positive. This is the same phenomenon as in our Figure 3, where about half of the groups exhibit opposite movement.

Before concluding this section, one more observation is worth mentioning. Using CompNet data, we can construct the concentration variable even at the most aggregated level. Figure 5 shows that the overall concentration in the total EU dropped. Although not as rapid as the US, the EU also experienced a decline in labor share. The drop in concentration is inconsistent with the drop in the labor share in the EU. We conclude that the Superstar hypothesis cannot explain a large portion of groups in the EU.

3 Figures

Figure 1: Markup-ratio

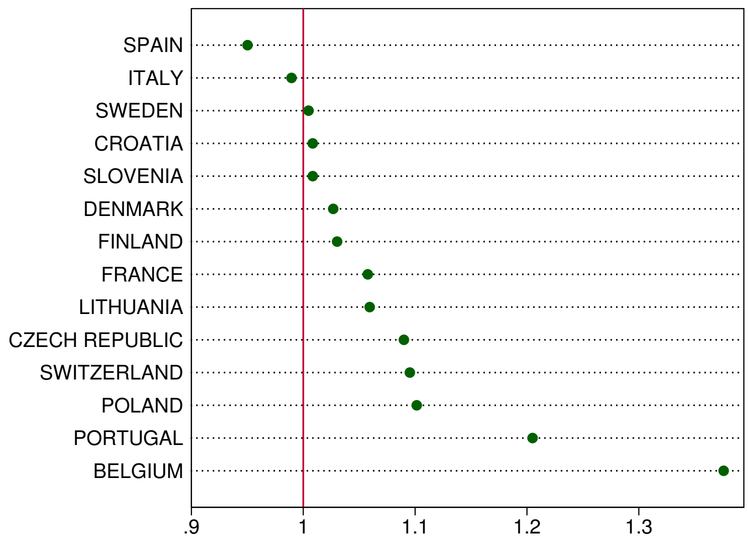


Figure 2: Concentration and markup (10-year growth rate)

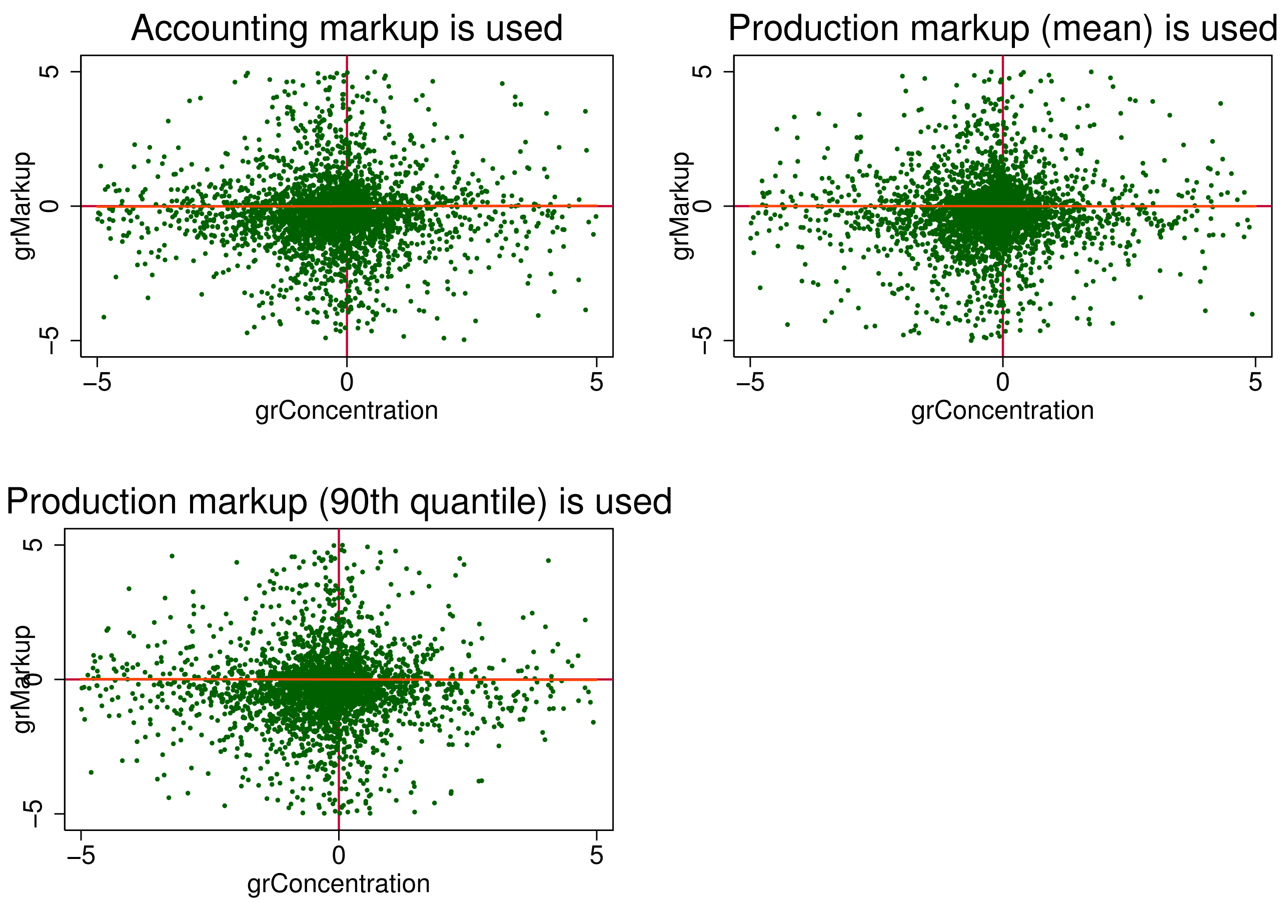


Figure 3: Concentration and laborshare (10-year growth rate)

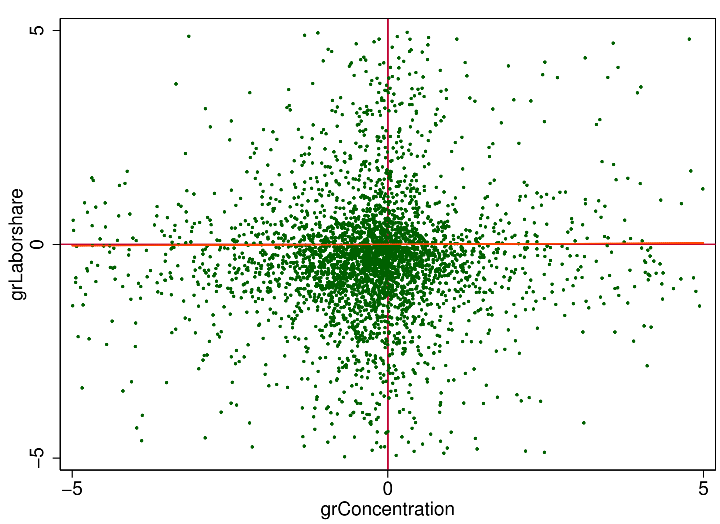
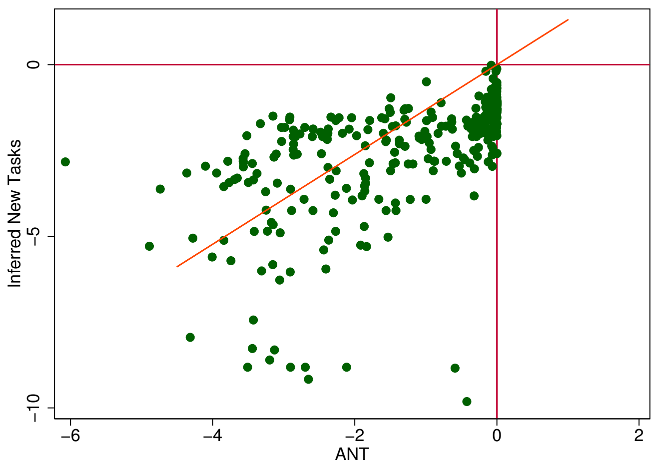


Figure 4

(a) ANT and inferred new tasks (10-year growth rate)



(b) Example

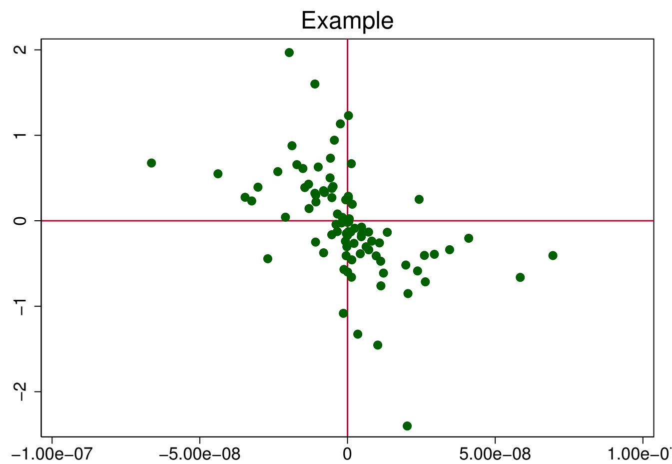
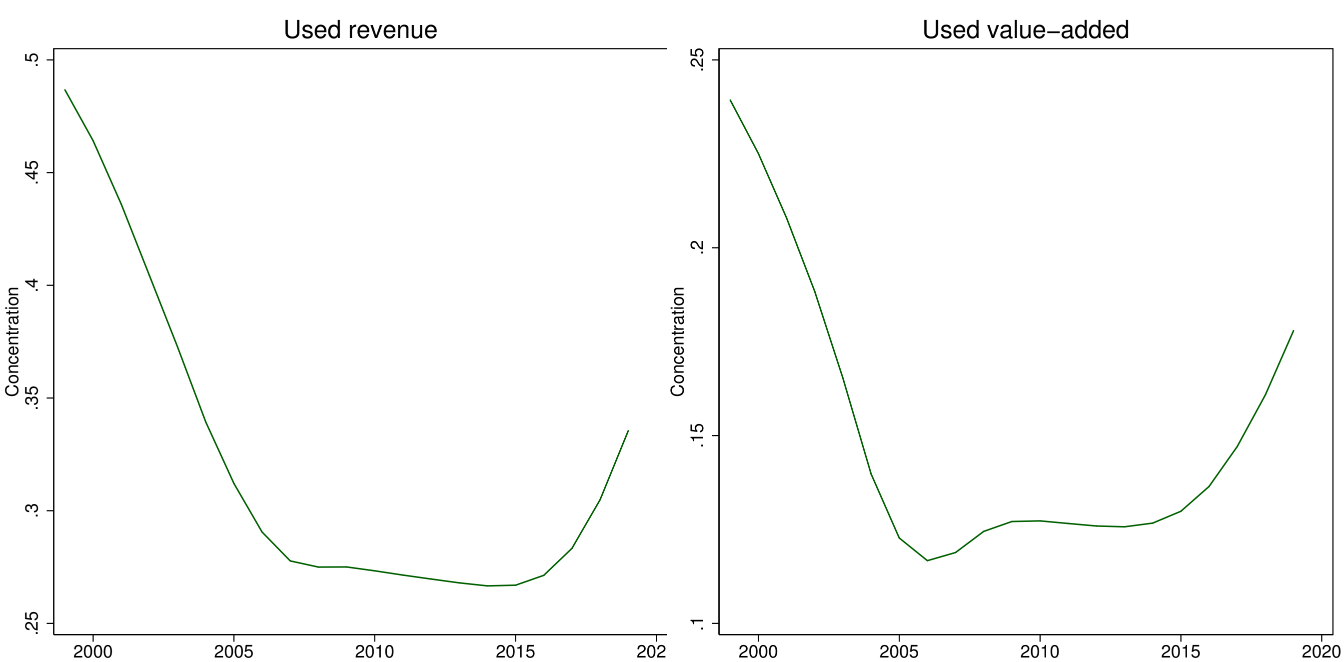


Figure 5: Concentration in EU in total



4 Tables

Table 1

	(1) dln(laborshare)	(2) dln(laborshare)
dln(Accounting markup)	-0.756***	
	(0.026)	
dln(Production markup)		-0.112***
		(0.020)
Observations	10557	9537
R^2	0.598	0.060

Standard errors in parentheses

Clustered by industry and country; used fixed effects but not reported.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

References

David Autor, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen. The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2):645–709, 2020. ISSN 0033-5533.

Jan De Loecker, Jan Eeckhout, and Gabriel Unger. The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*, 135(2):561–644, 2020. ISSN 0033-5533.