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Abstract
Markup, or the ratio of price to cost, depends on the firm's attributes and the market environment where the firm operates. This paper empirically studies the relationship between the markups of firms and their firm-to-firm transactional status. More specifically, we analyze the correlation between markups and the number and variety of the firm's transactional partners. Based on a comprehensive panel dataset of Japanese firms derived from the Basic Survey of Japanese Business Structure and Activities, provided by METI, and the Firm Relation File of TSR (Tokyo Shoko Research) for 2007-2018, we find that a firm's markup level decreases as the number of suppliers (upstream transactional partners) increases, after controlling for firm attributes such as size and age, and industry-specific time effects. This empirical pattern is observed for both manufacturing and non-manufacturing sectors. As for the firm's number of customers (downstream transactional partners), the empirical results differ between manufacturing and non-manufacturing sectors. We further examine the correlation between the number of transactional partners a firm has and the characteristics of those transactional partners.

Keywords: markup, firm-to-firm transaction, supplier
JEL classification: L13, L14, L22

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1 Introduction

Markup, the ratio of price to marginal cost, is an important measure of firm performance. It reflects the firm's market power and is influenced by competitive environment and technological capability of the firm. Firms can easily raise their prices relative to marginal costs if competitive pressure is weak. When firms have superior technologies that gives them cost advantage over the rival firms, they can enjoy higher markup, too.

This paper investigate the relationship between firms' markups and a part of their status in an economy, that is, their transactional links with other firms. Firms procure resources and input goods from their suppliers (upstream firms), produce their goods and services, and sell them to their customer (downstream firms). The transactional relationship reflects determinants of markups. Firms with many suppliers may have complicated production process, which gives the firm technological edge over the competitors, or many suppliers mean that the production process is standardized and the firm's market power is low. The goods and services of firms with many customers may be so attractive that they can earn more profit, or conversely, thin margin allows the firm to obtain the wide customer base.

Many studies reveals that firms' transactional relationship is one of the key factors for firm performance. For example, Bernard, Moxnes, and Saito (2019) summarize several stylized facts about Japanese firms' transactional relationship and examines how transactional relationship affects firms' sales, labor productivity, and TFP. Bernard, et al. (2022) tackle to figure out the origin of firm heterogeneity in terms of size by examining supplier-customer relation. This paper contributes to this line of research by adding how the status of firms' transactional relationship correlate with firms' markups.

Studies of firm level markups have drawn attention from both academia and policy makers. Especially, recent studies in this research field analyze a comprehensive dataset of firms and provide general trend of markups and discuss the macroeconomic implications. Autor, et al. (2020), De Loecker, Eeckhout, and Unger (2020), Crouzet and Eberly (2021), and Eeckhout and Veldkamp (2022) are among others. We also use a comprehensive dataset of Japanese firms that includes around 30,000 firms in each year. The enormous size of our dataset allows our empirical analysis to be flexible and gives an advantage to find stylized facts about transactions and markups.

These studies reveal the increasing trend of aggregate markups, mainly driven by a small number of 'superstar firms' in the US and Europe [1]. On the contrary, it seems that no significant upward trend is observed for markups of Japanese firms [2]. This paper tries to find possible policy implication to enhance Japanese firms' markups by finding stylized facts behind how they are determined.

More specifically, we analyze how firms' markups correlate to the number of their suppliers and customers. As mentioned above, there are several possibilities about the relation between firms' markups and how many suppliers and customers they link to. We try to find stylized facts in this regard, exploiting richness of our dataset for Japanese firms.

The rest of this paper is organized as follows. Section 2 describes the framework of our empirical analysis. It includes how we estimate time-variant firm-level markups and how to construct our transactional relationship variables. Section 3 explains our dataset of Japanese firms. We use a comprehensive dataset of Japanese firms provided by METI and Tokyo Shoko Research (TSR). Our empirical results are reported in Section 4. Our findings are apparently puzzling, so we further delve into the characteristics of suppliers and customers in Section 5 to consider what is behind the findings. Section 6 is the concluding remarks.

2 Framework

2.1 Estimating Markups

Our main variable of interest is time-variant firm-level markup. We estimate the values of markup by using 'production funcation approach' proposed by De Loecker and Warzynski (2012). Based on the solution of a firm's cost minimization problem, they show that firm-level markup rate can be recovered from the elasticity of variable input (such as materials) to production and the value ratio of the variable input to sales.

We define markup firm i at t, μ_{it} as the ratio of output price P_{it} and marginal cost MC_{it}

$$\mu_{it} \equiv \frac{P_{it}}{MC_{it}}. \tag{1}$$

[1] De Loecker, Eeckhout, and Unger (2020) and IMF (2019) are among others.

[2] See Nakamura and Ohashi (2019).

For the production function of firm i at time t

$$Y_{it} = F_j(X_{it}, L_{it}, K_{it}, \omega_{it}), \tag{2}$$

where Y_{it} is output, X_{it} is variable input, L_{it} is labor, K_{it} is capital stock, and ω_{it} is productivity, we define the elasticity of variable input to production, $\beta_{X,it}$, as

$$\beta_{X,it} \equiv \frac{\partial F_j}{\partial X_{it}} \frac{X_{it}}{Y_{it}}. \tag{3}$$

When firm i minimizes its production cost

$$P^X_{it} X_{it} + w_{it} L_{it} + r_{it} K_{it},$$

where P^X_{it} is unit price of variable input, w_{it} is wage rate, and r_{it} is user cost of capital, the first order condition for the choice of X_{it} leads to the following equation for markup:

$$\frac{\mu_{it} = \beta_{X,it}}{\frac{P^X_{it} X_{it}}{P_{it} Y_{it}}}. \tag{4}$$

We can obtain the value ratio of variable input to output $P^X_{it} X_{it} / P_{it} Y_{it}$ from financial data and estimate the value of $beta_{X,it}$ from production function estimation.

We assume that our production function takes the form of translog without interaction terms

$$\begin{aligned}\log Y_{it} = {} & \beta_l \log L_{it} + \beta_{ll} (\log L_{it})^2 + \beta_k \log K_{it} + \beta_x \log X_{it} + \beta_{xx} (\log X_{it})^2 \\ & + \text{control} + \omega_{it} + \epsilon_{it},\end{aligned} \tag{5}$$

following De Loecker, Eeckhout, and Unger (2018). This functional form allows $\beta_{X,it} = \beta_x + 2\beta_{xx} \log X_{it}$ to be different among firms even though the parameters of (5) are the same. ϵ_{it} is an error term unobservable to both firms and econometricians. Our estimation is conducted by industry, so the parameters depend on the industry where firm i belongs.

Since ω_{it} influences the firm's choice of input level, while it is treated as a part of error term due to unobservability to econometricians, we need to deal with this endogeneity problem. To this purpose, we adopt a proxy variable approach proposed by Levinsohn and Petrin (2003) (LP, hereafter) [3].

[3] Using the similar dataset to this paper, Nakamura and Ohashi (2019) finds that the estimation results of LP method are essentially similar to those from another type of proxy variable approach of Olley and Pakes (1996) (OP, hereafter).

As for variable input X_{it}, we use cost of goods sold (COGS) less labor cost. Some studies including Traina (2018) propose another measures such as the sum of COGS and selling, general, and administrative expenses (SG&A), but they also suffer from concerns pointed out by De Loecker, Eeckhout, and Unger (2018) [4].

One practical issue for markups estimated as mentioned above is unrealistic values of estimates especially for small firms. Table 1 shows this issue. Most of estimated values are within the 'reasonable' range, but some are incredible negative values and others are extremely large. Thus we screen the obtained values according to the following objective criteria. First, we omit all negative values of estimated markups. Second, the estimates for firm-years with extraordinary change (100% or more growth, or -50% or larger drop) in sales or employment. Third, we exclude the data with low frequency (three or less observation of sales and employment during the sample period). As a result, the remaining observation is 87.1% of the original dataset.

2.2 Transaction Variables

Our data source of trasactional relationship is Firm Relation File (Kigyo Soukan File) provided by Tokyo Shoko Research (TSR). In this database, firms reports the names of their suppliers and customers. If a firm has many suppliers and/or customers, they pick up 24 suppliers and 24 customers at most. This rule is so restrictive especially for large firms that we should miss the large part of transactional relationship. So following Bernard, Moxnes, and Saito (2019), we recover the missed relationship as much as possible by using 'other-reported' links. If Firm A reports Firm B as one of its suppliers (customers), then Firm A is one of Firm B's customers (suppliers), even though Firm A is dropped from the 30 customers (suppliers) reported by Firm B.

Figure 1a shows the distribution of the number of suppliers and customers for each firm-year constructed as above. The graph for the number of suppliers has a peak at nine and one for the number of customers. However, many observations are out of the range set by TSR. 35.2% of observations in our sample have 25 or more suppliers and the ratio of observations with 25 or more customers is 35.9%. We recover the significant part of transactional relationship by using the information of

[4]Nakamura and Ohashi (2019) checks how the type of variable input affects the obtained markups. Main results show insignificant difference among the specifications.

'other-reported' links. We see no discontinuity around 25, so judging from Figure 1a, such supplement of data gives smooth result.

The distribution of the number of transactional partners is different by sector as shown in Figure 1b. In the range depicted in the figure, the manufacturing sector has a more right-skewed distribution than the non-manufacturing sector. Note that the distribution for non-manufacturing sector has a longer tail, so the mean values of the number of suppliers and customers is larger for non-manufacturing.

It is important to distinguish the industries of suppliers and customers. The competitive environment and technological properties for a firm should be different in the case when it has all of its ten suppliers (customers) in a single industry, from the case when those ten suppliers (customers) belongs to ten different industries. TSR data assigns industry code to each firm in reference to Japan Standard Industrial Classification (JSIC). Our definition of industry to construct transaction variables is based on it. Four-digit TSR industry code classifies the economy into more than 1,200 industries. Since this definition of industry is very fine (comparable to SIC four-digit code), we also use three-digit code (first three digit of four-digit code), which distinguishes more than 400 industries.

Figure 2a-2d summarize the distribution of the number of industries for suppliers and customers. Figure 2a and 2b show that most of our sample firms have connection to multiple industries. For both suppliers and customers, only a handful (2% for suppliers and 6% for customers) of firms have a single-industry connection. About 5% to 15% of the sample firms connect to 30 or more industries upstream or downstream. Figure 2c and 2d depict the distribution patterns by sector. Similar to Figure 1b, the peak of graph is right skewed for manufacturing. Single-industry connections are a bit more common in non-manufacturing, but the ratio is less than 10% in any case.

3 Data

The data used in this paper comes from two annually collected and comprehensive dataset of Japanese firms. To estimate production functions, we use the data from the Basic Survey of Japanese Business Structure and Activities (Kikatsu), METI. This data source contains financial data such as sales, the number of employees, book values of tangible and intangible assets, cost of goods sold (COGS), and labor cost of individual firms in the wide range of industries including both manufacturing and non-manufacturing sectors. The foundation years of each firm is also available and used to construct firm age data. Firms investigated Kikatsu are those with 50 or more employees and 30 million yen or more in capital. Our sample period of production function estimation is 2001-2018.

The data of Kikatsu includes around 30,000 firms in each year, but some of listed firms do not respond to the survey. We supplement the figures for those firms by the data from their financial reports. The supplemented data accounts for less than 5% of our dataset [5] and we include the dummy for being supplemented by financial reports in our analyses to control possible influence by using two different data sources.

In our production function, we treat sales and variable input (COGS less labor cost) in real values, while the reported figures in Kikatsu are nominal. We convert those nominal values into real ones by using industry-level deflators derived from JIP 2021 provided by RIETI. JIP 2021 dataset provides both nominal and real values of industry-level output and intermediate input. Dividing nominal values by real ones, we obtain industry-level deflators, then deflate firms' sales and variable input data by output deflators and intermediate input deflators, respectively. Since industry classification of JIP 2021 is different from that of Kikatsu, we match the two types of industry classification manually.

Production functions are estimated by industry in view of heterogeneity of industries. The industry classfication in the production function estimation follows that of Kikatsu, which is also wider than TSR industry classification. To obtain reliable estimates, we omit the industries with less than 10 observations per year on average. Table 2 shows descriptive statistics of variables used in production function estimation.

The second data source is Firm Relation File (Kigyo Soukan File) provided by Tokyo Shoko Research (TSR), which provides the detailed information about transactional relationship among more than 1 million Japanese firms. We collect the firms' transactional relationship data annually from 2007 to 2018. As mentioned in the previous section, this database also assigns narrowly defined industry codes to each firm [6]. We use this information to construct transaction variables.

[5]For production function estimation, 3.6% of the observations are supplemented as mentioned here. For the analysis demonstrated in the next section, the ratio of supplemented data is 4.7%.

[6]Some firms have multiple industry codes. We use primary codes to assign the industry to each firm.

4 Results

In this section, we analyze how firm-level markups depend on the firm's status of transcational relationship based on a comprehensive dataset of Japanese firms from 2007 to 2018.

Our basic estimation equation is to explain markup level of firm i in sector s at year t as

$$\mu_{ist} = \sum_{a=2}^{30} \beta_a^{NS} NS_{ist}^a + \sum_{b=2}^{30} \beta_b^{NC} NC_{ist}^b + \sum_{c=2}^{31} \beta_c^{NSI} NSI_{ist}^c + \sum_{d=2}^{31} \beta_d^{NCI} NCI_{ist}^d + \gamma \mathbf{X}_{ist} + \delta_{st} + \epsilon_{ist}, \quad (6)$$

where NS_{ist}^a is a dummy for the firm i's number of suppliers at t being a, NC_{ist}^b is a dummy for the firm i's number of customers at t being b, NSI_{ist}^c is a dummy for the firm i's number of suppliers per industry at t being in the interval c, and NCI_{ist}^d is a dummy for the firm i's number of customers per industry at t being in the interval d. NS_{ist}^{30} and NC_{ist}^{30} means that the number of suppliers and customers is 30 or more, respectively. We classify the number of suppliers and customers per industry into 31 intervals with range of 0.1, from 1.0-1.1 to 3.9-4.0, and the interval of 4.0 or more. Vector $\mathbf{X}_{ist}$ means control variables representing firms' attributes including firm size, firm age, log of intangible assets, and log of TFP level relative to industry mean. We also control sector-specific semi-macro shock δst.

Our main interest is in β_a^{NS}, β_b^{NC}, β_c^{NSI}, and β_d^{NCI}. These values semi-parametrically capture how firm-level markup changes according to the number of suppliers and customers, with or without considering their industry components. The results are presented in Figure 3a. The circles mean the value of estimated coefficients β_a^{NS}, and so on. The navy lines show 95% confidence intervals and gray lines for 90% confidence intervals of each estimated coefficients. The definition of industry is 3-digit one, but we obtain the similar results when using 4-digit industry classification.

The upper-left panel depicts the result for β_a^{NS}. This graph shows a clear pattern of smaller values of β_a^{NS} for larger a. That is, firms' markups negatively correlate to the number of suppliers they transact. In contrast, the results for the number of customers do not have remarkable patterns. The upper-right panel is the results for β_b^{NC}. All of the estimated coefficients are insignificant (the confidence intervals range from negative to positive zones). The two lower-right panels are influenced by outliers and it is hard to see the pattern of estimated coefficients of β_c^{NSI} and β_d^{NCI}, but the truncated graphs shown in the two lower panels of Figure 3b show no remarkable patterns of estimated coefficients.

The sharp decreasing pattern of β_a^{NS} is confirmed even when we divide the sample into manufacturing and non-manufacturing. Figure 4a and Figure 4b (since the lower panels suffer from outliers in Figure 4b, we also present its truncated version in Figure 4c) are the results for manufacturing and non-manufacturing, respectively. In both figures, we can see the decreasing pattern of β_a^{NS}, though significance is weakened in Figure 4b. We can regard the negative correlation between markups and the number of suppliers as the stylized fact for the relation between firms' markups and transactional relationship.

As for the number of customers, we observe quite different pattern for manufacturing compared to non-manufacturing. In the upper-right panel of Figure 4a, evident increasing pattern of β_b^{NC} appears. In manufacturing, firms connecting to more customers have higher markups, especially in the range of small number of customers. The estimated values of β_b^{NC} increases as b grows up to eight, then levels off. Such a remarkable pattern of estimated β_b^{NC} is not observed for non-manufacturing as shown in the upper-right panel of Figure 4b.

We check the robustness of the main findings mentioned above. As compared to the number of suppliers, the number of suppliers' industries has various interpretation. It depends on substitutability and complementarity of intermediate input coming from different industries. Given this point, the interpretation of β_a^{NS} may be influenced by the components of industries of the suppliers. To deal with this issue, we confine the sample into observations with suppliers or customers from a single industry. Obviously this confinement heavily shrinks the sample size (less than one-tenth of the original sample) and leaves a rather biased subsample [7]. Nevertheless, we find the similar pattern for β_a^{NS}. The left panel of Figure 5a shows the results of estimating

$$\mu_{ist} = \sum_{a=2}^{11} \beta_a^{NS} NS_{ist}^a + \gamma \mathbf{X}_{ist} + \delta_{st} + \epsilon_{ist}. \tag{7}$$

for observations with suppliers coming from a single industry. Due to the small sample size, we include NS_{ist}^a up to $a = 10$ and a dummy for observations with

[7] By t test and Kolmogorov-Smirnov test, we find that these subsamples are different from the rest of our sample at the significance of 0.1%.

11 or more suppliers. Here we see the decreasing pattern of β_a^{NS} again. We also estimate a counterpart from 'customer side' of (7)

$$\mu_{ist} = \sum_{b=2}^{11} \beta_b^{NC} NC_{ist}^b + \gamma \mathbf{X}_{ist} + \delta_{st} + \epsilon_{ist}. \tag{8}$$

The result is shown in the right panel of Figure 5a and it is hard to find significant pattern of coefficients β_b^{NC}.

Figure 5b and 5c give the results for manufacturing and non-manufacturing, respectively. Since the subsample of manufacturing is very small (#obs=1,187), the pattern of β_b^{NC} becomes ambiguous. On the other hand, non-manufacturing gives the similar results to Figure 4c and Figure 5a.

We mention the results for other variables. Tables 4 to 6 reports the results about γ. Table 4 is the results of our basic equation (6). Table 5 and 6 are the results from our robustness checks. The results in Table 5 is based on estimations for the single-supplier-industry case (7) and Table 6 for the single-customer-industry case (8). These tables show the similar results on γ with a handful of exceptions, so we focus on the results in Table 4. Firm size and age are positively correlate to markups, and the correlation is significant for manufacturing. Higher TFP level also means higher markup level, while it is insignificant for non-manufacturing. Interestingly, the coefficient of intangible asset is significantly negative. Some studies such as Crouzet and Eberly (2021) and Eeckhout and Veldkamp (2022) emphasize the positive role of intangible assets for higher markups. The results in Table 4 discord with this line of literature. There are two things to notice. First, there are many studies [8] pointing out less active investment in and less effective utilization of intangible assets in Japan than in the US and Europe. Second, the definition of intangible assets here is based on what is adopted in financial reports. They include patent, mining rights, software, and so on, but do not include human capital and digital data collected through business activities. This conceptual issue may be a part of reason why intangible assets defined here do not enhance markup.

[8] For example, Miyagawa, et al. (2016).

5 The Number of Suppliers and Customers and Characteristics of the Transactional Partners

We find two stylized facts about the correlation of firms' markups and their transcational relation variables. First, a firm's markup is lower if the firm has more suppliers with controlling firm and industry attributes. Second, on the other hand, a firm's markup is higher if the firm has more customers with controlling firm and industry attributes, as for manufacturing. These findings are puzzling, because if a firm has many procurement sources, it should be able to suppress procurement cost and obtain the ground for higher markups.

To examine the factors behind these findings, we delve into the relation between the number and the types of transaction partners a firm has. Our main interest is in how *distant* or *different* from the firm its suppliers and customers are. Distance and difference is one of the key characterisitics of the relation between two firms.

We use four measures to evaluate distance and difference between a firm and its transaction partners. For all of them, we first evaluate distance or difference between firm i and a single supplier or customer of firm i, and then average them for all suppliers or customers of firm i to define the value for firm i. Our first measure is geographical distance. TSR data includes address of each firm. By using this information, we define two dummies: a dummy for the same prefecture and a dummy for the same region. A dummy for the same prefecture of firm i takes one if firm i and its supplier/customer locate in the same prefecture. A dummy for the same region is a dummy variables that firm i and its supplier/customer locate in the same region [9]. In the case of two or more suppliers/customers, we use mean values of these dummies, so our measure of geographic distance is the ratio of suppliers/customers located in the same prefecture or region as firm i. For a larger value of this measure, the suppliers/customers of firm i is geographically proximate to firm i on average. We call this variable 'suppliers' geographic proximity' if it is defined for firm i's suppliers, and 'suppliers' geographic proximity' for firm i's customers, hereafter.

Second, we look at technological distance based on Jaffe (1986). It is the distance of 'technological vector' for one firm and another. We define firm i's

[9] The definition of region follows that used in *Regional Economic Trend* (Chiiki Keizai Doukou) provided by Cabinet Office. It divides Japan into twelve regions: Hokkaido, Tohoku, Koshin-etsu, Kita-Kanto, Minami-Kanto, Tokai, Hokuriku, Kinki, Chugoku, Shikoku, Kyushu, and Okinawa.

technology vector F_i as one whose elements are the number of suppliers in each industry. Intuitively, if two firms procure their input from similar composition of industries, we think that they use similar production technology. The distance of technology vector between firm i and its supplier or customer firm j, T_{ij}, is defined as the uncentered correlation coefficient between F_i and F_j:

$$T_{ij} = \frac{F_i F_j}{\left(F_i F_i'\right)^{1/2} \left(F_j F_j'\right)^{1/2}}. \tag{9}$$

Tij ranges from zero to one. If firm i and firm j do not share any supplier industry, $T_{ij} = 0$. If T_{ij} is large, production technologies of firm i and firm j are resemblant. In the extreme case where the two firms' technology vector coincide, $T_{ij} = 1$. We call T_{ij} 'suppliers' technological proximity' or 'customers' technological proximity' if firm j is a firm i's supplier or customer, respectively.

The third measure is the counterpart of the second one. Instead of technology vector F_i, we define the vector of the number of customers by industry for firm i as G_i. This vector describes the composition of firm i's market. The distance of this 'market' vectors between two firms indicates market proximity, or market rivalry (Bloom, Schankerman, and van Reenen (2013)), between them. The uncentered correlation coefficient between G_i and G_j

$$S_{ij} = \frac{G_i G_j}{\left(G_i G_i'\right)^{1/2} \left(G_j G_j'\right)^{1/2}}. \tag{10}$$

is our measure of 'suppliers (customers)' market proximity' if firm j is a firm i's supplier (customer).

Forth, we also pay attention to the relative size of firm i's suppliers or customers by examining log difference of the number of employment: $\ln L_j - \ln L_i$, where firm j is a firm i's supplier or customer.

We regress one of these distance or difference measures, D, on the set of dummies NS^a or NC^b with controlling year dummies and industry dummies:

$$D^S_{ist} = a + \sum_{a=2}^{30} \delta^{NS}_a NS^a_{ist} + \lambda^S_t + \mu^S_s \tag{11}$$

or

$$D^C_{ist} = a + \sum_{b=2}^{30} \delta^{NC}_b NC^b_{ist} + \lambda^C_t + \mu^C_s, \tag{12}$$

and investigate the patterns of estimated δ_a^{NS} and δ_b^{NC}. D^S means the distance or difference measure defined for the supplier side (proximity of suppliers for firm i, etc.), and D^C for the customer side (proximity of customers for firm i, etc.). We also control the size of firm i (log of firm i's employment) except for the analysis of firm size difference, since the number of suppliers and customers positively correlate to firm size.

The results are summarized in Figure 6 to Figure 9. Figure 6a and 6b shows positive correlation between geographical proximity of suppliers and the number of suppliers, that is, a firm with many suppliers connects to suppliers closely located. The correlation of the number of customers and the customers' geographical proximity is ambiguous. As for the same-prefecture dummies, we see negative correlation, but the correlation is unclear for the same-region dummies.

In Figure 7, the estimated coefficients are larger for the large number of suppliers and customers. A firm with more suppliers or customers has more similar technology to its suppliers or customers on average. The similar pattern is observed for suppliers' market proximity as shown in Figure 8. If a firm has more suppliers, the output market composition of those suppliers are proximate to the firm's one. Customers' market proximity exhibits a different pattern. The graph is an invert-U shape with the peak at 19.

Finally, when a firm has more suppliers or customers, the relative size of those suppliers and customers is smaller (Figure 9). This is consistent with the fact that the number of suppliers or customers positively correlate to the firm size.

In order to explain the correlation between markup and the number of suppliers or customers demonstrated in the previous section, we also need to provide explanation consistent with the above-mentioned findings. For example, when a firm is small and procure from a small number of suppliers, they may produce specialized goods from intermediates that is technologically distinct from the goods, then sell customers whose market belongs to a different industry. This specialty of the goods may allow the firm to exert higher markup. As the firm succeeds in the product market and grows larger, it may outsource the significant part of production to technologically proximate suppliers, while its markup may be suppressed. This is just one of possible hypotheses. Further investigation is necessary.

6 Concluding Remarks

This paper examine the relationship of markups and the states of transactional relationship for Japanese firms based on a comprehensive dataset of Japanese firms. We find the robust negative correlation between markups and the number of suppliers, after controlling the firm's characteristics such as firm size, age, intangible assets, and TFP, and industry-specific year effects. It is important to consider the relation to upstream firms, when enhancing markups for Japanese firms. On the other hand, the number of customers has a significantly positive correlation to markups only for manufacturing firms.

The fact that a firm with many suppliers has a lower markup indicates necessity of further investigation, because procurement from suppliers competing with each other does not lead to the larger margin of profit. One possible explanation is selection and concentration of procurement to a small number of suppliers. Firms may be able to enhance markups using cost advantage created by rationalizing procurement.

The findings in Section 4 indicates the mere number of suppliers is insufficient to explain the variation of firms' markup. In Section 5, we delve into the characteristics of suppliers and customers, and how they differ in accordance with the number of suppliers or customers. This examination provides the basis for the further investigation. To tackle this issue, we propose one possible explanation at the end of the section.

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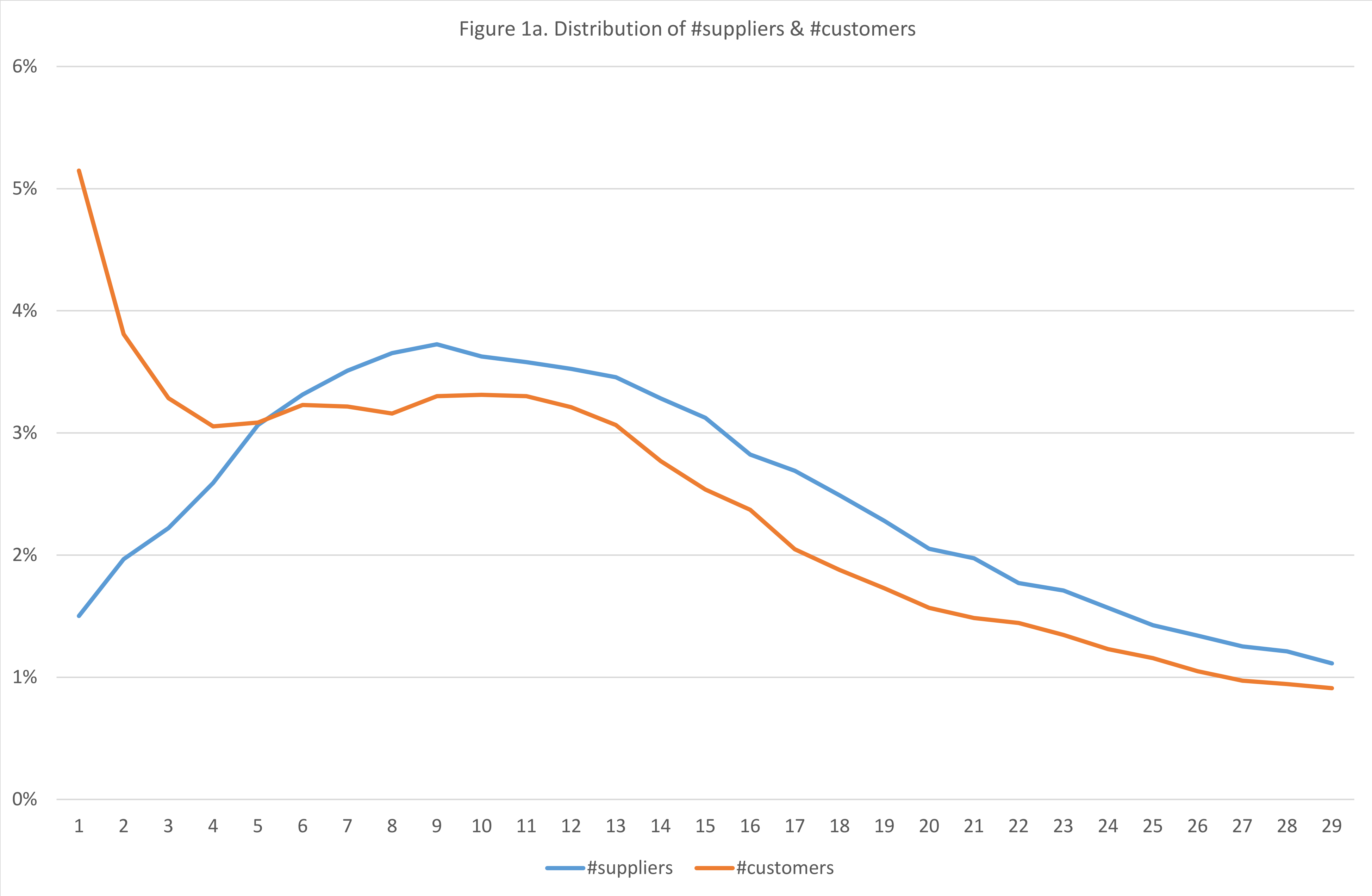


Figure 1a. Distribution of #suppliers & #customers
6%
5%
4%
3%
2%
1%
0%
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29
#suppliers
#customers

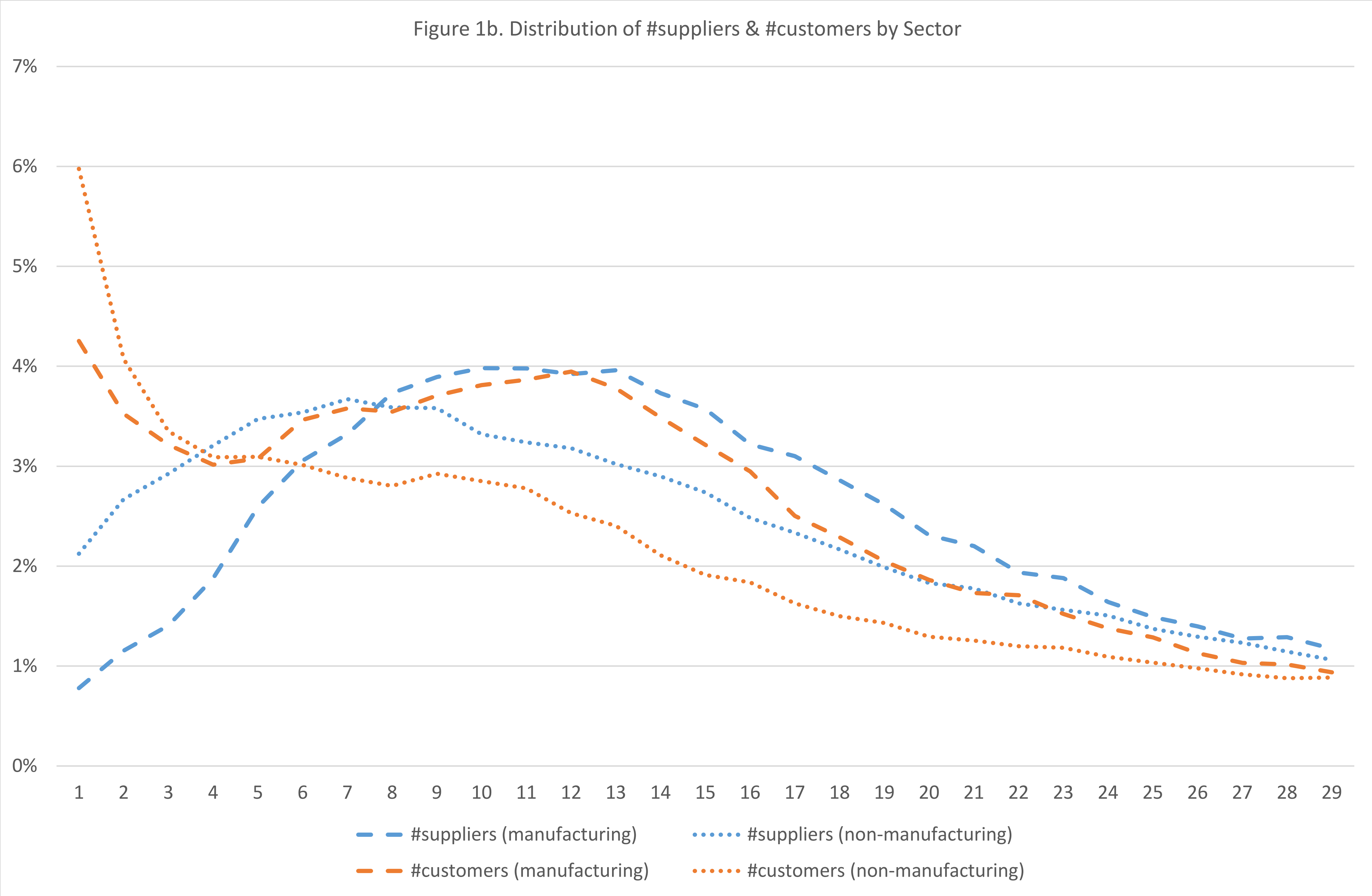


Figure 1b. Distribution of #suppliers & #customers by Sector
7%
6%
5%
4%
3%
2%
1%
0%
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29
#suppliers (manufacturing)
#suppliers (non-manufacturing)
#customers (manufacturing)
#customers (non-manufacturing)

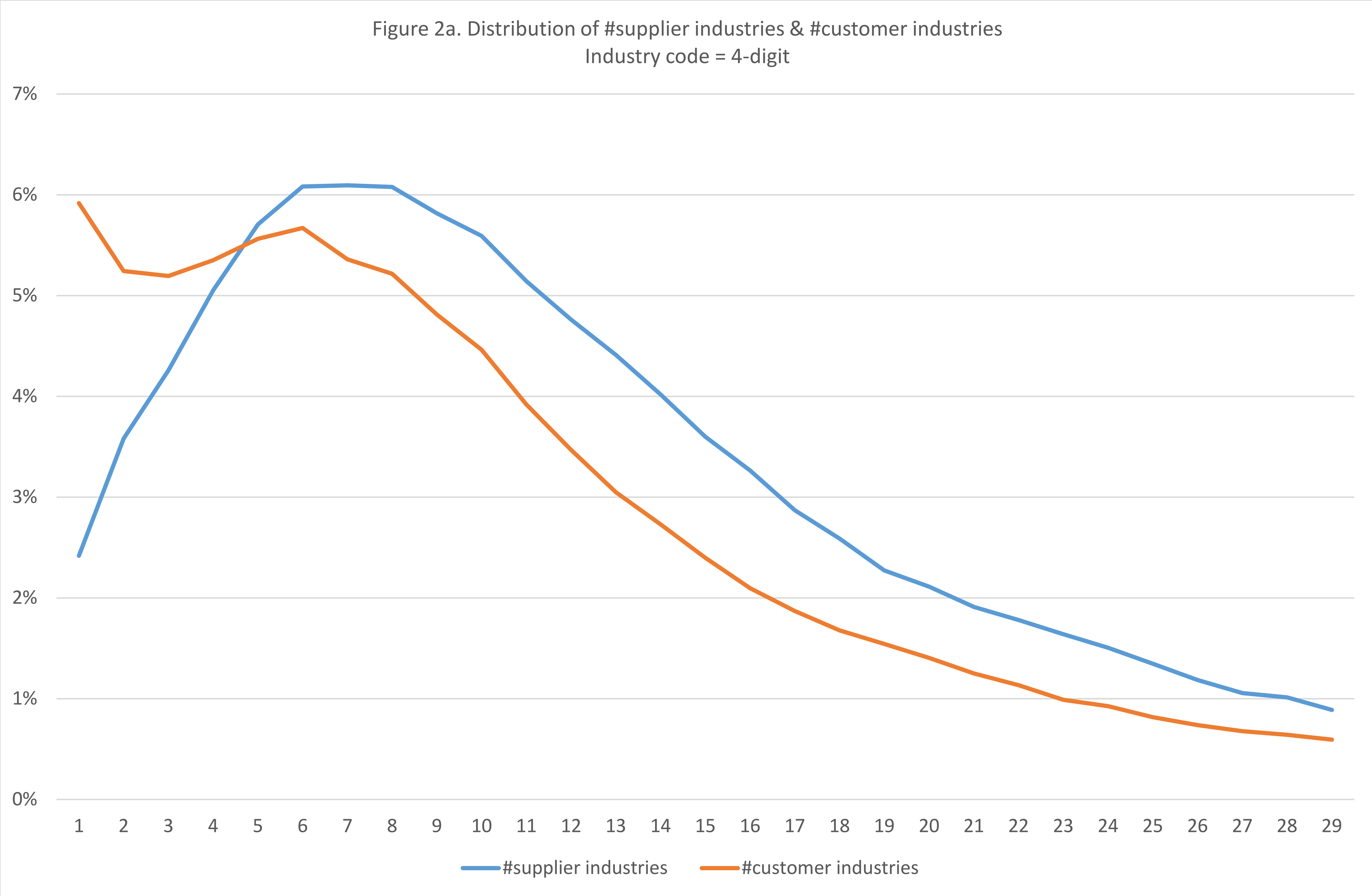


Figure 2a. Distribution of #supplier industries & #customer industries
Industry code = 4-digit
7%
6%
5%
4%
3%
2%
1%
0%
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29
#supplier industries
#customer industries

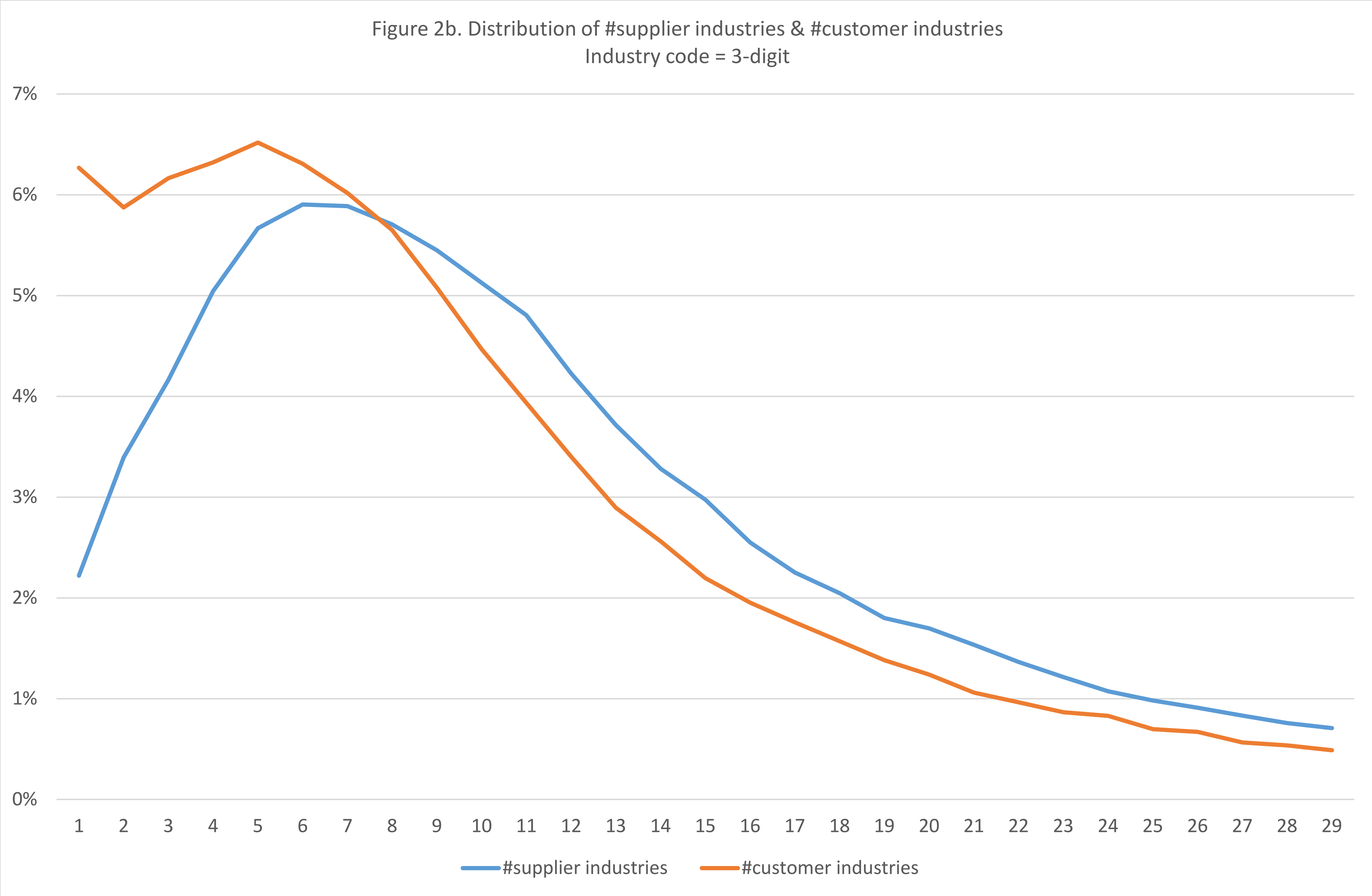


Figure 2b. Distribution of #supplier industries & #customer industries
Industry code = 3-digit
7%
6%
5%
4%
3%
2%
1%
0%
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29
#supplier industries
#customer industries

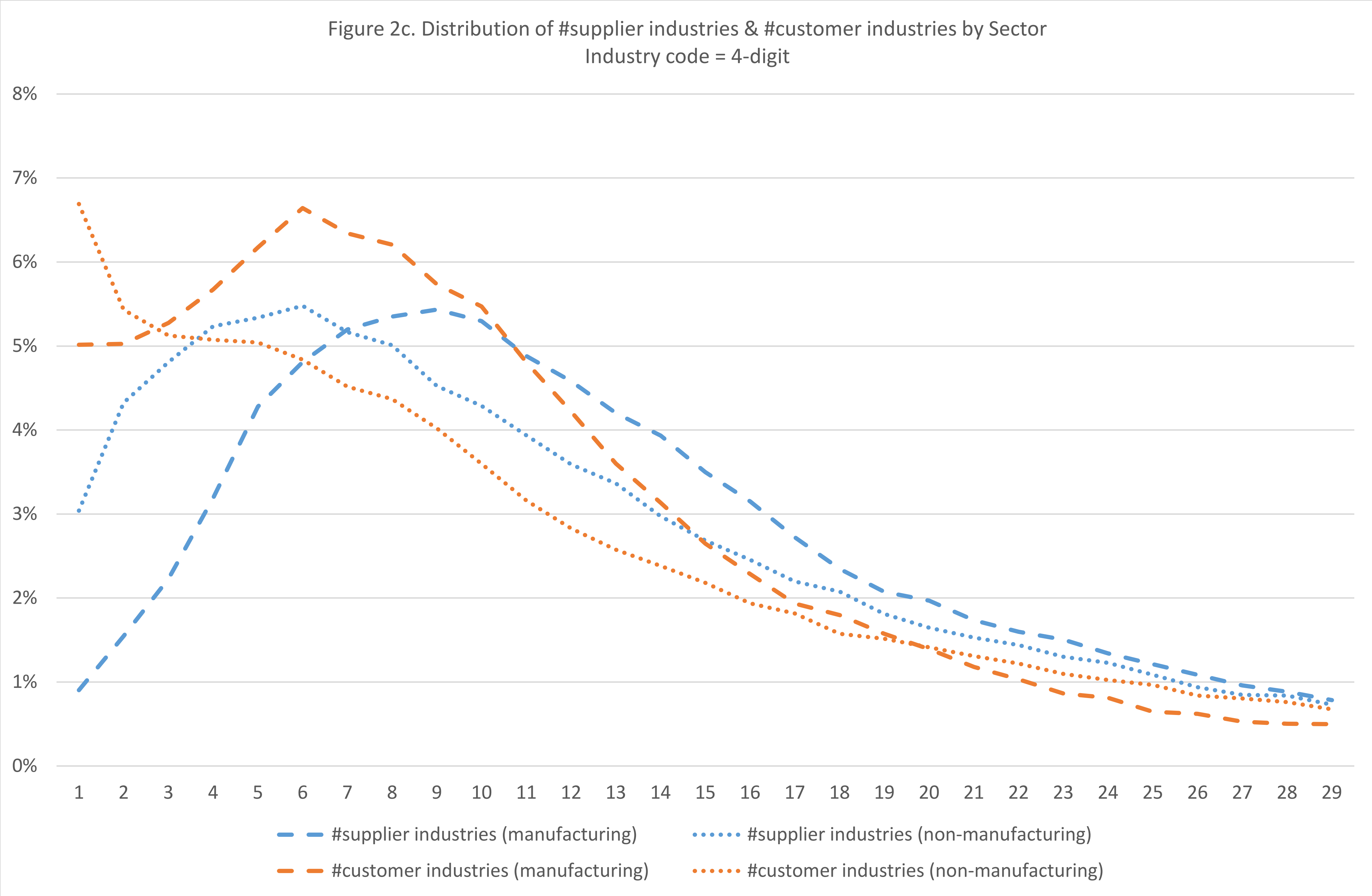


Figure 2c. Distribution of #supplier industries & #customer industries by Sector
Industry code = 4-digit
8%
7%
6%
5%
4%
3%
2%
1%
0%
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29
#supplier industries (manufacturing)
#supplier industries (non-manufacturing)
#customer industries (manufacturing)
#customer industries (non-manufacturing)

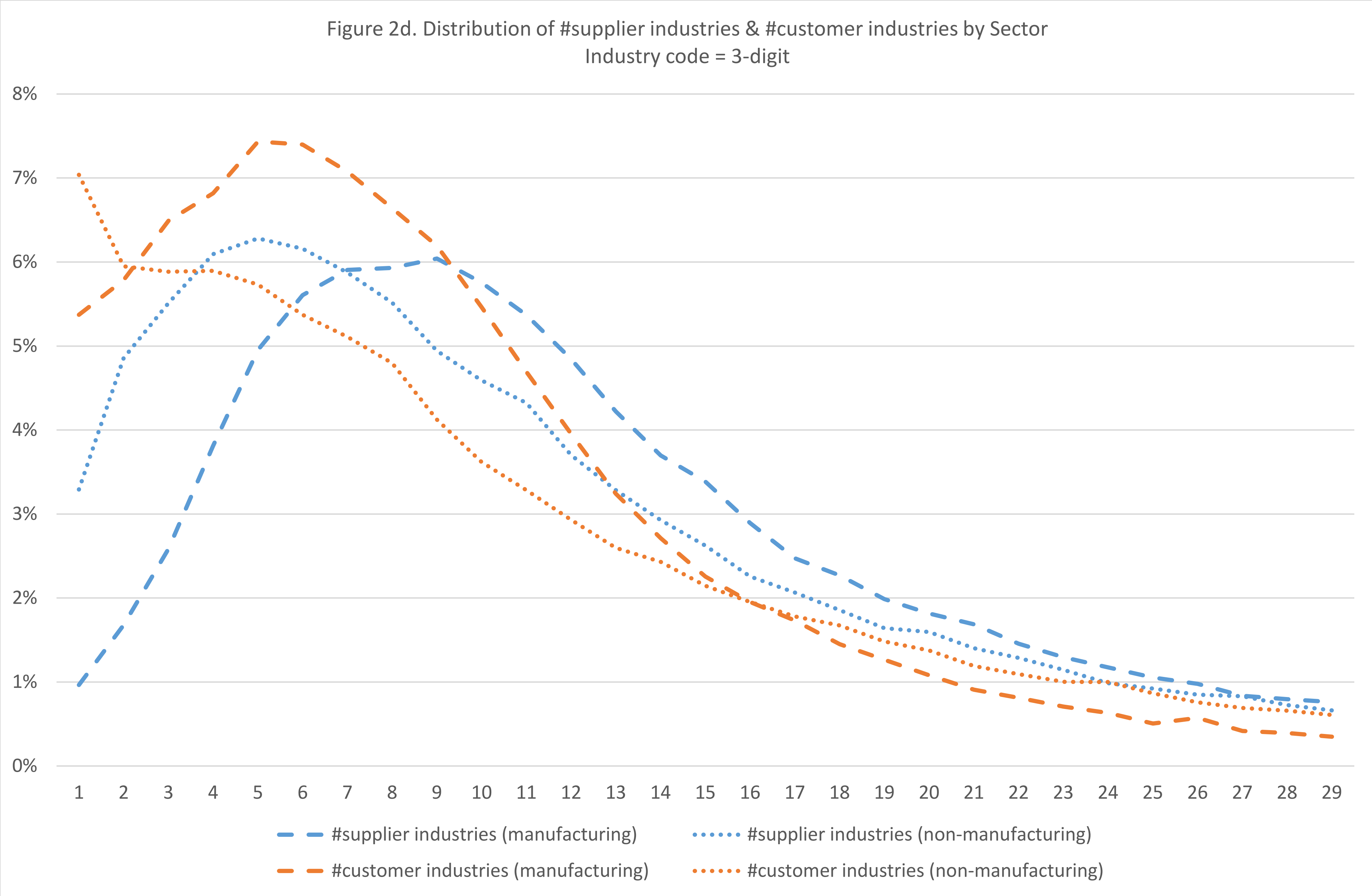


Figure 2d. Distribution of #supplier industries & #customer industries by Sector
Industry code = 3-digit
8%
7%
6%
5%
4%
3%
2%
1%
0%
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29
#supplier industries (manufacturing)
#supplier industries (non-manufacturing)
#customer industries (manufacturing)
#customer industries (non-manufacturing)

Figure 3a. Estimation Results of Coefficients for Transaction Variables: All Industries

Figure 3b. Estimation Results of Coefficients for Transaction Variables: All Industries

* The lower panels truncate the range of x-axis between -1 and 1.

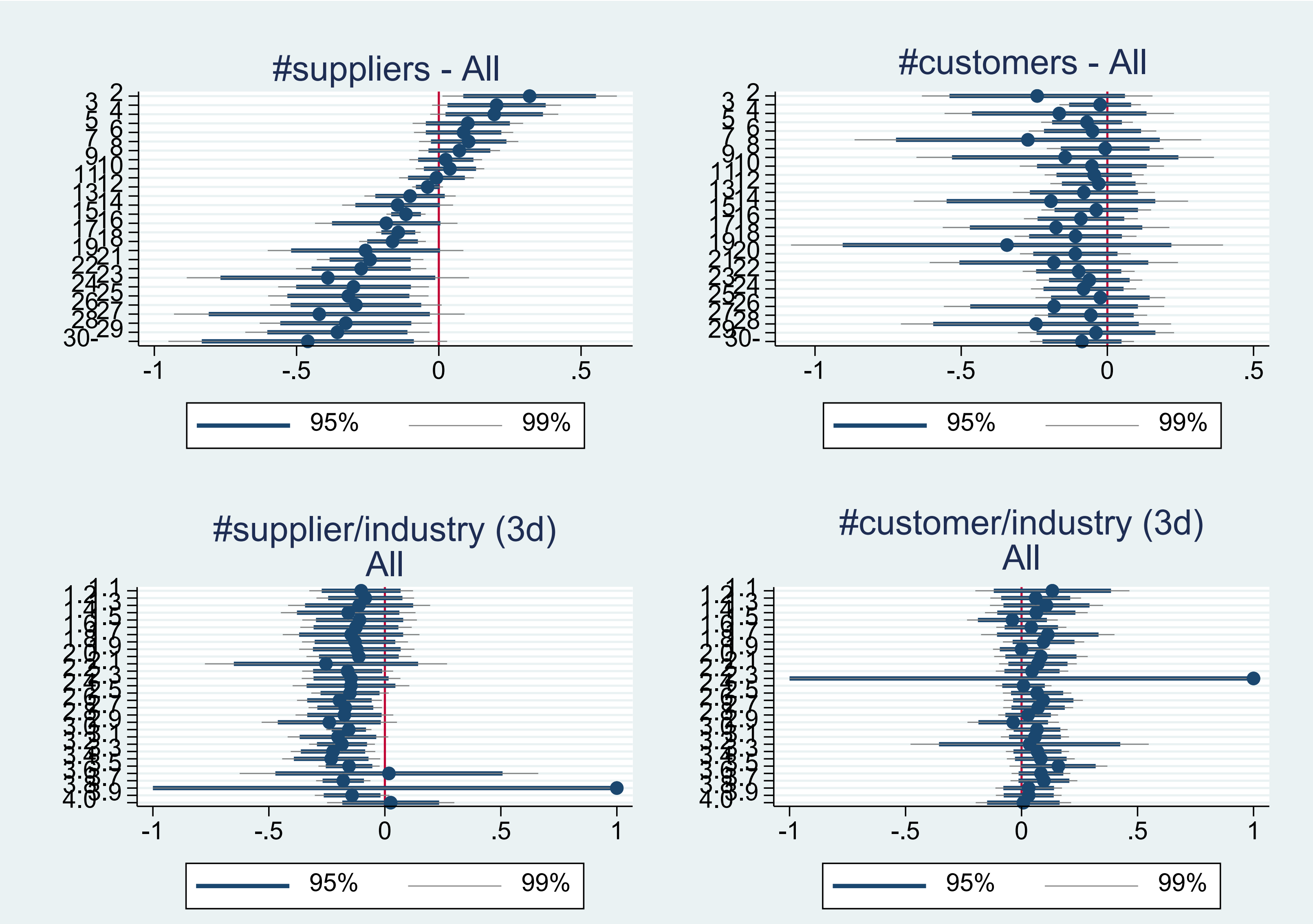


Figure 4a. Estimation Results of Coefficients for Transaction Variables: Manufacturing

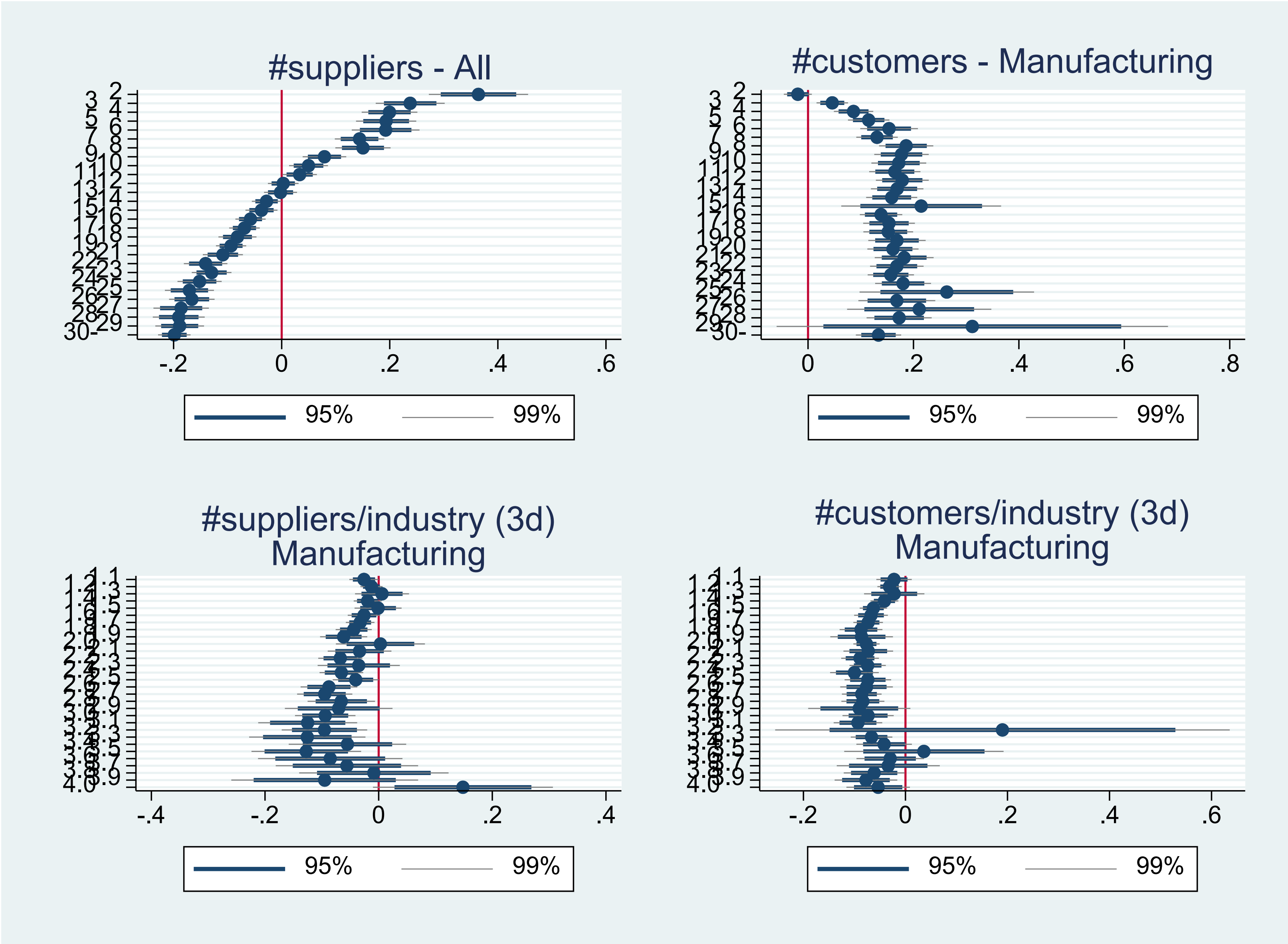


Figure 4b. Estimation Results of Coefficients for Transaction Variables: Non-Manufacturing

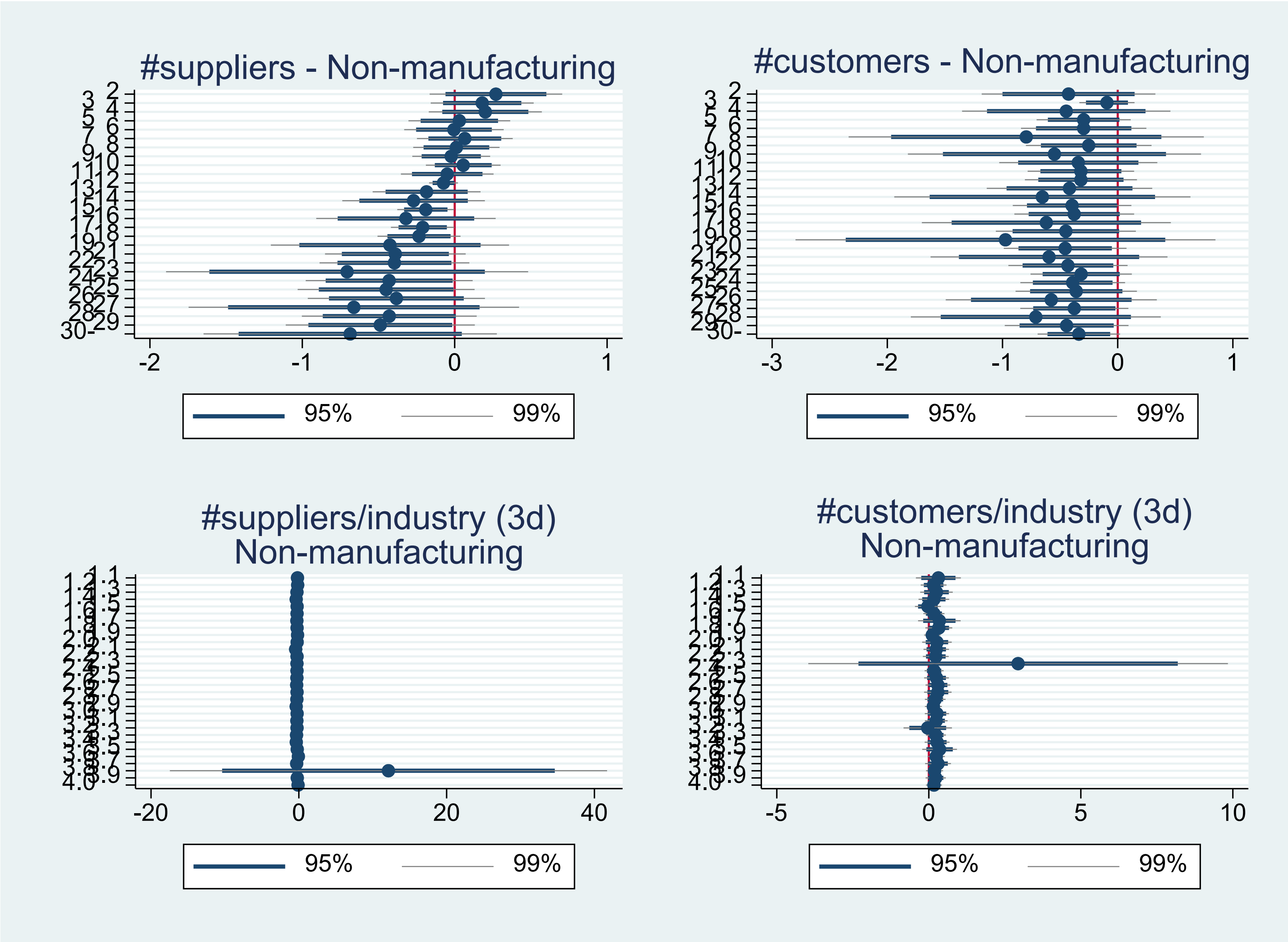


Figure 4c. Estimation Results of Coefficients for Transaction Variables: Non-Manufacturing

* The lower panels truncate the range of x-axis between -1 and 1.

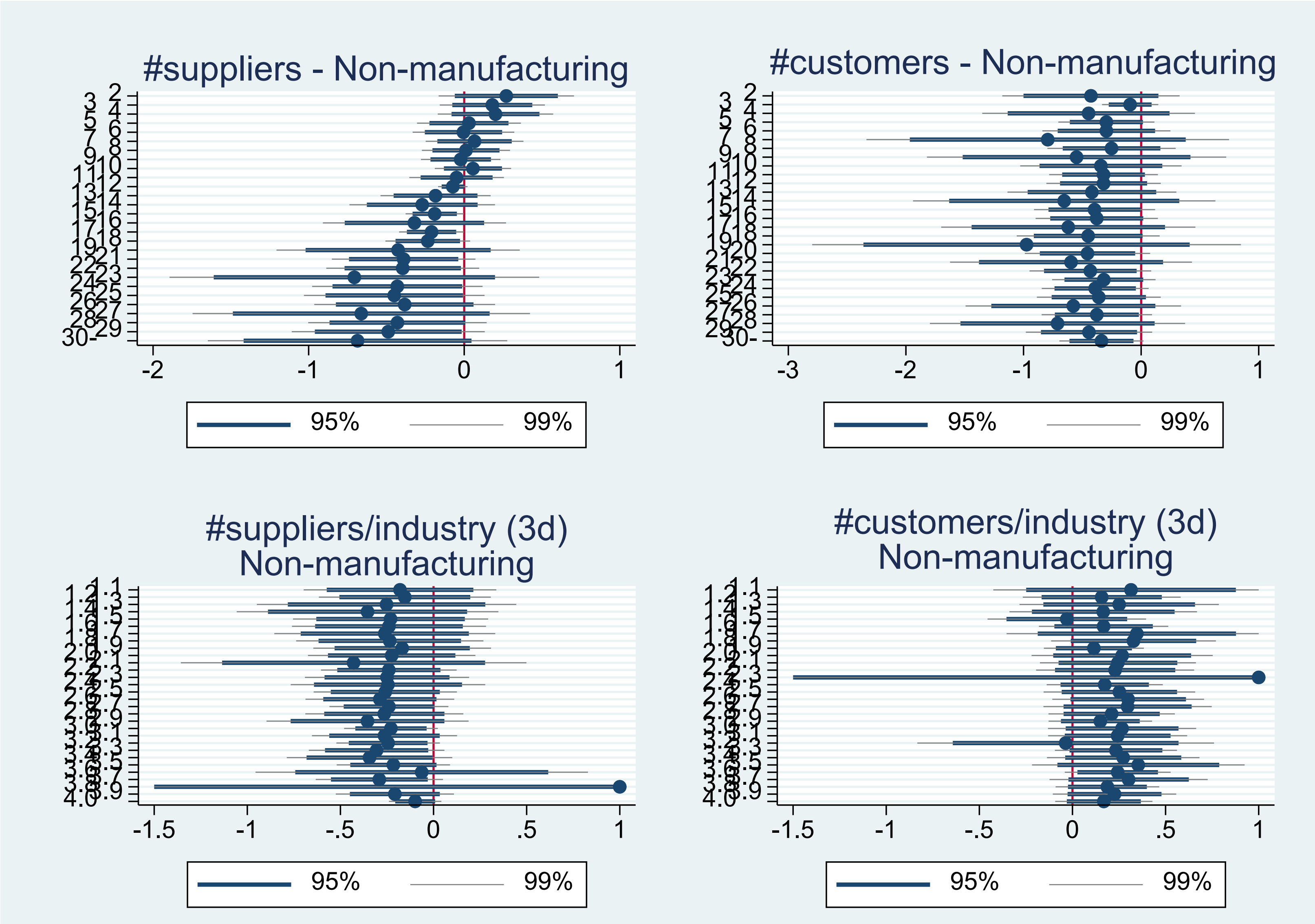


Figure 5a. Estimation Results of Coefficients for Transaction Variables: All Industries

* Subsample of a single supplier industry, or a single customer industry

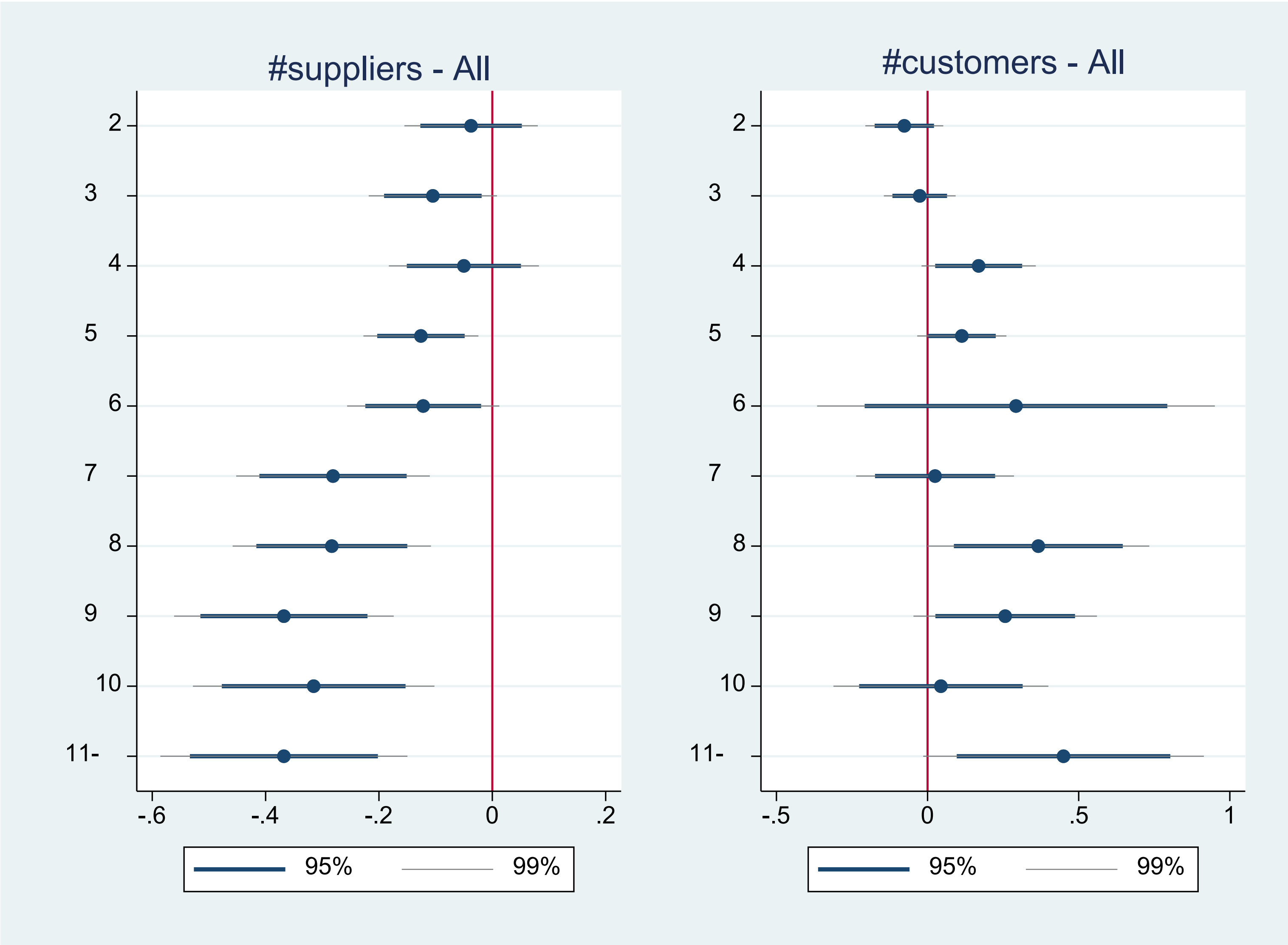


Figure 5b. Estimation Results of Coefficients for Transaction Variables: Manufacturing

* Subsample of a single supplier industry, or a single customer industry

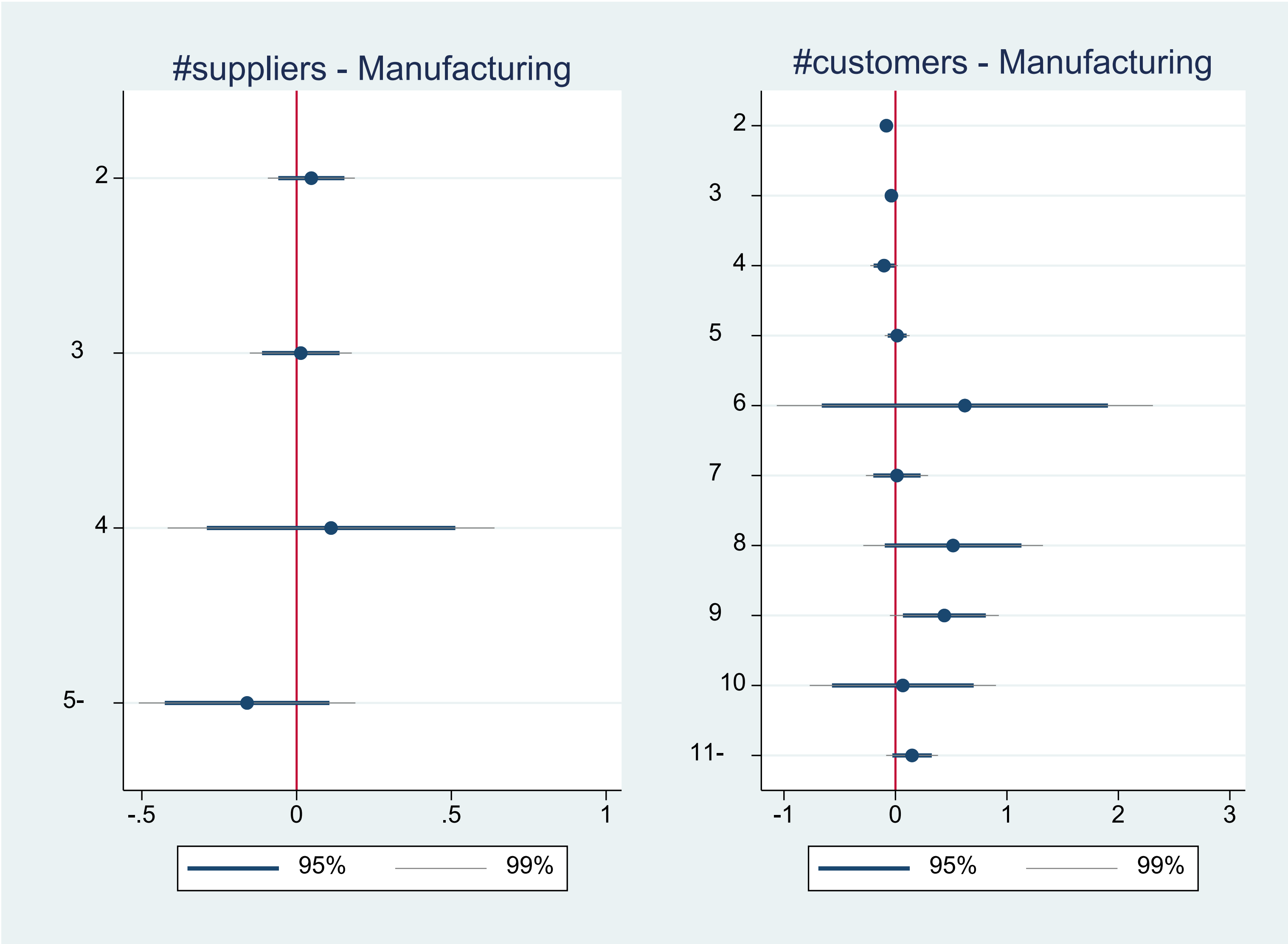
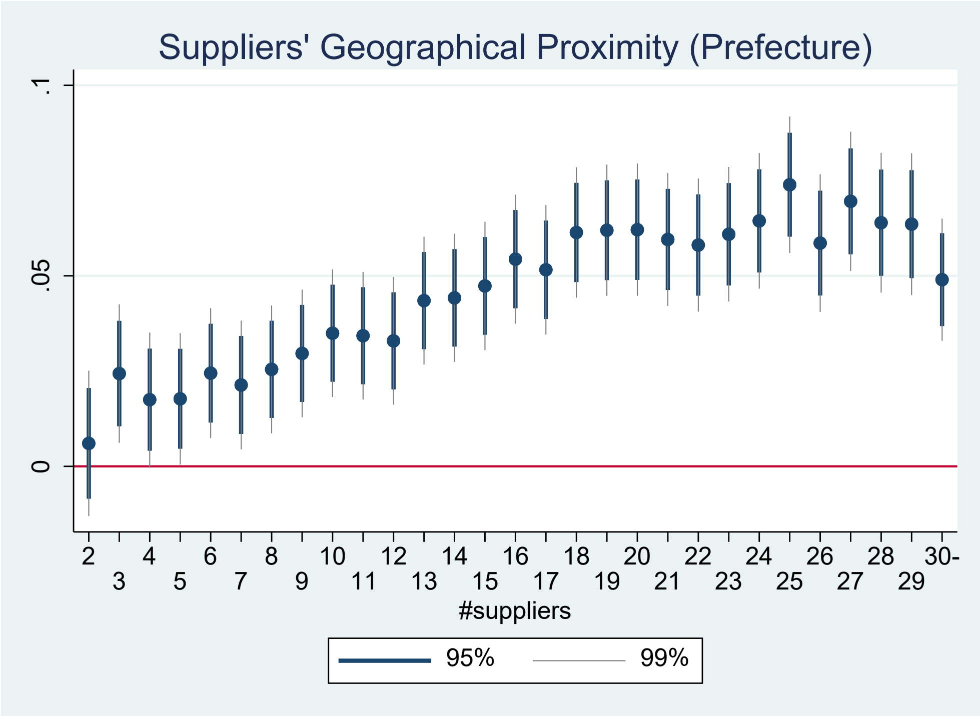


Figure 5c. Estimation Results of Coefficients for Transaction Variables: Non-Manufacturing

* Subsample of a single supplier industry, or a single customer industry

Figure 6a. Correlation between #transactional partners & Geographical Proximity - Same-prefecture



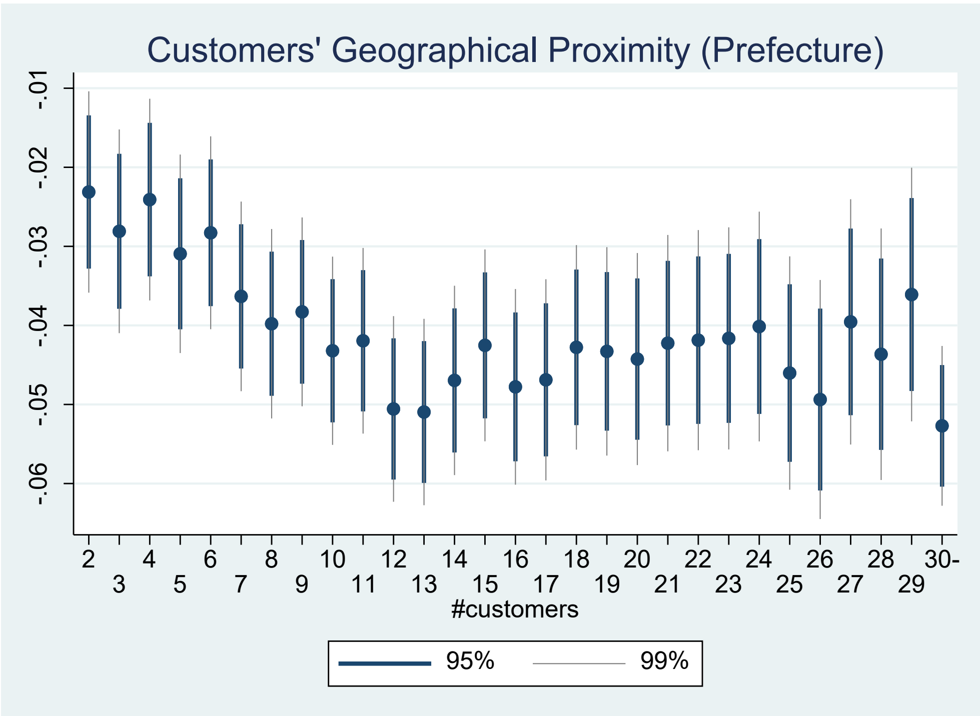
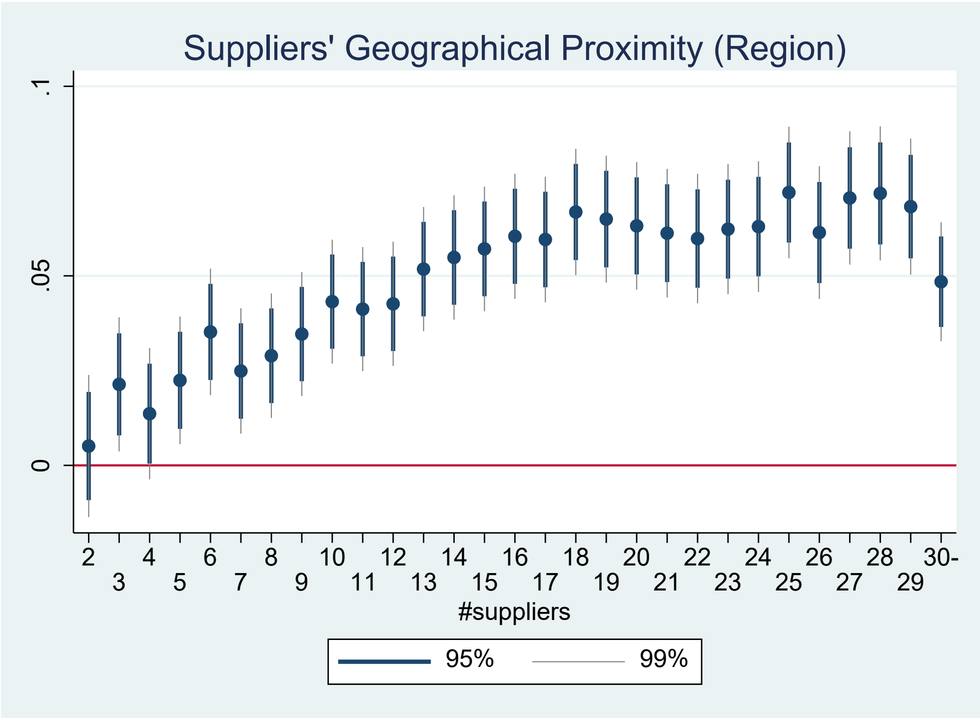


Figure 6b. Correlation between #transactional partners & Geographical Proximity - Same-region



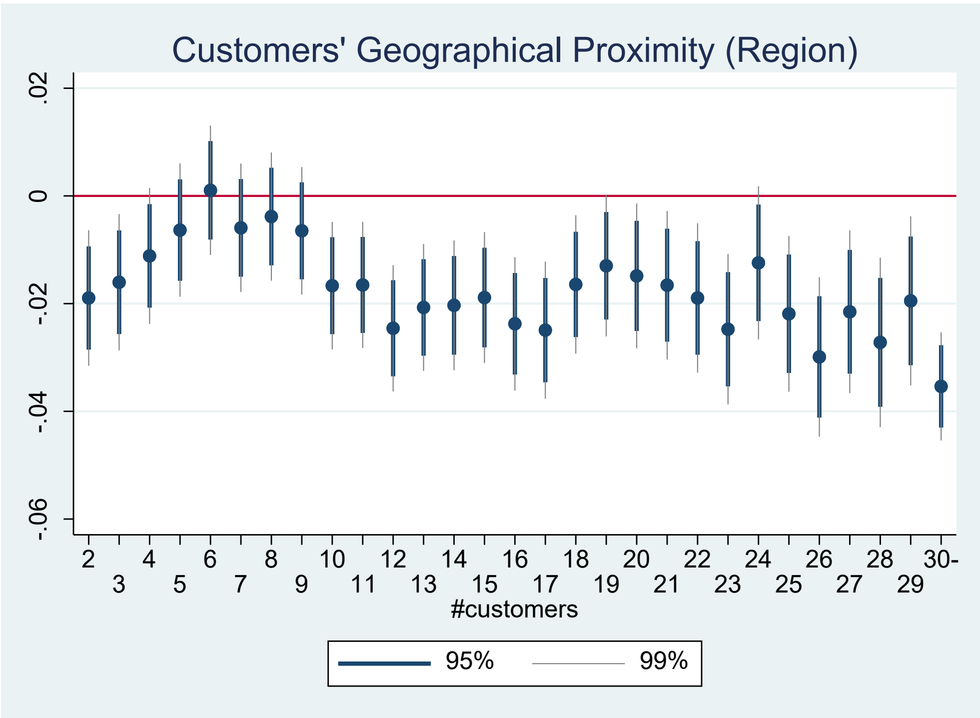
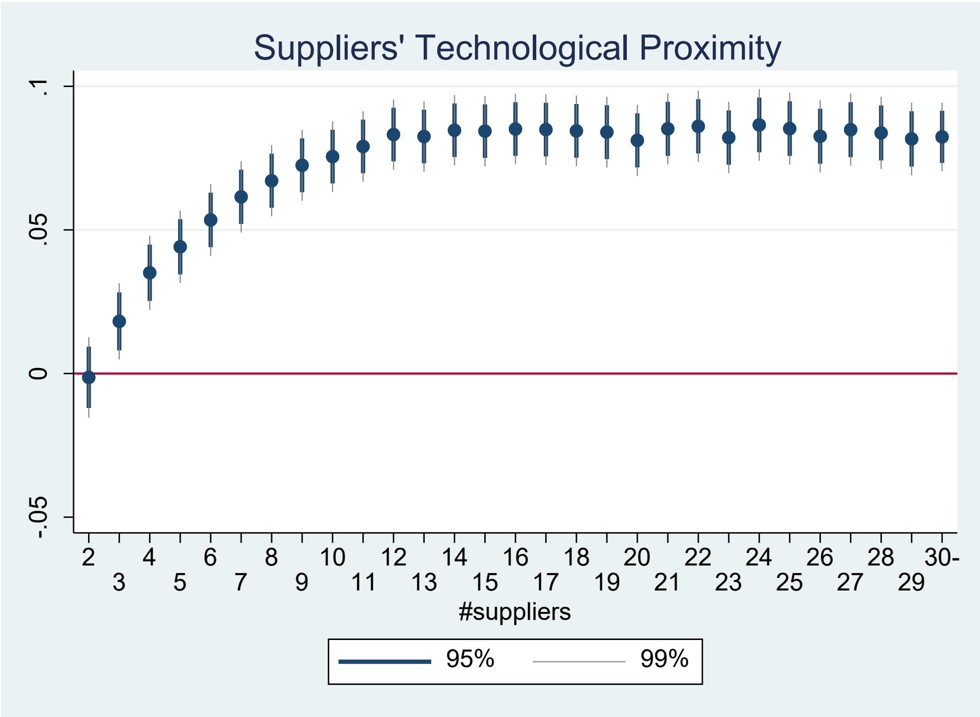


Figure 7. Correlation between #transactional partners & Technological Proximity



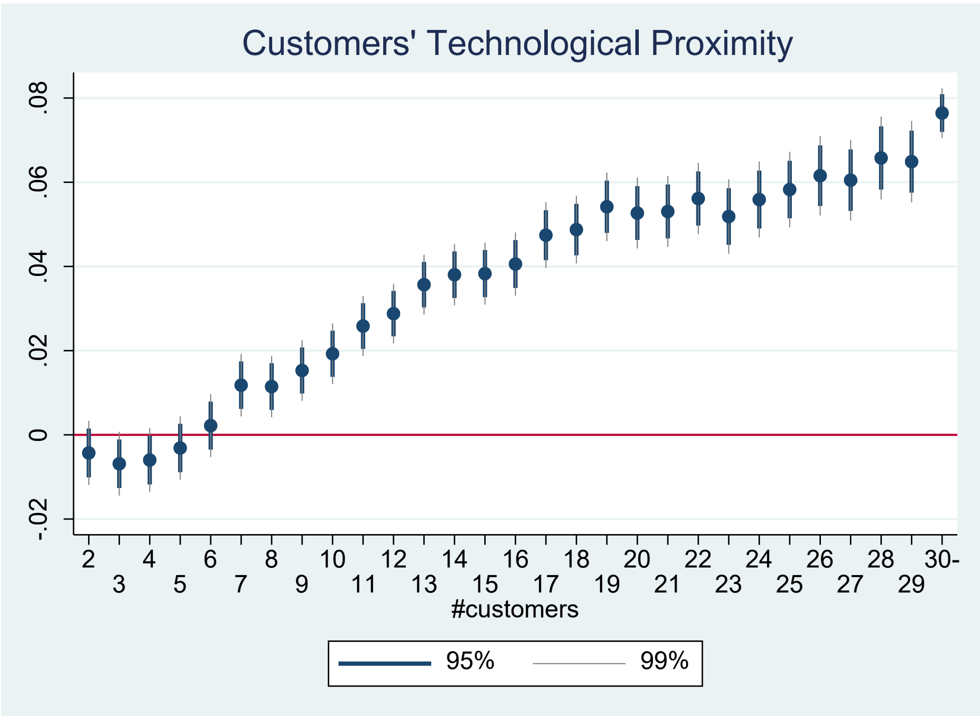
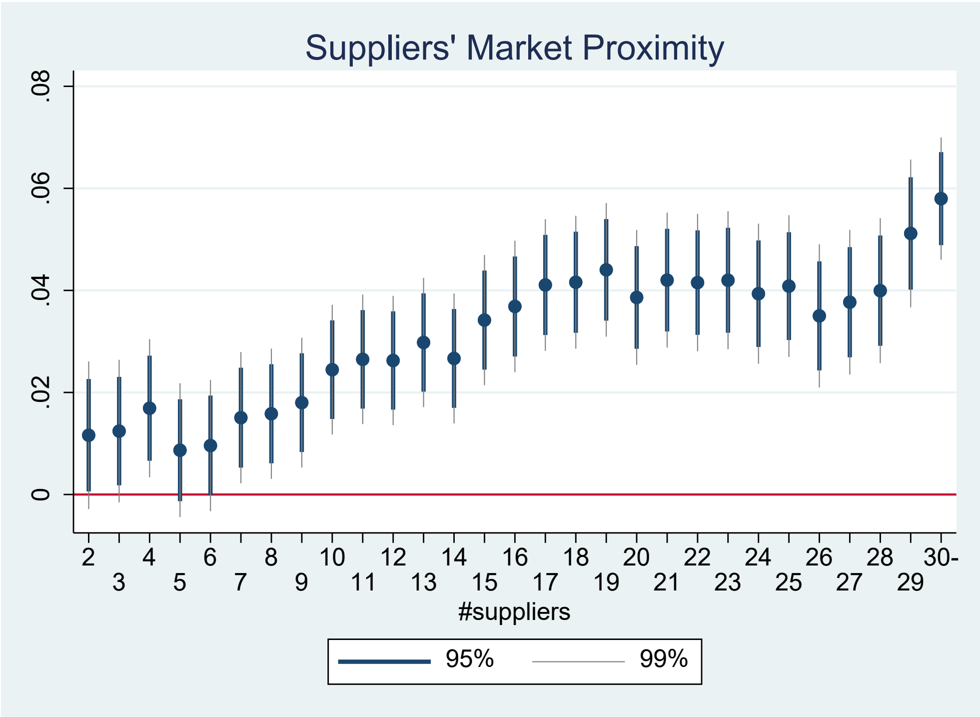


Figure 8. Correlation between #transactional partners & Market Proximity



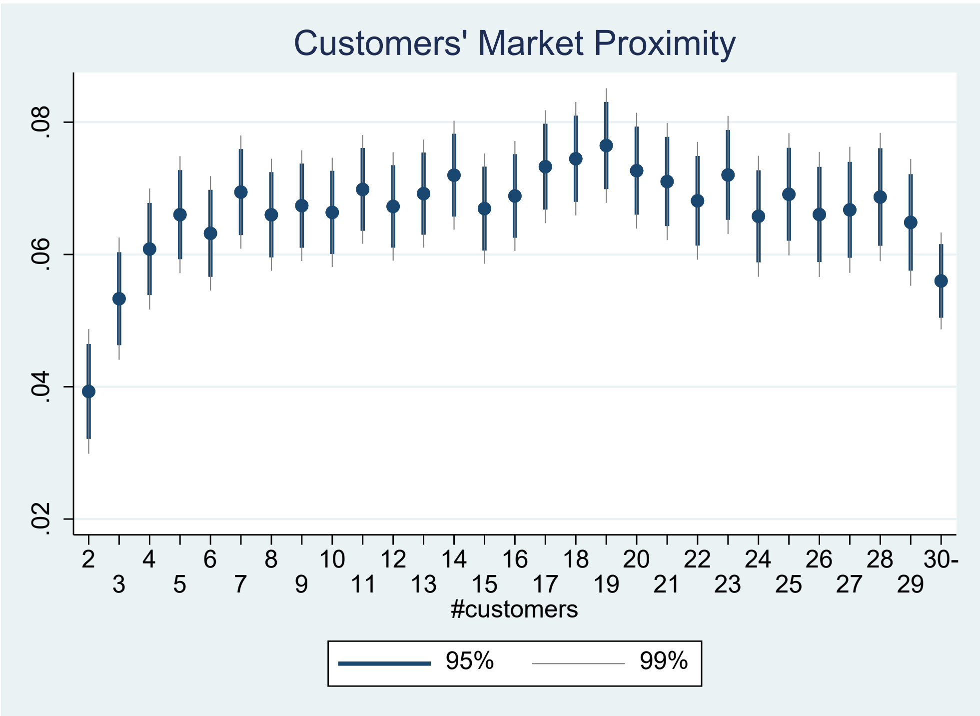
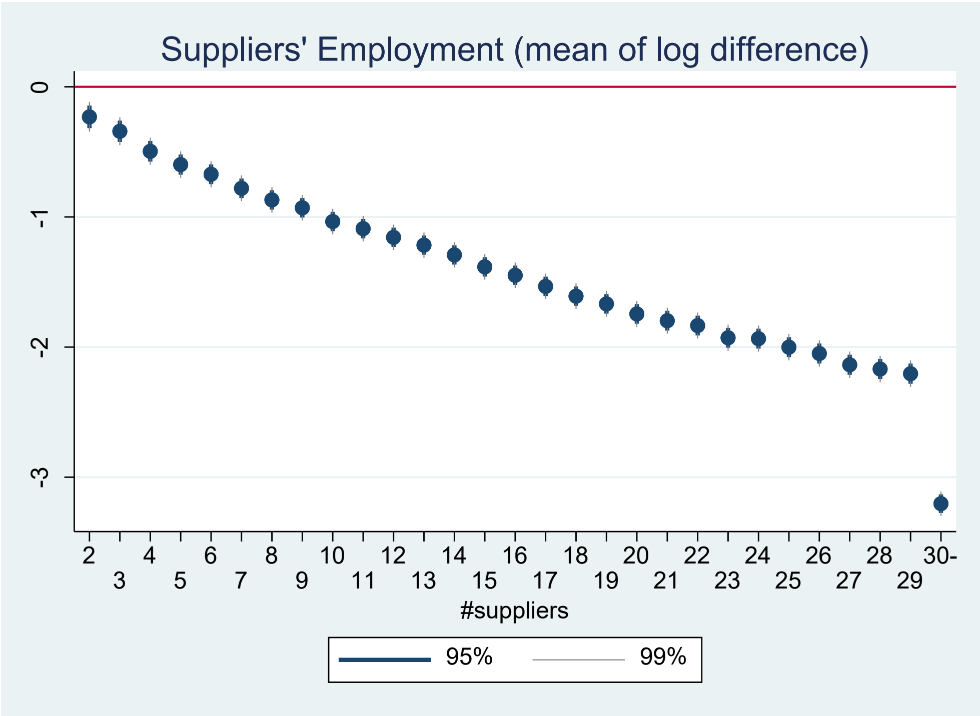


Figure 9. Correlation between #transactional partners & Relative Firm Size



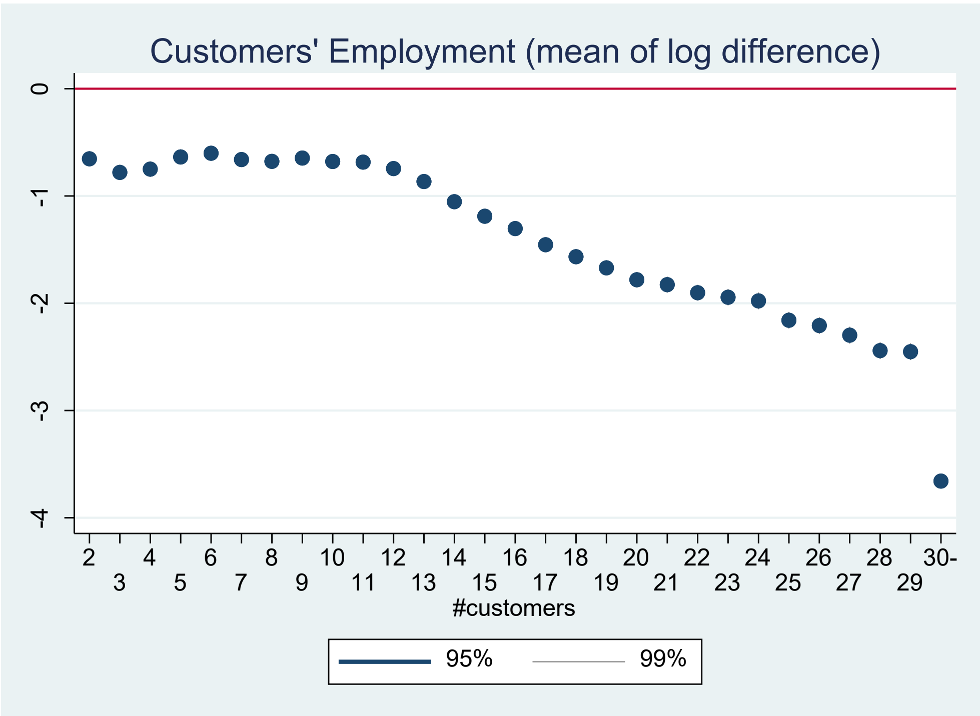


Table 1. Distribution of Estimated Markups

	Before Screening	After Screening
N	341,439	297,448
Mean	1.118	1.188
SD	11.985	11.816
Min	-1470.762	0.002
p1	0.341	0.410
p5	0.649	0.672
p10	0.763	0.779
p25	0.912	0.921
p50	1.057	1.062
p75	1.232	1.234
p90	1.500	1.495
p95	1.810	1.795
p99	3.266	3.198
Max	6392.781	6392.781

Table 2. Descriptive Statistics of Variables Used in Production Function Estimation

	N	Mean	p50	Min	Max	SD
sales (real value)	494,636	25548.9	4982.0	6.8	12209546.2	166985.7
variable input (real value)	494,636	18970.6	2988.9	0.9	11780673.2	146028.6
number of employees	494,636	445.9	145.0	1.0	153405.0	1830.8
tangible asset	494,636	7442.2	908.0	1.0	11906138.0	96187.6

Unit of sales, variable input (COGS less labor cost), and tangible asset are 1 million yen. Unit of number of employees is person.

Table 3. Descriptive Statistics of Variables Used in Markup Equation Estimation

	N	Mean	p50	Min	Max	SD
Number of suppliers	314,294	40.37	15.00	0.00	7477.00	157.77
Number of customers	314,294	44.53	13.00	0.00	12729.00	163.76
Number of suppliers' industries (4-digit)	307,233	18.54	11.00	0.00	552.00	27.88
Number of customers' industries (4-digit)	293,320	13.73	9.00	0.00	570.00	19.00
Number of suppliers' industries (3-digit)	307,233	15.05	10.00	0.00	270.00	18.42
Number of customers' industries (3-digit)	293,320	11.17	8.00	0.00	254.00	12.94
Number of suppliers per industry (4-digit)	306,973	1.61	1.40	1.00	21.68	0.89
Number of customers per industry (4-digit)	292,894	2.34	1.64	1.00	59.58	2.34
Number of suppliers per industry (3-digit)	306,973	1.89	1.57	1.00	37.39	1.34
Number of customers per industry (3-digit)	292,894	2.82	1.88	1.00	104.00	3.20
firm size (log of number of employees)	321,461	5.26	5.02	0.00	11.79	1.08
firm age	321,359	43.98	45.00	-7.00	302.00	20.75
log of TFP	297,448	3.64	3.69	-2.92	9.93	1.16
log of TFP - log of TFP (industry mean)	297,448	0.00	0.00	-2.44	4.21	0.19

Table 4. Estimation Results for Firms' Characteristics Variables

	[A]		[B]		[C]	
	Coef	Std Err	Coef	Std Err	Coef	Std Err
Firm Size	0.098	0.078	0.130[a]	0.012	0.075	0.128
Firm Age	0.005	0.003	0.002[a]	0.000	0.009	0.007
ln(Intangible Assets)	-0.024[a]	0.007	-0.012[a]	0.003	-0.027[a]	0.010
ln(TFP) - industry mean of ln(TFP)	3.702[c]	2.150	1.879[a]	0.348	4.711	3.303
Industries	All		Manufacturing		Non-manufacturing	
Nobs	252,801		122,224		130,577	
Adj. R-sq	0.060		0.083		0.060	

Standard errors are based on the robust estimator of variance.

a: signifincant at 1%, b: signifincant at 5%, and c: signifincant at 10%.

A dummy for using financial report data is omitted from this table. Its estimated coefficient is insignificant in all cases.

Industry-specific year effects are also included in the estimations.

Table 5. Estimation Results for Firms' Characteristics Variables: Single-Supplier-Industry Cases

	[A]		[B]		[C]	
	Coef	Std Err	Coef	Std Err	Coef	Std Err
Firm Size	0.378[a]	0.028	0.224[a]	0.054	0.395[a]	0.030
Firm Age	0.004[a]	0.001	0.002[b]	0.001	0.004[a]	0.001
ln(Intangible Assets)	-0.054[a]	0.014	-0.046[a]	0.014	-0.054[a]	0.016
ln(TFP) - industry mean of ln(TFP)	0.007	0.464	0.328	0.371	-0.032	0.519
Industries	All		Manufacturing		Non-manufacturing	
Nobs	5,927		1,187		4,740	
Adj. R-sq	0.149		0.668		0.133	

Standard errors are based on the robust estimator of variance.

a: signifincant at 1%, b: signifincant at 5%, and c: signifincant at 10%.

A dummy for using financial report data is omitted from this table. Its estimated coefficient is significantly positive for [A] and [C] while insignificantly negative for [B].

Industry-specific year effects are also included in the estimations.

Table 6. Estimation Results for Firms' Characteristics Variables: Single-Customer-Industry Cases

	[A]		[B]		[C]	
	Coef	Std Err	Coef	Std Err	Coef	Std Err
Firm Size	0.207[a]	0.031	0.075	0.054	0.271[a]	0.039
Firm Age	0.000	0.001	0.003[a]	0.001	-0.002	0.003
ln(Intangible Assets)	-0.062[a]	0.021	-0.033[a]	0.007	-0.076[b]	0.031
ln(TFP) - industry mean of ln(TFP)	0.301	0.311	1.270	0.705	0.053	0.342
Industries	All		Manufacturing		Non-manufacturing	
Nobs	16,749		6,627		10,122	
Adj. R-sq	0.039		0.088		0.042	

Standard errors are based on the robust estimator of variance.

a: signifincant at 1%, b: signifincant at 5%, and c: signifincant at 10%.

A dummy for using financial report data is omitted from this table. Its estimated coefficient is significantly positive for [A] and [B] while insignificantly positive for [C].

Industry-specific year effects are also included in the estimations.