RIETI Discussion Paper Series 19-E-107

Linkage of Markups through Transaction

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https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 19-E-107
December 2019

Linkage of Markups through Transaction*

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Abstract

This paper analyzes how a firm's markup correlates to its suppliers' markups. Our research targeted more than 40,000 Japanese firms during 2001-16. The dataset is based on the Basic Survey of Japanese Business Structure and Activities, provided by METI, and supplemented by data from financial reports. Transactional relationships between firms are provided by the Firm Relation File, 2006, 2007, 2011, 2012, 2014, TSR. Markup values are estimated by the so-called 'production approach' proposed by De Loecker and Warzynski (2012) and De Loecker, Eeckhout, and Unger (2018). Controlling for firm characteristics such as productivity and age, and year- and industry-specific factors, a firm's markup has a significantly negative correlation with its suppliers' markups. For the entire sample, a firm whose suppliers observe 10% point higher markups has 2% point lower markup on average. This negative correlation is more remarkable for non-manufacturing firms than manufacturing ones. We discuss the factors for variation within Japanese firms' markups that produce these results.

Keywords: markup, vertical relation of firms, transaction between firms
JEL classification: L11, L13, L16, O33

*This study is conducted as a part of the Project "Policy Analyses on Industrial Organization" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). This study utilizes the micro data of the questionnaire information based on "the Basic Survey of Japanese Business Structure and Activities" which is conducted by the Ministry of Economy, Trade and Industry (METI), and the Kikatsu Shoken converter, which is provided by RIETI. The authors thank seminar participants at RIETI.

1 Introduction

Markup is an indicator of the firm's market power and reflects the intensity of competition and the attractiveness of products. It is one of key determinants for various firms activities such as investment in tangible and intangible assets. Now many researchers and policy makers pay a great attention to systematic patterns of markups over the economy from various viewpoint. As a result, there is an increasing trend in analyses about firm-level markups across the economy. De Loecker and Warzynski (2012), De Loecker, Eeckhout, and Unger (2018), Gutiérrez and Philippon (2017), are among others.

This paper extends this line of research by considering the interaction of markups between firms through their transactions. A firm's pricing strategy depends on the structure of market where it sells the product, and it also affects pricing strategy of the customer firms. In addition, when a customer firm exerts a higher markup, the volume of demand is smaller. This may affect the markup that its supplier firm sets. This paper examines a entire picture of such interplay of markups for Japanese firms in recent years.

Variation of markups come from various sources. One is the intensity of competition firms face. Firece competition puts the downward pressure on firms' markups, because they need to keep market share from rivals by lowering price. Another is (in)elasticity of demand for the firm's product. If a firm's product is very attractive to consumers, the firm earns significant demand even when the price is high. These factors interplay for vertically related markets and the pattern of such interplay depends on what mainly affect markups. Thus, analyzing the interaction pattern of markups among vertically related firms enables us to get a clue of what forces mainly affect the firms' pricing strategy.

This paper sheds light on this issue by empirically examining the correlation patterns of markups between suppliers and customers. As mentioned above, this correlation pattern should be affected by the pattern of sources that bring variation of markups among firms. Exploiting this property, we obtain implication about factors behind the observed heterogeneity of firms' markups by a reduced form analysis.

To this aim, we utilize a rich dataset of more than 40,000 Japanese firms across all industries, including both manufacturing and non-manufacturing. We construct the panel data for these firms during 2001-2016. This richness of the data enables us to obtain detailed information about economywide patterns of firms' markup in various respects, as well as correlation patterns through transactions.

We estimate firms' markups by the so-called 'production approach [1].' We obtain estimates of parameters for industry-level production functions, then combine the results with sales and cost data to calculate firms' markups [2]. Then we link those markups by transaction relation to examine the correlation patterns of markups between suppliers and customers. In the analysis, we find remarkable difference between manufacturing and non-manufacturing, so we also report the results for the subsamples of manufacturing and non-manufacturing.

The rest of this paper is organized as follows. Section 2 describes the framework of our empirical analysis. It includes the production approach of estimating markups, methods and specifications to estimate production function, and our main estimation equation that captures correlation of markups between suppliers and customers. To check the robustness of our empirical results, we examine various specifications and methods. Section 3 explains how to construct our dataset, which contains sales, input, costs, and other firm characteristics for Japanese firms. We also summarize the pattern of transcation observed in our sample. Our empirical results are reported in Section 4. We also discuss policy implications of our main results in the section. Section 5 is concluding remarks.

2 Framework

2.1 Estimating Markups

The key variable of our analysis is the time-variant firm-level markup. To estimate it, we adopt the method proposed by De Loecker and Warzynski (2012) and De Loecker, Eeckhout, and Unger (2018) based on Hall (1988). They show that firm-level markup rate can be recovered from a parameter of production function and the ratio of variable input to sales, when firms minimize their production cost given input prices.

[1] De Loecker, Eeckhout, and Unger (2018)

[2] There are some other approaches to estimate markups. For example, Nishioka and Tanaka (2019) follows Diewert and Fox (2008)'s cost approach to estimate markups of Japanese firms. Kiyota, Nakajima, and Nishimura (2009) also analyze markups of Japanese firms with taking an approach that utilizes firms' cost share structures. These alternative approaches have both advantages and disadvantages compared with ours.

Markup of firm i at t, μ_{it}, is defined as the ratio of output price P_{it} and marginal cost MC_{it}

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

Here output price P_{it} is a firm-level variable and difficult to observe as compared to industry-level price indecies. Observing the value of MC_{it} is more problematic. Firms report cost data as an accounting information, but they are different from cost of an economic concept. The production approach circumvents these issues with utilizing the properties of firms' cost minimization based on a production function.

Let production function of firm i whose industry is j at time t be

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

where Y_{it} is output, X_{it} is variable input, L_{it} is labor, K_{it} is capital stock, and ω_{it} is productivity. Production cost is defined as

$$P_{it}^X X_{it} + w_{it} L_{it} + r_{it} K_{it}. \tag{3}$$

P_{it}^X is unit price of variable input, w_{it} is wage rate, and r_{it} is user cost of capital. Then the Lagrangian for cost minimization is given by

$$\begin{aligned}\mathcal{L}(X_{it}, L_{it}, K_{it}, \lambda_{it}) = P_{it}^X X_{it} &+ w_{it} L_{it} + r_{it} K_{it} \\ &+ \lambda_{it} \left[Y_{it} - F_j(X_{it}, L_{it}, K_{it}, \omega_{it}) \right]. \end{aligned} \tag{4}$$

Note that the Lagrangian multiplier λ_{it} means the marginal cost of production.

From the first order condition for X_{it}, we obtain [3]

$$P_{it}^X - \lambda_{it} \frac{\partial F_j}{\partial X_{it}} = 0. \tag{5}$$

Let the output elasticity of variable input as

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

then (5) can be rearranged after being multiplied by $X_{it}/(P_{it} Y_{it})$ like

$$\frac{P_{it}^X X_{it}}{P_{it} Y_{it}} - \lambda_{it} \frac{\beta_{X,it}}{P_{it}} = 0. \tag{6}$$

[3] We can define estimated markups like (7) from the first order condtion for L_{it} if it is also a flexible input. However, the flexibility of labor input is arguable especially in Japanese economy. Thus, we treat X_{it}, material and energy input in practice, as a sole flexible input. Nishioka and Tanaka (2019) report that their markup estimation using the cost approach brings the results highly correlated with one using production approach with X_{it} as a variable input. This suggests that using X_{it} as a variable input gives a robust estimation of markups irrespective of estimation approach.

Since the markup rate is defined as (1) and λ_{it} means marginal cost of firm i at t, from (6), we obtain

$$\mu_{it} = \frac{\beta_{X,it}}{\alpha_{X,it}}, \tag{7}$$

where $\alpha_{X,it}$ is the ratio of the value of variable input to nominal sales:

$$\alpha_{X,it} \equiv \frac{P_{it}^{X} X_{it}}{P_{it} Y_{it}}. \tag{8}$$

The value of $\alpha_{X,it}$ is observable, so we can calculate the markup rate for firm i at t from (7) once we obtain the value of $\beta_{X,it}$.

$\beta_{X,it}$ is a parameter of production function (2). To obtain it, we need to properly estimate production function (2) parametrically. Speficication and estimation method of production function is described in the next subsection.

2.2 Estimating Production Function

We specify the production function (2) as a translog form without interaction terms [4]

$$\begin{aligned} \log Y_{it} = {} & \beta_l \log L_{it} + \beta_{ll} \left(\log L_{it}\right)^2 + \beta_k \log K_{it} + \beta_x \log X_{it} + \beta_{xx} \left(\log X_{it}\right)^2 \\ & + \text{control} + \omega_{it} + \epsilon_{it}, \end{aligned} \tag{9}$$

following De Loecker, Eeckhout, and Unger (2018). ϵ_{it} is an error term unobservable to both firms and econometricians. We mention about cotrol variables later. All parameters are assumed to be industry-specific and time-invariant.

This functional form is more flexible than the conventional Cobb-Douglas form. In a Cobb-Douglas case, $\beta_{X,it}$ is constant for the same production function. Then the variation of μ_{it} comes only from the variation of α_{it}. Using (9) enables us to use

$$\beta_{X,it} = \beta_x + 2\beta_{xx} \log X_{it}. \tag{10}$$

Estimating (9) is subject to an endogeneity problem caused by ω_{it}, which is observable to firm i, but not to econometricians. To deal with it, we take a proxy variable approach proposed by Olley and Pakes (1996) (OP, hereafter) and Levinsohn and Petrin (2003) (LP, hereafter). This approach recovers unobservable

[4] We estimate production functions by using Stata's `prodest`. The syntax of this command does not allow multiple state variables when using multiple proxy variables. Since we opt for a flexible form for $\log X_{it}$, which is also used as a proxy, we do not include $(\log K_{it})^2$.

ω_{it} as a function of an observable proxy variable such as investment (OP) and variable input (LP). Therefore we can address the issue caused by the correlation between unobservable ω_{it} and explanatory variables. Since our sample includes many small firms that rarely record positive investment, which is a proxy for OP, we choose LP type method as our basic approach. We also estimate (9) by OP type approach to check robustness of the results [5].

We use three types of specification of (9) depnding on the definition of X_{it} and L_{it}. Definition of X_{it} is an important part to estimate firm-level markup values. Our basic case uses cost of goods sold (COGS) less labor cost as X_{it}. This concept roughly means material and energy inputs. These inputs are easily adjustable in response to annual change in market structure and other shocks to minimize production cost.

Another option of X_{it} is operating expense (OPEX), i.e., the sum of COGS and selling, general, and administrative expenses (SG&A), less labor cost. Traina (2018) points out increasing importance in production process of marketing and management expenses, which are not included in COGS, but in SG&A. Using OPEX is motivated by this fact. However, De Loecker, Eeckhout, and Unger (2018) critisizes using OPEX as X_{it}, mentioning several flaws. For example, this measure unrealistically assumes perfect substitution between COGS and SG&A. Thus, we use OPEX less labor cost just as an 'imperfect option [6]' of defining X_{it}.

We take another specification to accomodate differential importance of management department from production department in the whole production process of firms. Our main data source reports the number of employees at headquarters and research department separately from others. So we divide labor into two parts: labor of headquarters and research department, L^h_{it}, and the rest of total employment (we call it 'core' employment), L^c_{it}. Including L^h_{it} and L^c_{it} separately in (9) eables us to capture differential impact of input in manegement from input in production, even when we define X_{it} as COGS less labor cost. This is our third specification of (9).

As for control variables, we include year dummies to take annual industrial shocks into account. In addition to that, we use firm i's sales share in the industry

[5] When using LP or OP type method, the correction proposed by Ackerberg, Caves, and Frazer (2015) (ACF, hereafter) is sometimes recommended. However, Rovigatti and Mollisi (2018) demonstrate that the estimation results with ACF correction is vulnarable to the choice of initial values. Thus, we does not exercise ACF correction in this analysis.

[6] See Syverson (2019).

s_{it} in the estimation. We need to deflate sales and cost variables to convert into real values. However, the deflator is not firm-level, but industry-level. De Loecker, Eeckhout, and Unger (2018) propose that controling market shares may mitigate the issue caused by the difference of industry-level deflators from firm-level ones.

2.3 Relationship of Markups between Suppliers and Customers

Our main research interest is in the size and sign of correlation between suppliers' and customers' markups. Thus, our main estimation equation is

$$m_{it} = \text{const} + \rho_s m_{it}^s + \gamma \mathbf{Z}_{it} + \delta_t + \theta_j + \eta_{it}. \tag{11}$$

m_{it} is firm i's markup at year t as conceptually defined by (7), but we modify it to correct unexpected part of output, ϵ_{it}, as:

$$m_{it} = \frac{\beta_{X,it}}{\widehat{\alpha}_{X,it}}, \tag{12}$$

where

$$\widehat{\alpha}_{X,it} = \frac{P_{it}^X X_{it}}{P_{it} Y_{it} / \exp(\hat{\epsilon}_{it})}. \tag{13}$$

$\hat{\epsilon}_{it}$ is the residual corresponding to ϵ_{it} for estimating (9).

Suppliers' average markup m_{it}^s is a simple mean value of markups for suppliers of firm i. We do not have the data on transaction volumes or values by supplier, so it is impossible to weight suppliers. The coefficient ρ_s is the key parameter in this analysis. We discuss the sign, significance, and absolute value of ρ_s in the following section.

Control variable vector $\mathbf{Z}_{it}$ contain log of TFP level of firm i at t, firm i's age at t, and mean value of HHI for the industries where firm i's suppliers belong. Firms with higher productivity than their rivals may exploit a larger market power as demonstrated in standard oligopolistic market models. Log of TFP level is defined as the difference from industry mean based on the estimate of ω_{it}, $\widehat{\omega}_{it}$, obtained from estimating (9), i.e., $\widehat{\omega}_{it} - \overline{\omega}_{jt}$. $\overline{\omega}_{jt}$ is the sample mean of $\widehat{\omega}_{it}$ for industry j.

Firm age captures various factors that potentially affect firm i's markup. For example, older firms have established their brand image that gives them a solid market power. However, the relation between firm age and markup may not be monotonic. Newer firms may be able to easily exploit new technology that helps their products and services discrimate from existing ones. Thanks to the richness of our dataset, we use dummies of five-year age brackets to describe the relation between firm age and markups semi-parametrically.

HHI for the suppliers' industries captures the market structure of suppliers. In the subsection to discuss our empirical results, we consider the model of two vertically related industries, given the degree of competition in the upper industry. This variable enables us to discuss the results based on the model. In the similar manner to constructing suppliers' markups and productivity levels, we define suppliers' HHI as a simple mean value of HHI for all suppliers. We also take care of year fixed effect δ_t and firm i's industry specific factor θ_j.

Note that firm i's markup can strategically relate to its suppliers' markups, as we discuss later. To deal with possible endogeneity biases due to this correlation, we take an instrumental variable approach. As instruments, we use average log of TFP level and average ages of firm i's suppliers. These variables should correlate with m_{it}^s since they are factors influencing markups, while they should be uncorrelated to η_{it}, which basically reflects unobservable firm i's characteristics determining m_{it}.

3 Data

We collect the data at firm level, because firm is the appropriate decision making unit of pricing strategy, as compared to plant. Our main data source is the Basic Survey of Japanese Business Structure and Activities (Kikatsu), METI. We obtain individual firm level data including sales, cost of goods sold (COGS), selling, general and administrative expenses (SG&A), labor cost, the number of employmee, book value of tangible assets [7], which are used in production function estimation. This data source also provides firms' foundation years used in calculation of firm ages.

Kikatsu covers Japanese firms from many industries including agriculture, construction, manufacturing, wholesale, retailing, service, and so on. However, some of listed firms do not respond to METI's survey and are omitted from Kikatsu. In some industries, most of listed firms are missing in Kikatsu. So we supplement missing data of those listed firms by their financial reports. The supplementary data accounts for less than 3% in number in all the sample. When estimating (9) and

[7] Note that this variable include not only depreciable tangible assets like machineries, but land. Data confined to depreciable assets is not avaiable in Kikatsu over the couse of our sample period.

(11), we add a dummy for using financial report data to deal with possible influence due to using different data source.

To estimate production function, we convert nominal values of sales and variable input into real values. The deflators are calculated from industry-level nominal and real output and intermidiate input data of JIP 2018, RIETI [8]. For sales deflators, we caclulate the ratio of nominal and real sales by industry and year. Variable input deflators are obtained in the similar manner using nominal and real intermidiate input. The end of JIP 2018 observation period is 2015, so we impute output deflators in 2016 by multiplying the values in 2015 with one plus GDP deflator growth rate for the corresponding industry in 2016. Variable input deflator in 2016 is imputed as those in 2015 multiplied by one plus economywide GDP deflator growth rate in 2016.

The source of transaction data is Firm Relation File (Kigyo Soukan File) provided by Tokyo Shoko Research (TSR), which is available for 2006, 2007, 2011, 2012, 2014. This database contains information about supplier names for more than 1 million Japanese firms. We manually match the TSR data to Kikatsu data. We uniquely match nearly 95% of firms included in Kikatsu with those in TSR data. Our sample is these matched data.

Since TSR data is infrequent, we assume firms transaction relationship holds constant as recorded in the nearest available one. More specifically, we use transaction relationship defined by 2006 file for the data between 2002-08, 2011 file for the data between 2009-11, 2012 file for the data between 2012-13, 2014 file for the data since 2014 [9].

The descriptive statistics used for production function estimation is provided in Table 1. Note that we exclude the data for industries whose number of observations is less than 50, because such small sample size may cause unreliable estimation results. After all, our basic dataset contains 47,752 firms from 132 industries. Our definition of industry is based on Kikatsu classification with arranging changes in classification in the course of our sample period [10].

[8]JIP 2018 database uses a different industry classification from Kikatsu. We match the two classification systems manually.

[9]As OP estimation provides the results since 2002 when using the data since 2001, we define transaction relatiohship since 2002.

[10]For example, 'manufacturer of other machinery' is divided into 'manufacturer of boiler and engine', 'manufacturer of pump and compressor', 'manufacturer of general industrial machine', and 'manufacturer of other general machine' since 2008. We adot the combined classification before

Our sample firms have about six or seven suppliers, only three or four of which are included in our sample, on average. This number is slightly higher in non-manufacturing sector than manufacturing. Table 2 shows top 5 industries for manufacturing and non-manufacturing sectors in the average number of suppliers included in our sample. Material and machinery industries are ranked high for manufacturing sector. These industries have a complex production process and require many kinds of ingredients and components. All of top 5 industries for non-manufacturing belong to wholesale industry. It is obvious that these industries purchases their goods from various producers.

On the other hand, each supplier provides their product and service to about two firms in our sample, while the distribution has a very long right tail and some suppliers have more than 200 customers in our sample.

Note that many firms have no record of transactions with any of our sample firms, because our sample is only a small portion of those included in TSR dataset. About 8% of firms does not have a supplier included in our sample, and one third of firms have no record of supplying any of our sample firms. These firms are smaller than those with transaction relation to any of our sample firms. Log of sales is smaller for firms with no within-sample supplier by about 0.7 on average than otherwise. This figure is about 0.8 for firms with no within-sample customer. In sum, the transaction relation discussed in the following section is among relatively large firms.

4 Empirical Results

4.1 Markups

We estimate firm-level markups based on (12) for more than 30,000 firms from 2001 to 2016. They are classified into four types according to the specification of production function estimation to obtain $\beta_{X,it}$. In the following part, we label them as:

LP1: X_{it} is COGS less labor cost and the estimation method is LP;

LP2: X_{it} is OPEX (the sum of COGS and SG&A) less labor cost and the estimation method is LP;

2008 for this case.

LP3: X_{it} is COGS less labor cost, L_{it} is divided into L_{it}^h and L_{it}^c, and the estimation method is LP;

OP1: X_{it} is COGS less labor cost and the estimation method is OP.

Our base case is LP1, while we check robustness of the results comparing them with those obtained for estimates of the other three types.

The distribution of estimated markups has an enormously large variance. Table 3 presents descriptive statistics for markups of all the four types. Except for LP2, the standard deviation is three to five times mean values. This fact means that we need to care about the issue of exterme values. So we winsorize our sample at 5-95% in the following part [11]. Correlation coefficients among these four types of estimated markups are between 0.54 and 0.85.

Before proceeding to analysis of the relation between customers' and suppliers' markups, we summarize macro trends in Japanese firms' markups in Figure 1. This figure dipicts weighted averages of markups using sales share as a weight. All four graphs in this figure give a similar picture of markups that does not show remarkable trend. The level is different among specifications, but no significant upward/downward trend is observed unanimously in all graphs. Markups recoverd after the severe recession triggered by the global financial crisis in 2008, but roughly stagnated in 2010s except for 2016.

Another common propery is that manufacturing firms have higher markups than non-manufacturing ones over the sample period. This may reflect that manufacturing goods are more differentiated than non-manufacturing service in Japan, but there are not a few non-manufacturing industries observing high markups [12]. The levels of markups are within those reported in previous studies in spite of different methods of estimation. De Loecker and Eeckhout (2018), who take the similar approach to this analysis, report that the sales share weighted average of markups is 1.33 in 2016 for Japanese firms listed in the Worldscope dataset [13]. This is a bit higher than what is reported in Figure 1, probably because our dataset contains much more small firms than the Worldscope dataset. Markups estimated by Nishioka and Tanaka (2019) using the cost approach show the mean of around

[11] We also examine the sample winsorized at 1-99% and obtain essantially simlar results to what is shown below.

[12] For example, movie theater industry records the highest median value of markups among all the industries.

[13] This dataset collects and standardizes financial statement data for over 70,000 firms worldwide.

1.3 and the median of around 1.2 during 2000s. Their sample is confined to manufacturing sector. They also report the figures calculated by the similar approach to this analysis, and the mean values are between 1.5 and 1.6 and the medians are around 1.2. These figures are a bit higher than we obtain, but on the contrary, Kiyota, Nakajima, and Nishimura (2009) present that the mean values of markups for various industries are around 1.0. Thus our estimates are within the range obtained from these previous studies.

4.2 Relation with Suppliers' Markups

Our main research interest is in the correlation of firms' markups with their suppliers' (average) markups with appropriate control of other factors influencing firms' markups such as productivities. This is captured by ρ_s in (11). The estimation results of ρ_s for all types of markups are shown in Table 4. They are very consistent among types of estimated markups, suggesting that there is a significantly negative correlation between firms' markups and their suppliers' markups. For a firm whose suppliers' average markup is 10% point higher, its own markup is about 2% point lower, all else being equal.

We also run (11) for two subsamples, manufacturing and non-manufacturing. The results are reported in Table 5. From this table, we see the following two points. First, ρ_s is estimated as significantly negative for non-manufacturing subsample irrespective of the type of markup estimates. Second, the absolute size of ρ_s is larger for non-manufacturing than manufacturing. ρ_s for manufacturing subsample is negative except for LP2 case, but insignificant in all but LP1 case. Thus, the negative correlation between firms' and their suppliers' markup is more remarkable in non-manufacturing sector than manufacturing.

Before discussing what is behind these results, we describe the results for other variables in (11). Figure 2 presents the point estimates of coefficients for each age barackt. These figures show that the relation between firm age and markup in the manufacturing sector is almost monotonically increasing, except for the oldest bracket, with controling other factors. Graphs for non-manufacturing sector show double-humped shape. Given other things constant, the highest markup is observed for firms around age of 80, and there is another hump around age of 30. Non-manufacturing firms starting their business in 1970s and 80s may exert their strong market power, probably due to then-newly introduced business models. Most of the coefficients after age of 20 for non-manufacturing subsample are insignificant, though. Another noteworthy result is negative value for youngest (except for baseline age bracket, 0-4) age bracket. In many specifications presented in Figure 2, the coefficients for age 5-9 and 10-14 dummies are significantly negative. Newly born firms have a relatively higher market power, but sustaining it after a while is a difficult task.

The coefficient of relative level of log TFP is positive for LP1, LP3 (insignificant in this case), and OP1, but insignificantly negative for LP2. In LP2, markup level is likely to be lower when firms need more SG&A. If higher TFP level correlates to larger administration cost, this difference in the results about TFP is reasonable. The results about suppliers' HHI are further mixed. The coefficients are significantly positive for non-manufacturing in the case of LP1 and LP3, but insignificantly positive or negative otherwise.

4.3 Implications

To consider the implications of our main results about ρ_s, we foucs on two factors affecting the correlation of markups between suppliers and customers. The first factor is the degree of competition in the customer's market. Suppose that there are two vertically related sectors, upstream (or suppliler) and downstream (or customer). Upstream firms sell their products to downstream firms. Downstream firms use upstream products as intermidiates and sell their product to their customers. Given marginal costs of upstream firms, higher markup of upstream firms means higher marginal costs for downstream firms. This shrinks demand for upstream firms and the extent of shrinkage is larger when downstream firms set higher price of their product. If upstream firms can gain at least part of downstream firms' profit through, say, two part tariff, their pricing strategy takes this effect into consideration, because upstream firms' decision making depends on total profit of upstream and downstream [14].

In this setting, there is a trade-off between upstream and downstream markups. If the competition among downstream firms is fierce and their markups are low, upstream firms will set higher markups, given the degree of upstream market structure, upstream firms' cost, and downstream firms' demand. This relation brings negative correlation between upstream and downstream markups.

The second factor is demand (in)elasticity of the downstream market. Now

[14] See, for example, Cabral (2000), Chapter 11.

consider the situation when a downstream firm has invented some valuable product. This will make its demand inelastic and/or shift it outward. This kind of change in market structure will lead to higher markups for both the downstream firm and its suppliers. This factor brings positive correlation between upstream and downstream markups.

In sum, there are two factors affecting the sign of correlation between m_{it} and m_{it}^s and they have an impact of opposite direction. If the degree of competition among downstream firms is the main cause of difference in m_{it}, then the correlation between m_{it} and m_{it}^s is likely to be negative. However, if the change in demand structure for downstream firms mainly explain the difference in m_{it}, then the correlation between m_{it} and m_{it}^s is likely to be positive [15].

Our empirical analysis provides the basis to infer which one is dominant. The robust results indicate that m_{it} and m_{it}^s negatively correlate with each other at least for non-manufacturing sector. This implies that difference in the degree of competition is the main source of heterogeneity of markups and movement to make a difference from rivals is weak in non-manufacturing sector. The similar pattern is observed in manufacturing, too, but the inclination is relatively weaker than non-manufacturing sector.

5 Concluding Remarks

We analyze the correlation pattern of markups between customers and suppliers based on rich panel dataset of more than 40,000 Japanese firms from 2001 to 2016. The obtained results show that firms' markups negatively correlate with their suppliers' markups. A firm whose suppliers record 10% point higher markups has 2% point lower markup on average, other factors being constant. This pattern is more remarkable for non-manufacturing firms than manufacturing ones.

This result implies that the variation of Japanese firms' markups mainly comes from the intensity of competition the firms face. On the other hand, it is unlikely that demand shift due to introducing discriminated products brings higher markups.

[15] Note that we do not consider monopsony power for downstream firms to explain the correlation pattern of markups between upstream and downstream firms. The production approach we adopt in this analysis assumes that firms minimize their costs given input prices. Morlacco (2019) proposes a method to estimate markups when firms can exert monopsony power in input markets. Her approach requires the data to distinguish two input markets, one of which is competitive and firms exercise buyer power only in the other.

Although there is little evidence that markups are increasing in Japan, it is not necessarily preferable, in view of weak movement of boosting firms' profitability in a good sense [16].

There are several remaining research topics to be further investigated. First, the correlation pattern of markups between suppliers and customers may depend on some attributes of transaction relationship. There is remarkable heterogeneity of transaction relationship for our sample firms. Some suppliers provide their goods and service to quite many customers, while others have sole customer. Such heterogeneity may affect the change in supplier's market power when their customer has invented superior goods.

It would be also meaningful to extend our framework to secondary and more transactions. The simple extrapolation of our results about direct transaction linkage implies that higher markups of upstream firms should be diluted through transactions. It would be clearer whether this is true by investigating correlation of firms' markups in secondary or tertiary transaction relation. Such an extension will provide another meaningful information for competition policy.

Our analysis does not clarify causality between markups of vertically related firms. It would be an interesting research topic to disentagle such a causality. This line of research may be possible by foucsing on a specific industry where some exogenous shocks on firms' markups like a policy intervention to firms' pricing.

Robustness check for alternative empirical framework is also a remaining issue. Measuring markups precisely is an ongoing research topic and new methods are still proposed. Incorporating such advance in research of this field may help improving reliability of our empirical results, as well as give an insight how sensitive our results are to methodological choices.

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Appendix

A Markups by industry and firm type

We see no significant sign of upward trend of markups in Japan, while concentration levels of Japanese industries have slightly increased as shown in Figure A1. Weighted average of HHI for all industries changed from 612 in 2001 to 646 in 2016. Changes in weighted average of HHI over the same period is from 688 to 737 for manufacturing and from 565 to 594 for non-manufacturing.

Lack of upward trend of markups is observed even for firms exerting high markups. Figure A2 depicts markups for two types of firms, top 10% in markup level and the rest of firms. Markups of top 10% firms fluctuate over the sample period, but there is no increasing trend. We see the similar pattern when using other estimation methods.

Figure A3 uses another categorization of industries based on export share in sales. We define 36 industries whose export share is 10% or higher as exporting industry. The rest of industries is defined as domestic. Although obtained time series patterns seem to depend on estimation methods, we robustly find no significant trend for both types of industries.

Intangible capital such as software, patents, and online platform plays an important role in boosting market power and productivities. Couzet and Eberly (2019) mention that it is associated with rising concentration in the United States. In Figure 4, we compare the share weighted average of markups between intangible capital intensive industries and others. In all four specifications, markupsare higher for intangible capital intensive industries, but the difference over other industries is narrowing in our sample period.

The relation with productivity is one of the important issues for markup analysis. We devide our sample firms into two groups based on if the firm outperforms or underperforms the industry with respect to TFP growth rate over the sample period. About 20% of our sample firms are outperformers. Figure A4 compares weighted averages of markups using sales share for the two groups. Markups of outperformers relatively increase as compared to those of underperformers, while the increasing trend is modest even for outperformers.

B Comaprison with other countries

Markups of Japanese firms we estimate show quite different properties compared to other major countries. De Loecker, Eekhout, and Unger (2018) and IMF (2019) apply the same estimation method of markups as ours to a large firm panel data covering a whole economy, and find a steady increase in markups, which is driven by a small portion of firms with extremely high markups. As shown in Figures 1 and A2, this pattern is not the case with Japanese firms. Figures B1 and B2 provide the comparison of our results based on LP1 with the results of IMF (2019) for 27 developed countries. Markups of Japanese firms in these figures are normalized to one in 2001 to be combined with the results of IMF (2019).

Table 1. Descriptive Statistics of Main Variables Used in Production Function Estimation

	N	mean	median	s.d.	min	max
Sales	412,723	8.736	8.567	1.398	0.976	16.311
COGS less labor cost	412,723	8.154	8.084	1.661	-0.111	16.283
COGS less labor cost + SG&A	412,294	8.528	8.381	1.470	2.024	16.300
Total employment	412,723	5.246	5.024	1.066	0.000	11.941
Core employment	387,867	5.069	4.852	1.081	0.000	11.936
HQ and research dep employment	387,867	2.943	2.833	1.195	0.000	10.721
Tangible asset	412,723	6.778	6.864	1.927	0.000	16.293

All variables are defined as log values.

Table 2. Top 5 industries about the average number of suppliers in 2014

Manufacturing (mean = 3.898)	
Oil processing product, soap, detergent, and paints	5.397
Pharmaceutical	4.918
Iron and steel	4.837
Motor vehicle and part and accessories of motor vehicle	4.486
Office and service equipment	4.370
Non-manufacturing (mean = 3.946)	
Wholesale of iron and steel products	7.016
Wholesale of chemical products	6.652
Wholesale of construction materials	6.628
Wholesale of electronic machinery and equipment	5.843
Wholesale of general purpose machinery	5.696

Ranked among industries with 100 or more firms recorded.

Table 3. Descriptive Statistics of Estimated Markups by Specification

	LP1	LP2	LP3	OP1
p1	0.4260	0.7481	0.3862	0.5172
p5	0.6897	0.8906	0.6789	0.7542
p95	1.6983	1.3207	1.7090	1.7759
p99	2.9780	1.6187	2.8965	2.8368
mean	1.1105	1.0816	1.1137	1.1558
median	1.0618	1.0614	1.0738	1.1190
std. dev.	4.4490	0.2949	5.7709	3.0628

Table 4. Estimation Result about ρ_s

	coef.	s.e.	p
LP1 (Nobs. = 251,299)	-0.176	0.054	0.001
LP2 (Nobs. = 259,817)	-0.208	0.090	0.021
LP3 (Nobs. = 242,100)	-0.201	0.051	0.000
OP1 (Nobs. = 221,490)	-0.150	0.043	0.001

Standard errors are adjusted for clusters in industry.

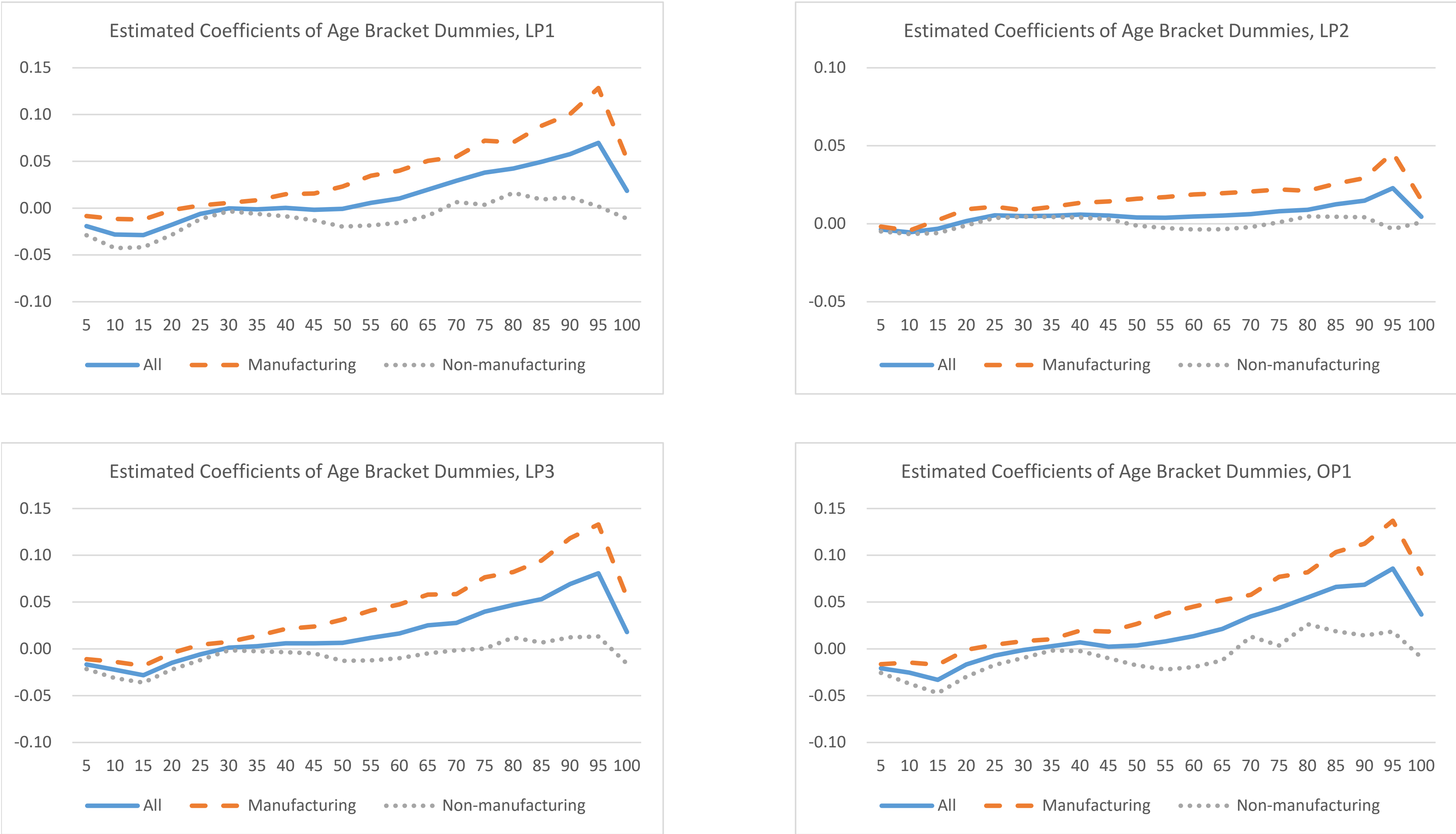
Table 5. Estimation Result about ρ_s for Manufacturing and Non-Manufacturing

	coef.	s.e.	p
Manufacturing			
LP1 (Nobs. = 126,032)	-0.080	0.035	0.022
LP2 (Nobs. = 123,775)	0.047	0.106	0.658
LP3 (Nobs. = 242,100)	-0.077	0.039	0.051
OP1 (Nobs. = 114,677)	-0.074	0.048	0.121
Non-Manufacturing			
LP1 (Nobs. = 125,267)	-0.294	0.088	0.001
LP2 (Nobs. = 136,042)	-0.471	0.161	0.003
LP3 (Nobs. = 124,527)	-0.328	0.075	0.000
OP1 (Nobs. = 117,573)	-0.192	0.060	0.002

Standard errors are adjusted for clusters in industry.

Figure 1. Weighted Average of Markups Using Sales Shares

Figure 2. Firm Age and Markups



These figures are dipicted based on the sample winsorized at 5-95%. 'Age bracket 5' is for firms at age 5-9, and so on. Our baseline is age bracket 0-4.

Figure A1. HHI (Weighted average using industry sales)

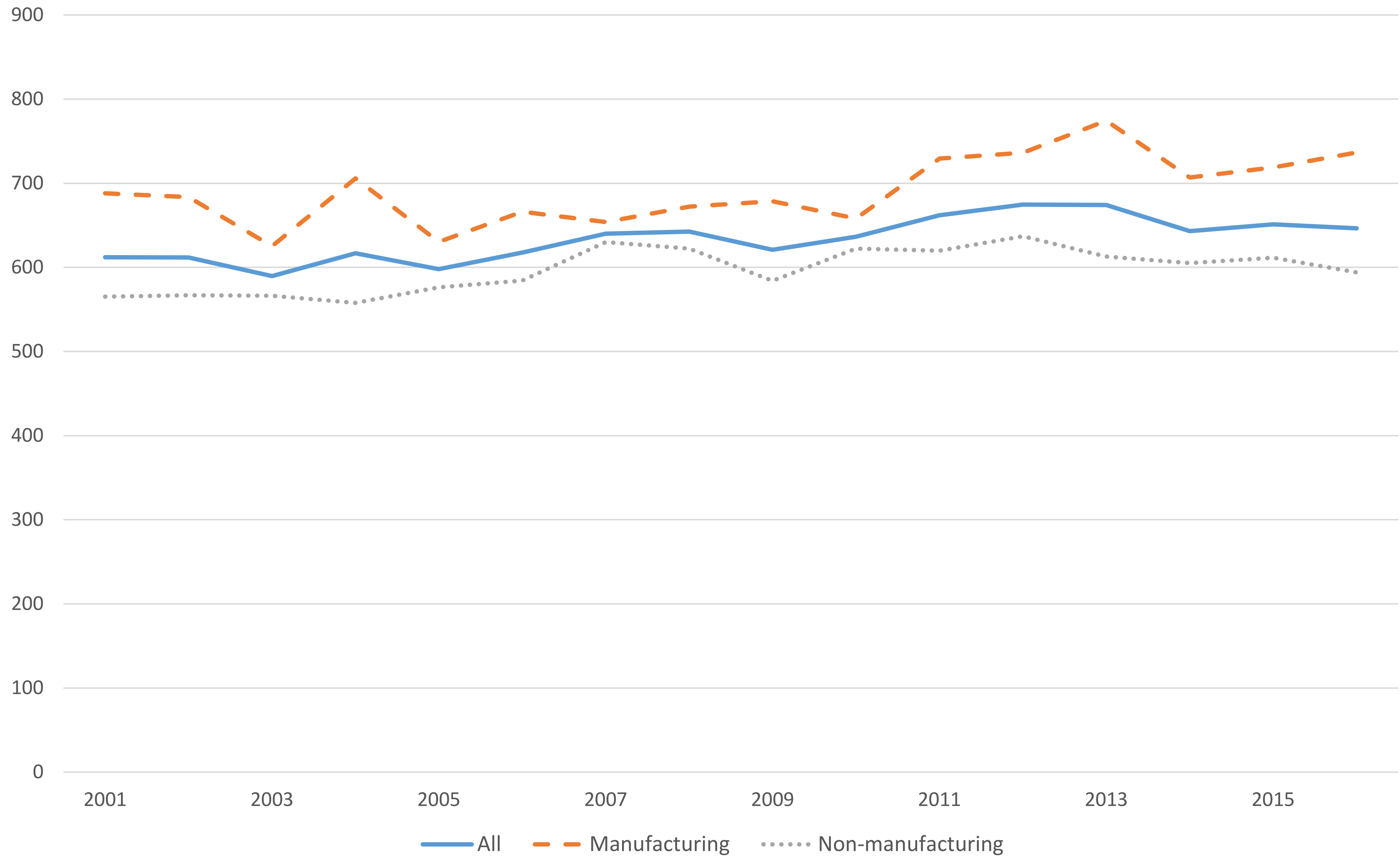
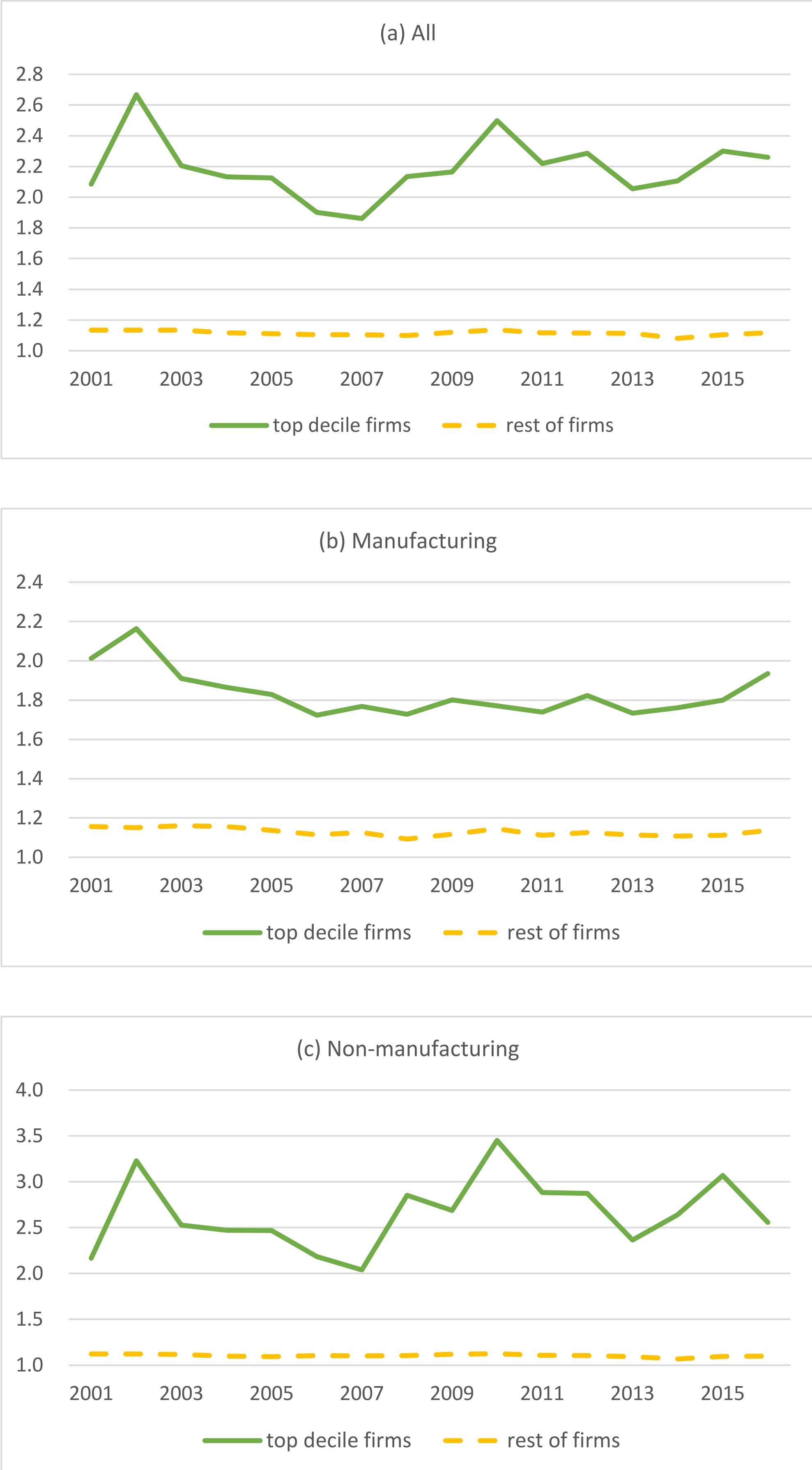
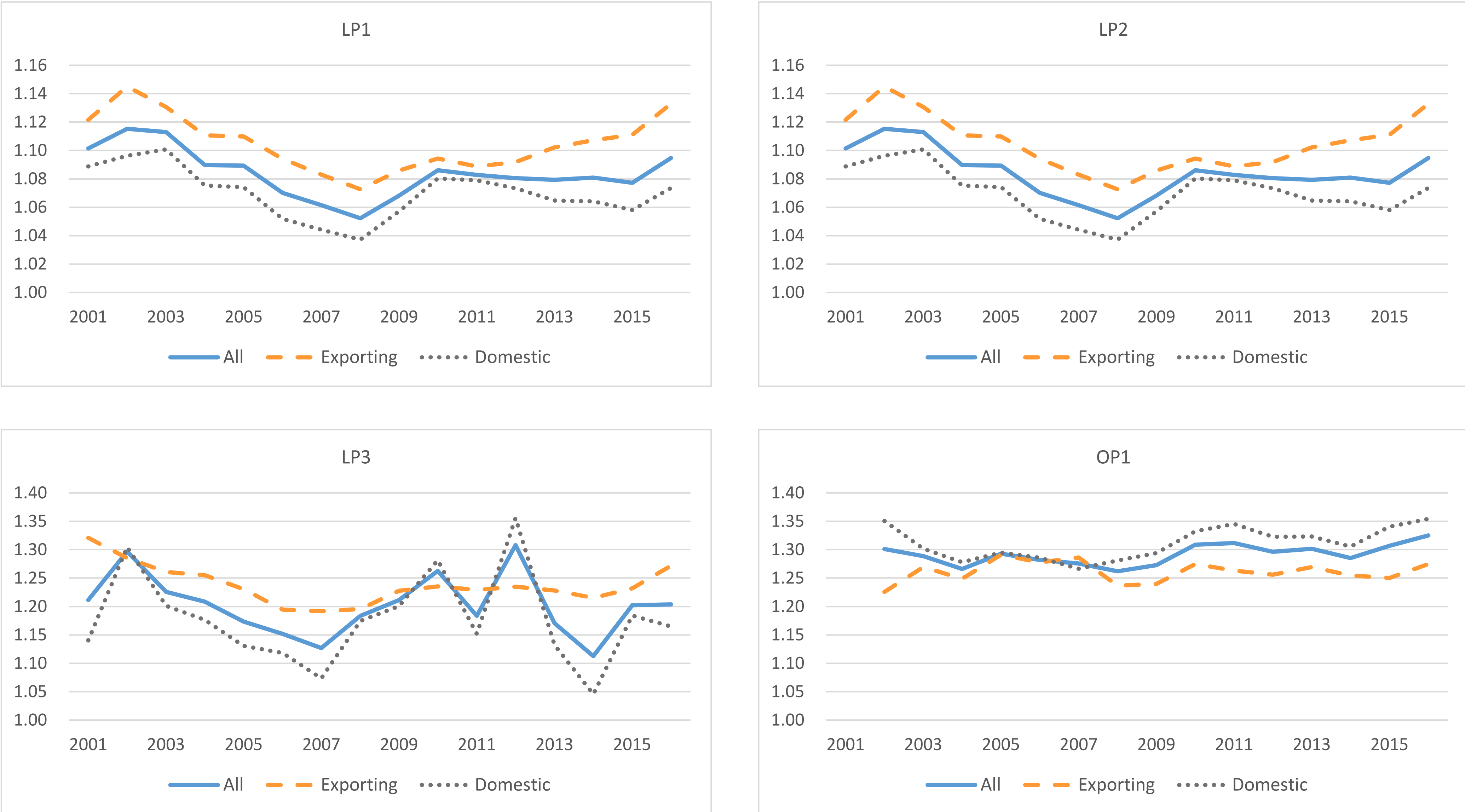


Figure A2. Markups by firm type: top 10% vs. rest of firms



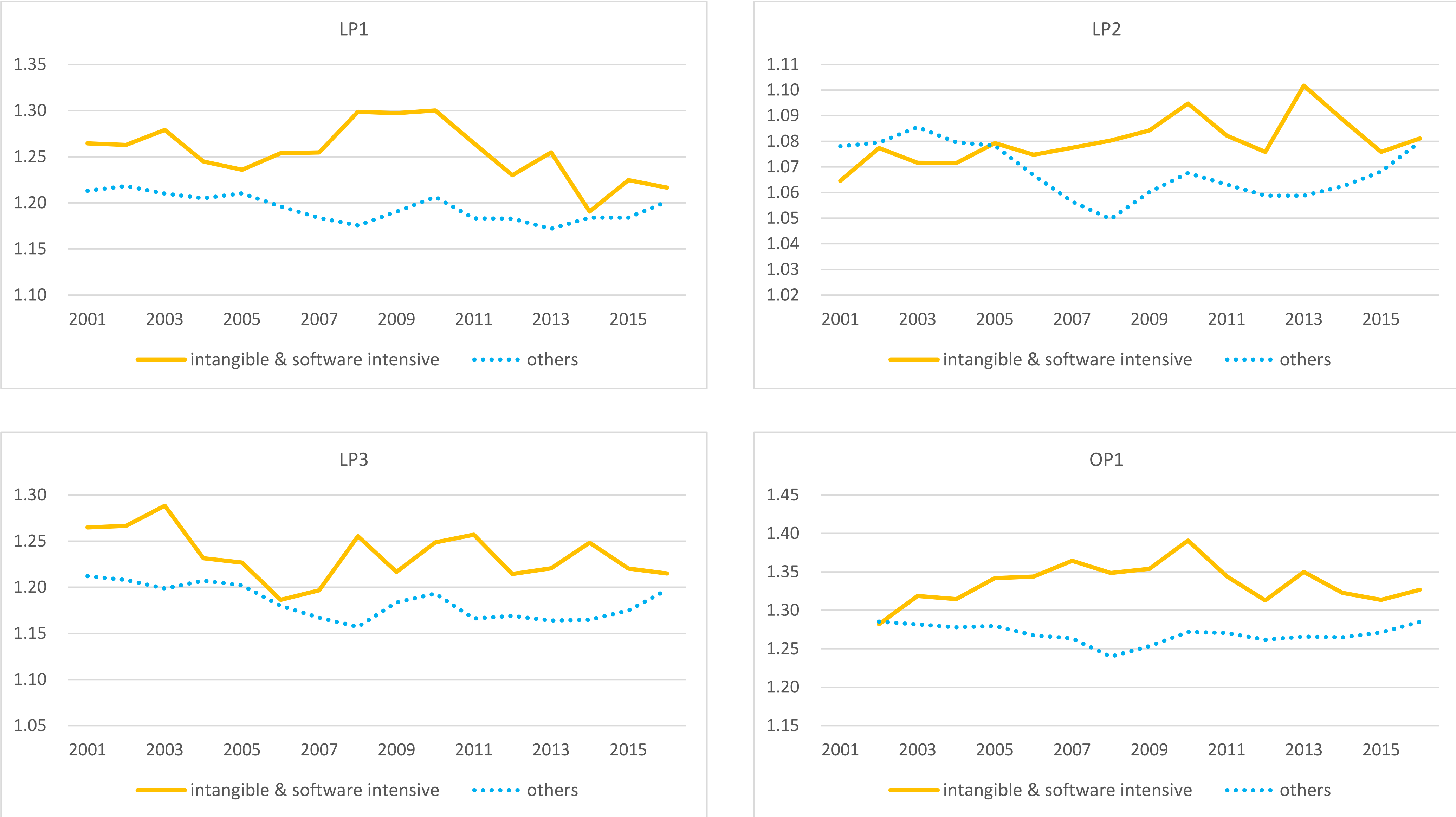
Note: These figures are based on the results using LP1.

Figure A3. Markups of exporting and domestic industry



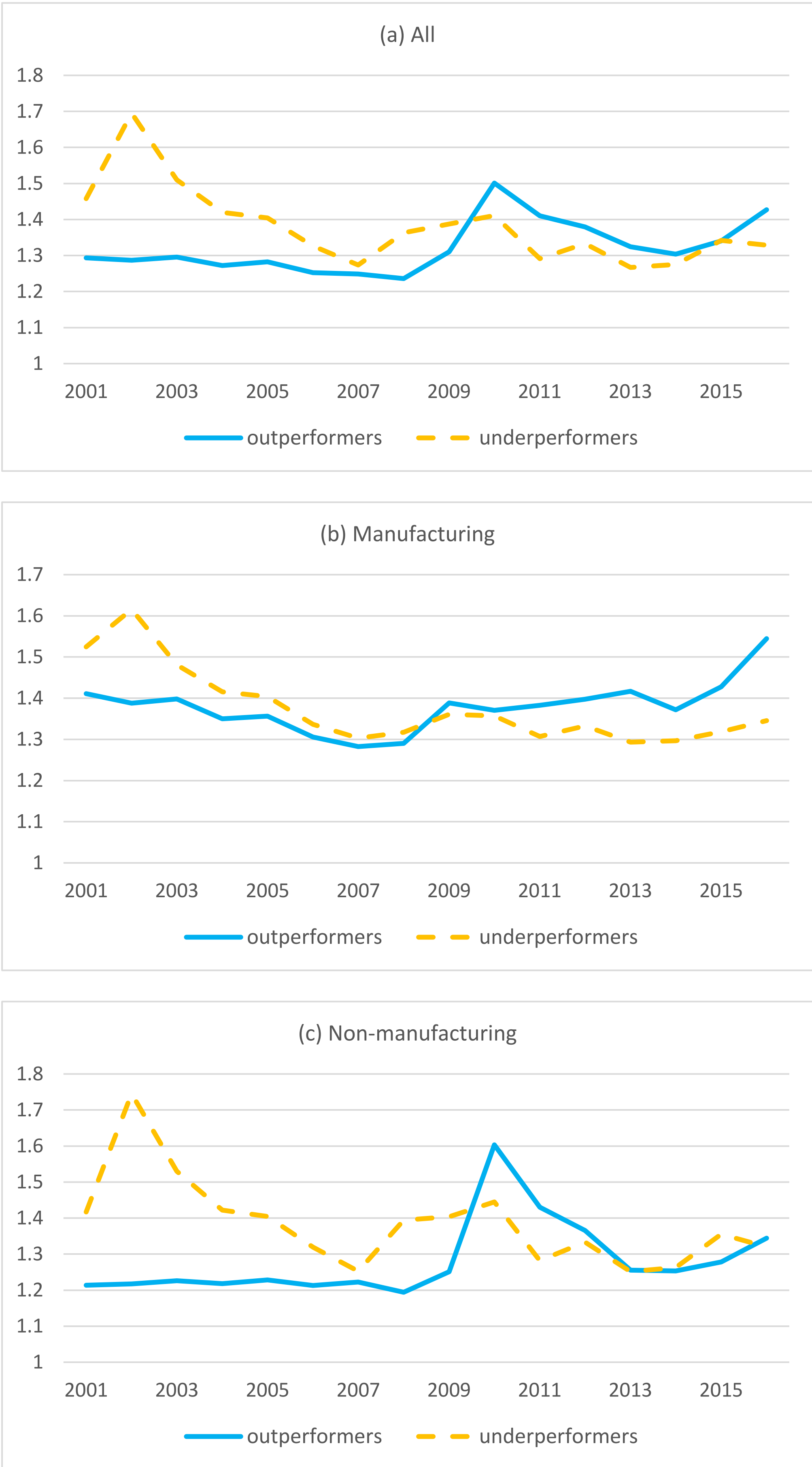
Note: Exporting industry is defined as one with 10% or higher export share in sales. Domestic industries are all the rest.

Figure A4. Markups of intangible-capital-intensive and other industries



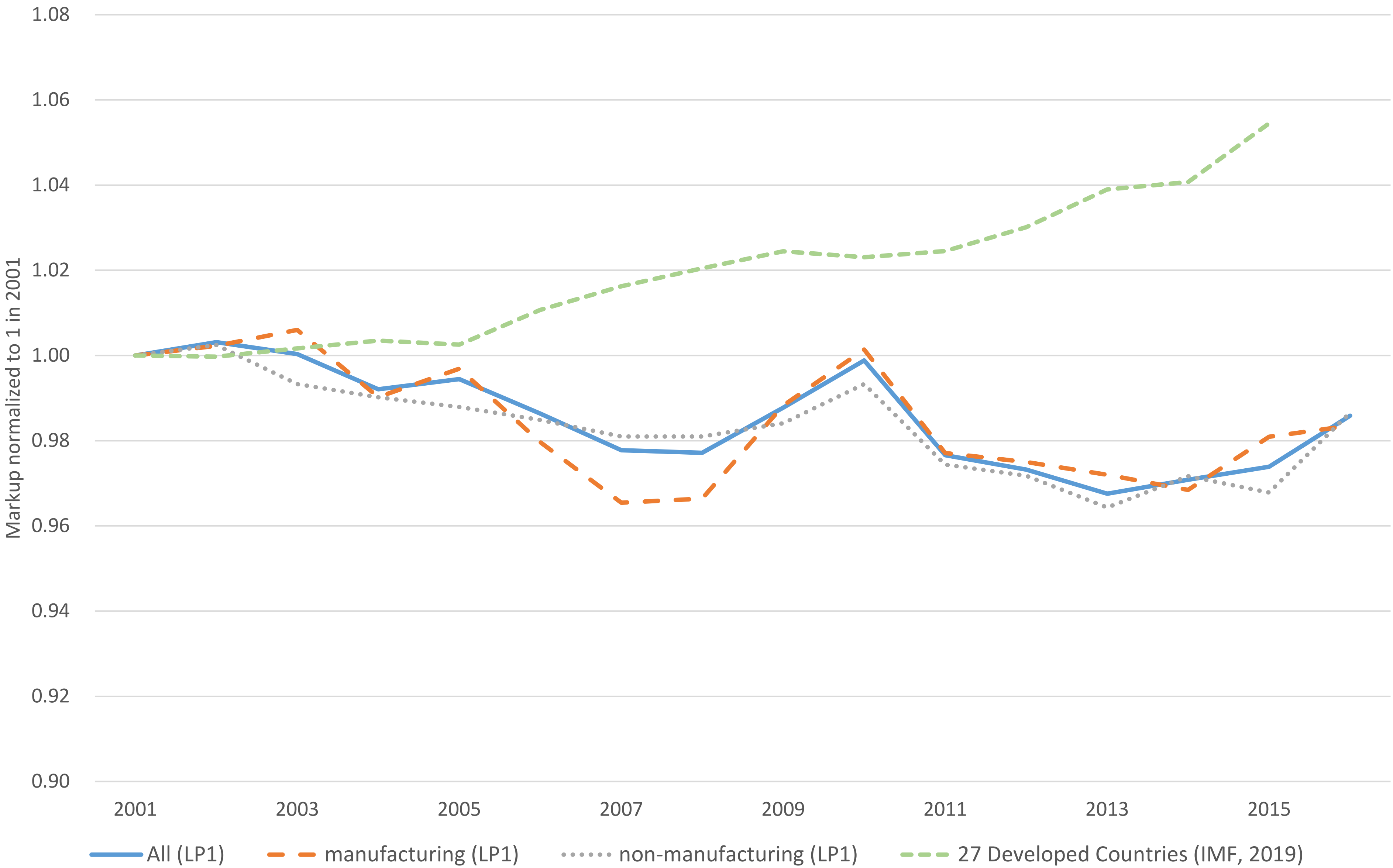
Note: Intangible & software intensive industries are those with 10% or more ratio of intangible capital to total capital, and 5% or more ratio of software to total capital based on JIP data (RIETI). Those ratios are averaged values over 2007-2016.

Figure A5. Markups and TFP growth

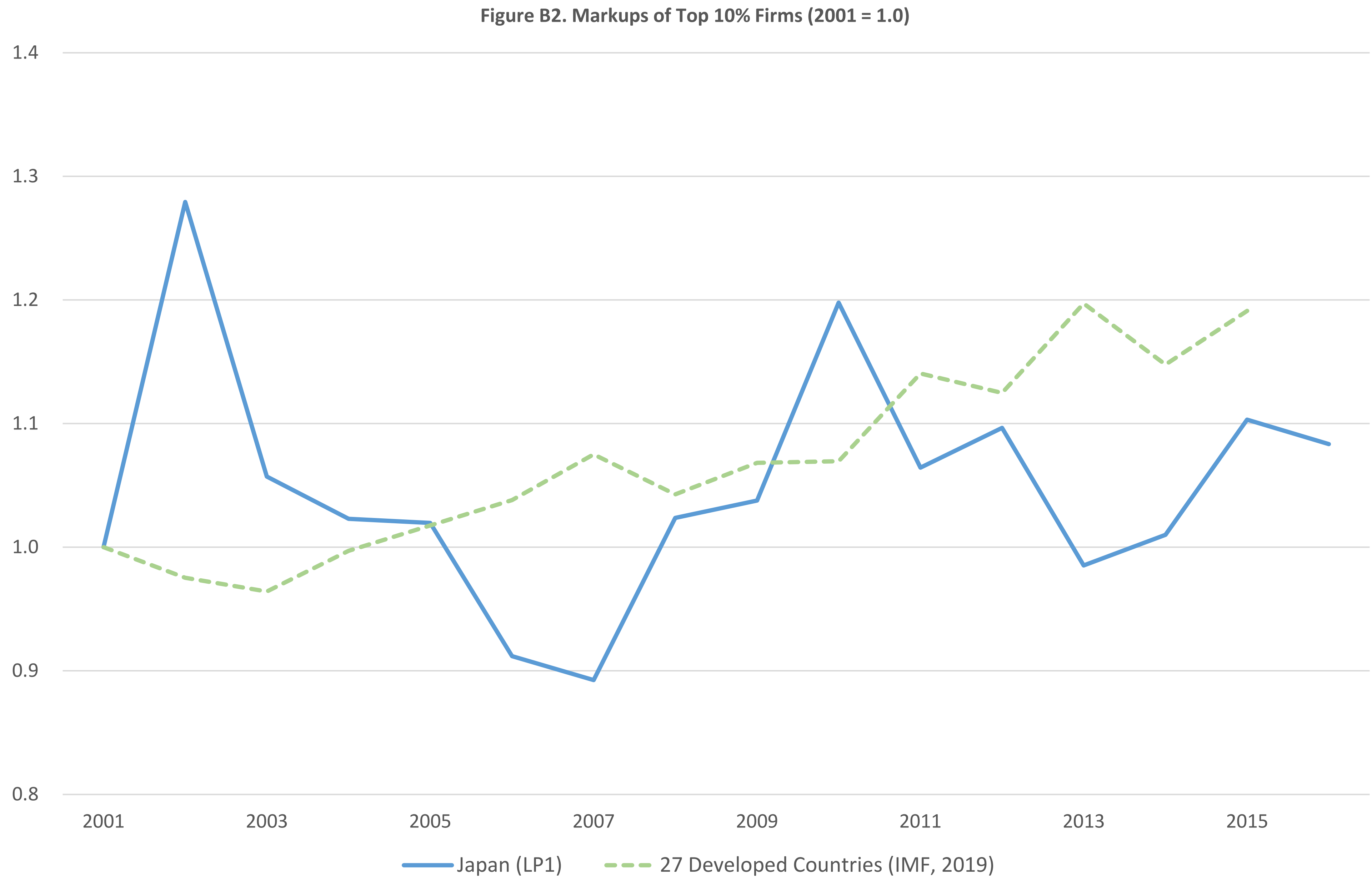


Note: These figures are based on the results using LP1.

Figure B1. Aggregated Markups (Sales Share Weighted) in Japan and Developed Countries



Note: Dashed green line is based on the data from Figure 2.2., IMF (2019). The other three lines are the results for LP1 in Figure 1. These values are normalized to one in 2001.



Note: Dashed green line is based on the data from Figure 2.5, IMF (2019). Solid blue line is based on the results for LP1 in Figure A2. These values are normalized to one in 2001.