Determinants of Potential Growth, Information Service Industries and Market Structure

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Abstracts

This research investigates possible determinants of potential growth in the Japanese economy. We focus mostly on market structure and concentrate our attention on industry dynamics determining productivity changes. We use large-scale panel data of Japanese firms, which enable us to examine interaction among firms. Thus, we are able to pin down strength and weakness of the Japanese industries, which is impossible if we use only aggregate industry data like most previous studies.

This study consists of three parts. The abstracts are described as follows.

Part I
This part presents a new econometric framework to estimate markups at the firm level from a panel data. The framework is applied to study markups of Japanese firms in manufacturing and trade from 1995 to 2002. The results indicated that estimated markups were lower than those obtained in Nishimura, Ohkusa, and Ariga (1999). The results imply that the Japanese markets become more competitive in the 1990s than before. Besides, the markups among firms vary and skewed in the industry. Even in the low markups industries such as iron and steel, more than one-third of firms enjoy the markups with greater than unity. The results imply that the heterogeneity of markups exists, suggesting the importance of firm-level study of markup estimation. The results also indicated that there was a pro-cyclical trend in the Japanese markups although its degree is different across industries.

Part II
This part examines the growth of productivity at the firm level, distinguishing between the effects of innovation and those of technology diffusion. We incorporate a Schumpeterian framework to the firm-level productivity growth model and apply the model to large-scale firm level data for 1994-2002 in Japan. We found that both innovation and diffusion were important factors in explaining the productivity growth of firms in Japan. The results also indicate that the role of innovation is much stronger for firms in information and communication technology (ICT) industries than for firms in other industries.

Part III
The Japanese information service industries are considered as not having high performance. As well as in other industries, competition between firms is one of most important to enhance firms’
productivity through the Natural Selection Mechanism (NSM). In this part, we investigate entry/exit behavior of Japanese information service industries and whether the NSM works properly. Empirical results show that Japanese information service industries are very active in terms of turnover. We find, however, that a breakdown of the NSM in the period of 2000-2001, in which so-called “IT bubbles” burst. That is to say, efficient firms in terms of TFP went out of business while inefficient ones survived in 2000-2001.

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Part I

Panel Data Estimation of Market Power: Evidence from Japanese Firms in the 1990s
1 Introduction

Estimation of the markups is one of the central issues in explaining the market power of firms.¹ Most of the previous studies, however, estimate markups at the industry level, not the firm level. Recent plant- and firm-level studies reveal that the heterogeneity of firm performance existed even in the same narrowly defined industry. This in turn implies that industry-level study of firm performance, including market power, may be misleading. For instance, when only a few firms have an extremely strong market power, industry-average market power will not capture the characteristics of industry very well.

Despite the importance of firm-level aspect of market power, only a few studies attempted to estimate firm-level markups. Klette (1999) estimated markups in Norway, extending the econometric framework of Hall (1988, 1990). Using the panel data of Norwegian manufacturing establishments between 1980 and 1990, Klette (1999) found statistically significant, but small, markups of establishments in most manufacturing industries. Another study by Nishimura, Ohkusa, and Ariga (1999) examined the markups of relatively large Japanese firms from 1971 to 1994. They found that markups were significantly greater than 1.0 (i.e., no market power) but smaller than 1.1 in almost all industries, implying that firms in the data possessed significant market power. They also found that the markups differed among firms in the same industry and the distribution of markups is skewed and that the markups are procyclical.

This paper presents a new econometric framework to estimate markups at the firm level from a panel data, building upon the previous studies mentioned above. The contribution of this paper is twofold. First, we propose a new econometric method to estimate firm-level markups. The distinguished feature of this method is the lower requirement of the data than previous studies. The limited availability of the data sometimes makes it difficult to estimate markups. Our method requires the data of total cost and sales only, which allows us to estimate firm-level markups more easily. Besides, our study allows both cross-section and time-series variation of firm-level markups.

Second, our contribution is the latest update of the markup studies in Japan, covering the period after 1995. Japan has been in long and severe economic stagnation since the burst of bubble economy, which is sometimes called “lost decade.” Accordingly, the various performance of firms such as productivity is examined and several unusual facts are reported.² But none of the previous

¹As we will explain in next section, this paper focuses on the markups over marginal cost.
²For instance, Nishimura, Nakajima, and Kiyota (2005) examined the productivity dynamics of Japanese firms and
studies examined market power of Japanese firms in this period. In order to understand the nature of firm performance in the severe recession period, the analysis on market power provides useful information.

The paper is organized as follows. Next section presents the econometric model. Section 3 explains about the data used in this paper. Estimation results of markups are presented in Section 4. Section 5 provides a summary and concluding remarks.

2 Model

Suppose that a firm produces output $Y$ using capital $K$, labor $L$, and intermediate inputs $M$ with linear homogeneous production function $Y = F(K, L, M)$. Denote the price of output, capital, labor, and intermediate inputs as $p$, $p_K$, $p_L$, and $p_M$, respectively, and total cost as $TC = p_KK + p_LL + p_MM$. Let $\mu$ be the markup of firm, where $p = \mu MC$ ($MC$ is marginal cost). We assume that $K$ is a “pre-determined” capital in the sense that it is fixed in the short run but flexible in the long run. In this paper, “pre-determined” means that firm must determine $K$ before market conditions are known.

Short-run cost minimization

Denote $\tilde{K}$ as “pre-determined” capital. For given $\tilde{K}$, the short-run cost minimization is:

$$\min_{L,M} TC = p_K\tilde{K} + p_LL + p_MM \quad s.t. \quad Y = F(\tilde{K}, L, M).$$

The first order condition is:

$$p_L = \lambda F_L(\tilde{K}, L, M) \quad and \quad p_M = \lambda F_M(\tilde{K}, L, M),$$

where the marginal cost $\lambda = dTC(p_L, p_M, \tilde{K}, Y)/dY$ and $F_L$ and $F_M$ represent the marginal product of labor and intermediate inputs, respectively. This in turn implies that the average-to-marginal cost ratio is:

$$\frac{AC}{MC} = \frac{(p_K\tilde{K} + p_LL + p_MM)/Y}{\lambda} = \frac{(p_K\tilde{K} + p_LL + p_MM)/\lambda}{Y} = \frac{p_K\tilde{K}/\lambda + F_L(\tilde{K}, L, M)L + F_M(\tilde{K}, L, M)M}{F(K, L, M)},$$

found that “natural selection mechanism” broke down in the severe recession period.
where \( AC \) is average cost. Because of the linear homogeneity of \( F \),
\[
\frac{AC}{MC} = 1 + \epsilon, \tag{2}
\]
where
\[
\epsilon = \frac{p_K/\lambda - F_K(\tilde{K}, L, M)}{F(\tilde{K}, L, M)/\tilde{K}}. \tag{3}
\]

The derivation of equation (2) appears in the Technical Appendix. Note that \( \epsilon \neq 0 \) since \( \tilde{K} \) must be determined before current market conditions (\( p_K \) and \( \lambda \)) are known. Thus, \( \epsilon \) is essentially a forecast error in terms of the average product of capital \( Y/\tilde{K} \).

Taking account of \( p = \mu MC = \mu \lambda \), we obtain:
\[
\frac{p_K\tilde{K} + p_LL + p_MM}{pY} = \frac{TC}{pY} = \frac{1}{\mu} \frac{AC}{MC} = \frac{1}{\mu}(1 + \epsilon). \tag{4}
\]

### Long-run cost minimization

In the long-run, capital stock is flexible (i.e., \( \tilde{K} = K \)). The marginal product of capital \( F_K \) equals to its shadow price \( p_K/\lambda \), implying \( \epsilon = 0 \). The result of cost minimization is:
\[
\frac{p_KK + p_LL + p_MM}{pY} = \frac{TC}{pY} = \frac{1}{\mu} \frac{AC}{MC} = \frac{1}{\mu}.
\]

In the long run, therefore, the markups are directly calculated from the cost-sales ratio.

#### 2.1 Estimation Strategy

Let \( i \) denote the \( i \)-th firm and \( t \) denote the year. The cost share is described as:
\[
\left( \frac{TC}{pY} \right)_{it} = \left( \frac{1}{\mu_{it}} \right) (1 + \epsilon_{it}). \tag{5}
\]

Assume that “base markup ratios” are different among firms but that their (mostly demand-driven) change between years is the same so that:
\[
\left( \frac{1}{\mu_{it}} \right) = \left( \frac{1}{\mu_i} \right) \times \left( \prod_{t=1}^{T} \delta_{it} \right), \tag{6}
\]
where \( 1/\mu_i \) is the reciprocal of the base markup ratio for firm \( i \), \( D_t \) is a year dummy and \( \delta_t \) is the year-dummy coefficient.
Substituting these relations (6) into (5), we obtain:

\[
\left( \frac{TC}{pY} \right)_{it} = \left( \frac{1}{\mu_i} \right) \times \left( \prod_{t=1}^{T} \delta_{it} \right) \times (1 + \epsilon_{it}),
\]

(7)

where forecast error \( \epsilon_{it} \) satisfies \( E(\epsilon_{it} | \Omega_{t-1}) = 0 \) and \( \Omega_{t-1} \) is an information set for individual firms to produce output available in year \( t-1 \). We assume that \( 1 + \epsilon \) follows lognormal distribution.

Taking log of both sides, we have:

\[
\ln \left( \frac{TC}{pY} \right)_{it} = \ln \left( \frac{1}{\mu_i} \right) + \ln \left( \prod_{t=1}^{T} \delta_{it} \right) + \ln(1 + \epsilon_{it}).
\]

(8)

Individual markups can be retrieved from \((1/\mu_{i})\) and \( \delta_{it} \). The regression equation thus is:

\[
\ln \left( \frac{TC}{pY} \right)_{it} = \alpha_{i} + \sum_{t=1}^{T} \beta_{i} D_{t} + u_{it},
\]

(9)

where \( \alpha_{i}(= \ln(1/\mu_{i})) \) is firm specific fixed-effect, \( \beta_{i}(= \ln \delta_{i}) \) captures demand shocks, and \( u_{it}(= \ln(1 + \epsilon_{it})) \) is an error term. In order to control for the industry-specific demand shocks, we include cross-term between year dummy \( D_{t} \) and industry dummy.\(^3\)

3 Data

We use the micro database of Kigyou Katsudou Kihon Chousa Houkokusho (The Results of the Basic Survey of Japanese Business Structure and Activities) prepared annually by the Research and Statistics Department, METI (1994-2002). This survey was first conducted in 1991, then in 1994, and annually afterwards. The main purpose of the survey is to capture statistically the overall picture of Japanese corporate firms in light of their activity diversification, globalization, and strategies on research and development and information technology. The strength of the survey is its sample coverage and reliability of information. The survey is comprised of all firms with more than 50 employees and with capital of more than 30 million yen.

The survey covers mining, manufacturing and wholesale/retail trade firms, although some wholesale/retail trade industries such as finance, insurance and software services are not included. The limitation of the survey is that some information on financial and institutional features such as

\(^3\)Nishimura, Ohkusa, and Ariga (2006) found the uniformity of the procyclical markups within the industry, which justifies the use of industry-level demand shocks in this paper.
keiretsu are not available and small firms with less than 50 workers (or with capital of less than 30 million yen) are excluded.

From these surveys, we constructed a longitudinal (panel) data set for the years from 1995 to 2002. We drop firms from our sample for which the firm-age (questionnaire-level year minus establishment year), total wages, tangible assets, value-added (sales minus purchases), or the number of workers were not positive and responses incomplete. We also drop firms whose total cost-sales ratio is outside 10σ to eliminate obvious outliers, where total cost is defined as the sum of labor costs, intermediate input costs, and capital cost (Technical Appendix provides the detailed description of these definitions). We focus on manufacturing, and wholesale and retail industries since the number of firms in other industries is rather small. The number of firms exceeds 16,000 annually.

Table 1 presents the sectoral distribution of firms used in this study. Sectoral classification is based on SNA used in Nishimura, Nakajima, and Kiyota (2005). In Japan, firms concentrated in wholesale trade, retail trade, electrical machinery, general machinery, and food products. In 2002, the share of the number of firms of these five industries accounts for 64.1 percent.

Table 2 indicates the industry-average of total cost-sales ratio. Two findings stand out from this table. First, the total cost-sales ratio varies across industries. The industry-average total cost-sales ratio ranges from 0.944 in chemical products (in 2000) to 1.045 in textile products (in 1994). Second, there is a sectoral difference in the total cost-sales ratio. In textile products, wearing-apparel and other ready-made textile products, furniture and fixtures, the total cost-sales ratio is larger than one throughout the period. On the other hand, the ratio is smaller than one in rubber products, chemical products, and transportation machinery.

4 Estimation Results

4.1 Estimation Results of Markups

Table 3 presents the estimation results of markups $\mu_{it}$. From equation (6), $\mu_{it}$ is decomposed into $\mu_i$ in Table 4 and $\delta_t$ in Table 5. Note that $\mu_i$ also changes because of the firm entry and exit.\footnote{If we use balanced panel (no entry and exit), $\mu_i$ becomes constant.} All
results are industry-year non-weighted averages.

??? Tables 3, 4, and 5 ???

Three messages stand out from these tables. First, the estimated markups are lower than those found in Nishimura, Ohkusa, and Ariga (1999). For instance, Table 3 indicates that the markup of electrical machinery industry in 2002 is 1.021, which is smaller than the markup of Nishimura, Ohkusa, and Ariga (1999) study (1.305). Table 4 indicates that, once we exclude the effects of demand shocks, the markup $\mu_i$ of electrical machinery is 1.016. Based on the fact that Nishimura, Ohkusa, and Ariga (1999) covered from 1971 to 1994, the results imply that the market power of Japanese firms become lower after the burst of the bubble period. In other words, Japanese markets become more competitive than before.

Second, however, in some industries, Japanese firms still enjoy some market powers. Table 4 suggests that the estimated markups are larger than unity in publishing and printing, rubber products, chemical products, petroleum and coal products, non-ferrous metals, and transportation machinery. By the same token, Table 4 also shows that Japanese firms in textile products, wearing-apparel and other ready-made textile products, timber and wooden products, furniture and fixtures, pulp and paper, leather tanning and leather products, iron and steel, and retail trade do not have market powers in this period. The results suggest that industry-specific effect play some roles in explaining market powers of firms and, therefore, supports the concept of “industrial organization” to some extent.

Finally, there are small but two demand shocks in this period. Table 5 indicates that $\delta_t$ increases from 1997 to 1998 and from 2000 to 2001 in almost all industries. Notice that $\mu_{it}$ becomes small if $\delta_t$ becomes large. In Japan, there is a financial crisis between 1997 and 1998. Also, the burst of the IT bubble hits the Japanese economy for 2000-01 period. The results suggest that our methodology capture the effect of negative demand shocks well and the decrease in the markups $\mu_{it}$ in this period is caused by the negative demand shocks $\delta_t$.

4.2 Robustness

Our results indicate that the markups are smaller than those in Nishimura, Ohkusa, and Ariga (1999). One may concern that the difference may be attributed to the measurement and the coverage of our data rather than the decline in markups. There are two differences between our study
and Nishimura, Ohkusa, and Ariga (1999). First, Nishimura, Ohkusa, and Ariga (1999) estimated markups based on value-added rather than gross-output. If some firms indicate large value-added, the estimated markups tend to be large. Second, Nishimura, Ohkusa, and Ariga (1999) used NIKKEI NEEDS Database which mainly covers large firms. If large firms tend to have larger market power, the estimated market also become large. In order to examine the robustness of our results, we address these two issues.

Table 6 presents the estimation results of value-added based markups.5 Three messages are evident from this table. First, the markups of heavy manufacturing industries tend to be large when we use value-added as outputs. For instance, the markups of electrical machinery in 2002 indicate 1.082, which is 1.065 times as large as the gross-output based markups. Similarly, the value-added based markups are large in such industries as non-ferrous metals, general machinery, transportation machinery, and so on. On the other hand, the value-added based markups are smaller than the gross-output based markups in such industries as textile products, wearing-apparel and other ready-made textile products, furniture and fixtures, and so on.

Second, although the markups become large in some industries, they are generally still smaller than the markups of Nishimura, Ohkusa, and Ariga (1999). Table 6 indicates that, in 198 industry-year (22 industries × 9 years) markups, about two-thirds of markups are smaller than 1.05. All industries except chemical products and other manufacturing indicate less than 1.1 markups. The results imply that our results of decline in markups in the 1990s are robust even when we change the measurements.

Third, the value-added based markups tend to have larger variance than the gross-output based markups. Table 7 presents the standard errors of $\mu_i$ by industry and by year for gross-output and value-added based markups. The results indicate that the standard errors of value-added based markups are 2.5-10.8 times as much as those of gross-output based markups. The results suggest that the heterogeneity in markups tend to be large when the markups are estimated using value-added than when the markups are estimated using gross-output. We discuss the heterogeneity in markups in detail in the next section.

--- Table 6 ---

5Value-added is defined as: total sales - (sales costs + administrative costs - wage payments - depreciation). Total costs are defined as the sum of labor and capital costs (intermediate inputs are excluded).
Next, we re-estimate value-added based markups for large firms such that the coverage and the measurement are much more comparable to those of Nishimura, Ohkusa, and Ariga (1999). Following the definition of Small and Medium Enterprise Agency, we define large firms with more than 300 workers for manufacturing and wholesale trade industries and with more than 100 workers for retail trade industries.

Table 8 presents the estimation results of value-added based markups for large firms. The estimated markups tend to be large for large firms, implying that large firms tend to have much stronger market powers. The results indicate that, in 2002, four out of 22 industries indicate markups larger than 1.1. However, the estimated markups are still smaller than those of Nishimura, Ohkusa, and Ariga (1999). For instance, the estimated markups of food products, electrical machinery, and wholesale trade are 1.024, 1.138, and 1.077, respectively while the estimated markups in Nishimura, Ohkusa, and Ariga (1999) indicate 1.213, 1.305, 1.224, respectively. The results suggest that, in general, markups decline in the 1990s and the Japanese market become more competitive than before.

5 Discussion

5.1 Heterogeneity in Markups

In Tables 3-5, we found that Japanese firms in some industries still enjoyed some market powers. But the market power can be different among firms even in the same industry. If the market power of firms indicates the large variation in the industry, the industry-level study might be misleading. To investigate the variation of firm-level markups within industries, we compute the share of firms above some threshold levels. Markups used in this study are $\mu_i$ rather than $\mu_{it}$ so that we can exclude the effects of demand shocks.

Table 9 presents the share of firms in each industry whose markups are larger than 1 and 1.05. The results suggest that there is a large variation of markups within the industry. For instance, the industry-average markups ($\mu_i$) of iron and steel is around 0.986 (Table 4). However, Table 6

--- Table 7 ---

--- Table 8 ---

--- Table 9 ---
indicates that more than one-third of firms enjoy market power (i.e., $\mu_i > 1.0$). Besides, about five percent of firms have relatively strong market power (i.e., $\mu_i > 1.05$). Similar findings are confirmed in such industries as retail trade.

--- Table 9 ---

Figure 1 indicates the distribution of markups in 2002 by industry. As Nishimura, Ohkusa, and Ariga (1999) found that the distribution of markups was skewed, most of distribution in Figure 1 does not look like normal distributions. To examine the normality of the distribution, we conduct Shapiro-Francia normality test for markups (Shapiro and Francia, 1972). In all industries, the hypothesis that the distribution is normal is rejected. We also rejected the log normality of markups. These results imply that the market power of firms is heterogeneous. In other words, although the concept of “industry” might help in explaining the market power, the concept of “firm” is also important. The results also imply that markups are skewed even within an industry.

--- Figure 1 ---

The heterogeneity in markups raises another question: what is the source of this heterogeneity? In order to answer this question, we examine the determinants of $\mu_i$: the cross-sectional variation among market powers. Three variables are introduced. The first variable is research and development ($R&D$). R&D plays an important role in improving the quality of products, in addition to innovate new products. This in turn implies that a firm can differentiate products in terms of quality, which enables a firm to charge higher prices for some specific groups. The second variable is advertisement $ADV$. It is often argued that advertisement increase the market power in a different way from R&D. The logic behind this argument is that advertisement can create or reinforce consumer preference for particular brands, which differentiates the brands from others. Such differentiation also allows firms to have market powers. The third variable is the market share of the firm that captures the relative size of the firm in the market. The regression equation thus is described as:

$$
\mu_i = \alpha_0 + \alpha_1 R&D_i + \alpha_2 ADV_i + \alpha_3 MARKET_i + e_i,
$$

(10)

where $R&D$ is R&D-sales ratio, $ADV$ is advertisement expenditure-sales ratio, $MARKET$ is market share of firm $i$, and $e_i$ is error term. All variables are averaged over the period.
Table 10 presents the estimation results. In almost all industries, R&D and advertisement expenditures have positive and significant effects on market power. Market share can also be an important factor to have market powers but not significant in many industries. A concern may be the correlation between R&D and market share since some studies such as Lee (2003) argued that the market share can be determined by the R&D activity. But the correlations between R&D and market share in Table 10 are generally small, implying that the correlation between R&D and market share is not a serious problem in our study.

--- Table 10 ---

5.2 Procyclical Markups

In Table 5, we found that the effects of demand shocks on markups. The related important question is whether the markups are procyclical or not. The relationship between business cycle and the markups is often discussed in the literature. Since theoretical studies predicts both directions, whether the markups are procyclical or not is empirical matter.

Table 11 presents the simple correlation between $\frac{1}{\delta_t}$ and the growth of industry sales. In all but leather tanning and leather products industries, positive correlation is confirmed. The results thus mean that there is a positive correlation between markups and demand shocks, implying that the procyclical behavior of markups. This result is consistent with the findings of previous studies that examined the movement of markups (Ariga and Ohkusa, 2006; Nishimura, Ohkusa, and Ariga, 1999).

--- Table 11 ---

It is also interesting to note that there are some differences in the degree of correlation. While wearing-apparel and other ready-made textile products and publishing and printing indicate higher correlation with the sales (0.844 and 0.842, respectively), food products indicate negative but almost no correlation (0.087). The results imply that the markups changes procyclically but the degree is different among industries.

One may concern that this procyclicality might be caused by other factors such as changes in market structure. Thus, we conduct regression analysis, controlling for other factors. As control

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8See, Nishimura, Ohkusa, and Ariga (1999) for the argument of this issue.
variables, we include the changes of labor costs, the changes of market structure, and entry/exit rates. The regression equation is described as:

\[
\Delta(1/\delta_{zt}) = \beta_0 + \beta_1 \Delta pY_{zt}^{ind} + \beta_2 \Delta HHI_{zt} + \beta_3 \Delta w_{zt} + \beta_4 ENTRY_{zt} + \beta_5 EXIT_{zt} + u_{zt},
\]

(11)

where \( pY_{zt}^{ind} \) indicates the sum of sales in industry \( z \) in year \( t \), \( HHI_{zt} \) is Herfindahl index, \( w_{zt} \) is industry average labor cost. The effects of entry and exit are captured by entry rate \( ENTRY_{zt} \) and exit rate \( EXIT_{zt} \) and \( u_{zt} \) is error term.

Table 12 presents the estimation results. Two findings stand out from this table. First, the growth of industry has positive effects on the markups. The coefficients of \( pY_{zt}^{ind} \) indicate positive and significant signs. The result implies that the markups are procyclical, which is consistent with the findings of Nishimura, Ohkusa, and Ariga (1999) and Ariga and Ohkusa (2006).

Second, the firm exit has positive effects on the markups but the entry has negative effects on the markups. The coefficients of \( EXIT_{zt} \) indicate positive and significant signs while the coefficient of \( ENTRY_{zt} \) indicates significantly negative sign. These results imply that the firms enjoy their market power when the rival firms are dropping out from the market.

### 5.3 Weighted Results

In Table 8, we confirmed that larger firms tend to present larger markups. In this connection, one may concern that industry-year non-weighted average of markups might be misleading in discussing the results since it is difficult to equally discuss the market powers of large and small firms. In order to take account of the firm scale, we recalculate industry-year markups, weighting by the sales share of firms. The weighted average markups reflect the relative size of the firms in the industry.

Table 13 presents the markups weighted by sales. As expected, the results indicate that weighted average markups are larger than non-weighted averages (Table 4) but the differences are very small. In 198 industry-year (22 industries × 9 years) markups, more than 87 percent of markups \( \mu_i \) are
smaller than 1.05 (i.e., 25 industry-year). None of the industries indicate larger than 1.1 markups. The results suggest that the decline of the markups in the 1990s is evident even after we control for the size of the firms.

6 Concluding Remarks

This paper presents a new econometric framework to estimate markups at the firm level from a panel data. The framework is applied to study markups of Japanese firms in manufacturing and trade from 1995 to 2002. Major findings are summarized as follows. First, estimated markups were lower than those obtained in Nishimura, Ohkusa, and Ariga (1999). The results imply that the Japanese markets become more competitive in the 1990s than before.

Second, markups among firms vary in the industry. Even in the low markups industries such as iron and steel, more than one-third of firms enjoy the markups with greater than unity. The results imply that the heterogeneity in markups exists, suggesting the importance of firm-level study of markup estimation. The heterogeneity in market power is partly explained by R&D and advertisement.

Finally, there is a procyclicality in the Japanese markups although its degree is different across industries. We also found that the changes of markups were affected by entry and exit of firms. That is, the entry of firm has negative effects on markups while the exit of firm has positive effects. The results suggest that it is more difficult for firms to have market powers with the increase in the number of firms in the industry.

Before closing this study, we point out several research issues for the future, which were not analyzed in this study. First, the detailed analysis on the distribution of markups might be an important issue. The analysis of skewed distribution is directly related to the source of industry dynamics if the industry dynamics are caused by a few leading firms with market power. Another important avenue is the effect of markup heterogeneity. In almost every industry, there are some firms with large market power. As is well known, without controlling for the effects of markups, the productivity can be biased in case of an imperfectly competitive market. Although average markups are small, such biases are large for some firms. If productivity and market powers have positive correlation, the productivity of leading firms is biased. Finally, the causal relationship between markups and their sources is also investigated more carefully. In order to examine the relationship, the choice of instruments should be discussed in more detail. These questions will be
clarified in our future research.

References


Technical Appendix

PROOF: The Derivation of Equation (2)

Because of the linear homogeneity of $F$,

$$
\frac{PK}{\lambda} \tilde{K} + F_L(\tilde{K}, L, M)L + F_M(\tilde{K}, L, M)M
$$

$$
= \left\{ \frac{PK}{\lambda} - F_K(\tilde{K}, L, M) \right\} \tilde{K} + F_K(\tilde{K}, L, M) \tilde{K} + F_L(\tilde{K}, L, M)L + F_M(\tilde{K}, L, M)M
$$

$$
= \frac{PK}{\lambda} - F_K(\tilde{K}, L, M)
$$

$$
= \frac{PK}{\lambda} - F_K(\tilde{K}, L, M)
$$

$$
= F(\tilde{K}, L, M) \left\{ 1 + \frac{PK/\lambda - F_K(\tilde{K}, L, M)}{F(\tilde{K}, L, M)/\tilde{K}} \right\}
$$

$$
= F(\tilde{K}, L, M)(1 + \epsilon),
$$

where

$$
\epsilon = \frac{PK/\lambda - F_K(\tilde{K}, L, M)}{F(\tilde{K}, L, M)/\tilde{K}}
$$

From equation (1),

$$
\frac{AC}{MC} = \frac{PK/\lambda + F_L(\tilde{K}, L, M)L + F_M(\tilde{K}, L, M)M}{F(\tilde{K}, L, M)}
$$

$$
= \frac{F(\tilde{K}, L, M)(1 + \epsilon)}{F(\tilde{K}, L, M)}
$$

$$
= 1 + \epsilon.
$$

Definition of Costs

Total cost is defined as the sum of labor costs, intermediate input costs, and capital cost. Labor cost is defined as total wage payments. Intermediate input is defined as: (operating cost - personnel cost - depreciation cost). Capital cost is defined as real capital stock $K_{it}$ times user cost $p_{Kit}$. Following Kiyota and Okazaki (2005), we define the user cost as:

$$
p_{Kit} = p_{It} \left( \frac{1 - \tau_i \phi_i}{1 - \tau_i} \right) \left( r_t + \delta_{it} - \frac{p_{It}}{p_{It}} \right),
$$
where \( p_{it} \) is investment goods deflator obtained from Toyo Keizai (2005); \( \tau_t \) is corporate tax rate on business income from the Ministry of Finance website;\(^9\) \( r_t \) is interest rate that is defined as 10-year bond yield (annual average) and from Toyo Keizai (2005); \( \delta_{it} \) is depreciation rate and from the KEO Data Base; \( \phi_i \) is derived so that the following equations are satisfied:

\[
\phi_i = \sum_{t=1}^{T} \frac{(1 - \delta_{it})^{t-1}\delta_{it}}{(1 + r_t)^{t-1}} \quad \text{and} \quad (1 - \delta_{it})^T \approx 0.05.
\]

The second equation means that the end point of the depreciation period is defined as the time when the accumulated depreciation cost approximately equal to 95 percent of the initial investment.

\(^9\) [http://www.mof.go.jp/jouhou/syuzei/siryou/houzin/hou03.htm]