RIETI Discussion Paper Series 13-E-098

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An analysis of Japanese industries on the basis of the industry-level panel data

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RIETI Discussion Paper Series 13-E-098
November 2013

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Abstract

This study mainly investigates the causal relation between the degree of competition, which is measured by the Lerner index, and the total factor productivity (TFP) growth rate on the basis of the Japanese industry-level panel data (Japan Industrial Productivity (JIP) Database) from 1980 to 2008. The central finding indicates that, although a positive effect of competition on the TFP growth rate is clearly observable in the manufacturing industries throughout the sample period, such effect in the non-manufacturing industries may be slightly negative in the latter half of the sample period (1995-2008). This finding of a negative competition effect may lend support to the claim that the Schumpeterian hypothesis can be applied in the case of the non-manufacturing industries. Furthermore, a weak inverted-U shape relation between the competition measure and TFP growth proposed by Aghion et al. (2005) can be seen limitedly almost exclusively in all industries.

Keywords: Competition; Productivity; TFP; Lerner index; Schumpeterian hypothesis; Inverted U-shape; Manufacturing and non-manufacturing industries.
JEL classification: L11; L60; L80; O30.

This study is supported by Research Institute of Economy, Trade and Industry (RIETI). In writing this paper, I am indebted to George Symeonidis and David Reinstein (University of Essex) for offering his generous time, support and invaluable comments. I would like to express my gratitude to Kyoji Fukao (Hitotsubashi University) and Toshiyuki Matsuura (Keio University) for their instructions of the JIP Database. I am grateful for helpful comments and suggestions by Tomohiko Inui (Nihon University) and Discussion Paper seminar participants at RIETI.

1 Introduction

As the Structure-Conduct-Performance (SCP) paradigm notes, it has been considered that market structures such as the degree of market competition or concentration and the level of entry barriers affect economic performance of the markets. Baily and Solow (2001), who compare productivity across countries on the basis of OECD data, have found large discrepancies in productivity across countries, possibly resulting from different market structures. It has been intriguing investigating which specific industrial market structures, especially the competitive environment in markets, produce the described discrepancies in productivity or growth.

With many economists addressing this complex and controversial question, two conflicting ideas regarding market competition and productivity have arisen. The first idea is that the more competitive markets derive a higher level of incentives to survive, that is, firms exposed to fierce market competition are forced to improve their productivity. In contrast, the second idea posits that firms in less competitive markets and having stronger market power can better afford to innovate. The complexities of market relations and characteristics necessitate empirical demonstration of the effects of market competition or market power that influence differences in productivity in a way to complement previous studies.

When attention is directed at the Japanese economy, a question arises as to why the productivity level of Japan actually continues to be extremely low. [1] As many researchers have pointed out (Hayashi and Prescott 2002, Hoshi and Kashyap 2011, Fukao 2012), Figure 1 depicts that the average contribution of the total factor productivity (TFP) growth to real GDP growth in the Japanese economy fell sharply to below 0% between 1990 and 1995, and has remained stagnant along with production factors such as capital and

[1] According to Baily and Solow (2001), while US labor productivity from 1993 to 1995 was normalized to on a scale of 100, estimates for other countries were Holland, 96; West Germany, 92; France, 92; the United Kingdom, 73; Japan, 70. Further, while US total factor productivity (TFP) was 100 for the same period, the figures for other leading nations were West Germany, 89; France, 89; UK, 79; Japan, 67.

labor since 1995, although it turned positive between 1995 and 2005. [2] Specifically, the TFP growth rate of the non-manufacturing industries (nearly the service industries) has remained quite low for a much longer time as compared to the manufacturing industries, as illustrated in Figure 2. Baily and Solow (2001), making an inter-industry comparison of productivity in the manufacturing and service industries across countries, propose that although, in Japan, the export-oriented industries such as automobiles and steel exhibit high productivity, the domestic service industries have much lower productivity due to the presence of government regulations providing protection from global competition. But contrasting claims have been made that the service industries in Japan, although not exposed to global market competition, are involved in a Bertrand-type overcompetition in domestic markets, which hinders service industry firms from increasing their productivity. I will later refer to the causes of low productivity accruing to the non-manufacturing industries in conjunction with the estimation results in Section 5.

Considering the views mentioned in the preceding discussion, this study attempts to explore whether the idea that increased market competition improves industrial productivity is valid by analyzing their statistical relations on the basis of the Japanese industry-level panel data from 1980 to 2008. In order to develop a detailed view of the competition effect, this study breaks down the total industries into the manufacturing and non-manufacturing industries and then empirically demonstrate the difference in such effects between them. The main finding is that, whereas the positive effect of market competition, calculated from the Lerner index, on TFP growth can be observed in the manufacturing industries throughout the sample period, the weak negative market competition effect may operate in the non-manufacturing industries during the latter half of the same period. This result would seem to support the Schumpeterian hypothesis being applied in the case of the non-manufacturing industries. The contribution of my study

[2] The conceivable reason why the average contribution of TFP growth showed an exorbitant negative figure between 2005 and 2009 is that the outbreak of the "Lehman Shock" in September of 2008 had a destructive impact on the world economies including Japan. Indeed, the relevant average figure between 2005 and 2007 was about 1.4%.

to the literature on the relation between market competition and productivity is that, although it employs undetailed industry-level data, but not micro firm-level data, it aims at focusing on the non-manufacturing industries, which few researchers have examined so far, as well as on the manufacturing industries. It is critically important from the perspective of competition and innovation policies to shed light on this relation in order to improve recent low productivity of the Japanese industries.

The reminder of the paper is organized as follows. Section 2 provides a survey of existing theoretical and empirical research and reviews several empirical studies focusing on Japan. Section 3 defines the empirical formulations while describing an endogeneity problem. Section 4 explains the construction of the variables. Section 5 reports empirical results and their interpretations in reference to other studies. Section 6 concludes and discusses significant implications followed by an appendix and full reference.

2 Survey of Existing Studies

2.1 Theoretical Backgrounds

In the case where technology is assumed to be appropriated, a simple reasoning suggested by Arrow (1962) tells that firms in a competitive market generally have stronger incentives to achieve technological progress that reduces costs than monopoly firms. More precisely, competitive firms are eager to innovate in order to achieve the status enjoyed by monopoly firms and to earn monopoly profits by owning a breakthrough innovative technology. In contrast, monopoly firms remain in the same positions even after achieving their own technological progress, and hence the incentive to further innovate would weaken. This mechanism in monopoly firms is often called the replacement effect. [3]

In contrast to the above-mentioned "static" efficiency of perfect competitive markets,

[3] Arrow (1962) also notes the possibility that, if technology is not appropriable, the amount of R&D expended for technology is less than the socially optimal level because every firm wants a free ride on the R&D outcomes achieved by other firms without facing the burden of expenses.

Schumpeter (1942) highlights the importance of a "dynamic" problem. As Ahu (2002) summarizes, Schumpeter's (1942) argument is that the organization of firms and markets that is most conducive to solving the static problem of resource allocation is not necessarily most conducive to rapid technological progress. Hence, Schumpeter (1942) concludes that primitive firms operating in competitive markets are not as dynamically efficient as large firms operating in more concentrated markets. [4] Schumpeter's (1942) work is reinterpreted as the "Schumpeterian hypothesis" by later economists who consider monopoly power conducive to the progress of innovative activity. Inspired by the intuitive works of Schumpeter (1942) and others, many economists have conducted theoretical and empirical studies to test whether or not the Schumpeterian hypothesis holds true, particularly, in terms of whether competition (or monopoly) promotes growth, technological progress, and innovation.

In addition to early theoretical works (Dasgupta and Stiglitz 1980, Gilbert and Newbery 1982), the contract theory approach is widely used to assess the relation between competition and productivity. Hart (1983) reveals that, if high-incentive entrepreneurial firms cause a general reduction in costs and prices, low-incentive managerial firms need to take part of the cost reduction in managerial slack as they are confronted with the thereat of the former. Thus, Hart (1983) suggests that competition in a product market reduces managerial slacks and improves productivity. In contrast, Scharfestein (1988) maintains that market competition may instead exacerbate incentive problems citing the case where it is more profitable for a business manager to feign low productivity when his/her productivity is high. Additionally, Schmidt (1997) demonstrates that, whereas increased competition reduces the profits of firms and forces a business manager to work harder to avoid liquidation, a reduction in profits also deteriorates the profitability of

[4] Cohen (1995) provides numerous reasons for the advantage enjoyed by large firms in concentrated markets that engage in R&D, illustrating the examples of capital market imperfections, fixed costs of innovation (particularly process innovation), complementarities between R&D activity and non-manufacturing activity, and diversification permitting economies of scale or risk reduction. Contrastively, Scheler and Ross (1990) point to the counter-argument disadvantages such as excessive bureaucratic control and scientists' or entrepreneurs' low morale in large firms.

cost-reduction. In short, such theoretical analyses are rather overall inconclusive as to the simple effect of market competition on productivity and innovative activity, depending upon the researchers' assumptions and model frameworks.

Meanwhile, Aghion et al. (2005) theoretically prove that the relation between aggregate innovation and the degree of competition can take an inverted-U shape. These studies insist that the inverted-U shape results from a combination of both the "escape-competition effect" and the "Schumpeterian effect". The former effect indicates that more competition motivates firms in neck-and-neck sectors to innovate in order to escape the competition, and the latter indicates that an increase in competition discourages firms in unlevel sectors to innovate because of dissipation of rents that can be captured by a follower after innovation. Hence, this theory can be interpreted as partially incorporating the Schumpeterian hypothesis into the model, which suggests a positive relation between market power and innovation.

2.2 Empirical Studies

Let me turn our attention to existing empirical studies. Most notably, Nickell (1996) investigates how market environment, for example, market share, market concentration, rent (the Lerner index or price-cost margin), and the number of competitors, affects the TFP level and TFP growth by estimating a production function including these independent variables from the data of roughly 700 UK manufacturing firms between 1972 and 1986. This study reveals that market power, represented by the market share, reduces the TFP level and that market competition, represented by the Lerner index, is associated with higher rates of TFP growth. Geroski (1990), using the UK data of 73 industrial sectors from 1970 to 1979, shows that a rise in market concentration reduces the number of innovation by a regression analysis, and hence concludes that there is nearly no support for the Schumpeterian hypothesis. Blundell et al. (1999), who designate counts of innovation and patents as dependent variables from the data of 340 UK manufacturing firms gathered between 1972 and 1982, find that increased product market competition in the industry measured by market concentration tends to stimulate innovative activity, although market share has a robust positive effect on headcounts of innovations and patents. In contrast, Crépon et al. (1998), using the cross-sectional data of innovation output of French manufacturing industries in 1990, demonstrate that the probability of conducting R&D increases significantly with firm size, market share and diversification as suggested by the Schumpeterian hypothesis. Further, Aghion et al. (2005) test the theoretical result of an inverted-U relation between market competition and innovation based upon a panel dataset of 311 UK firms from 1973 to 1994. Citation-weighted patent count is used as a dependent variable, and competition index calculated by the Lerner index and the square of this competition index are used as independent variables. Constructing the industry-specific variables from these datasets, this study shows that the coefficient of the squared competition index is significantly negative and that the upward-sloping part of an inverted-U shape is steeper if the set of industries is restricted to those above the median degree. [5]

A limited number of studies on Japan have been conducted centering on the relation between competition and productivity, largely because of a lengthy delay in the establishment of a reliable database. Nevertheless, prominent research has appeared in recent years mainly using the firm-level data. Okada (2005), following Nickell's (1996) empirical approach and using the *Basic Survey of Business Structure and Activities* (*BSBSA*) data of roughly 100,000 manufacturing firms from 1994 to 2000, demonstrates that competition measured by the lower Lerner index at the industry level reinforces productivity growth and that market power measured by either the Lerner index or market share at the firm level negatively affects the productivity level of firms performing R&D. Focusing on both productivity and innovative activity using the *BSBSA* data of about 2,400 firms from 1994 to 2001, Motohashi et al. (2005) reveal that a drop in the Herfinahl index has

[5] Scherer (1965) produces the initial empirical study that finds a non-linear relation between market structures (firm size and concentration ratio) and innovative outputs (patents).

a positive impact on productivity but a negative impact on R&D expenditure and the number of registered patents. Arai (2005), who uses the *Japan Industrial Productivity Database* (*JIP Database*) of 84 industrial sectors from 1970 to 1998, show that although many sectors exhibit positive correlation between the TFP growth rate and the approximated Lerner index, the inverted-U relation is scarcely observable. Thus, Arai (2005) concludes that competition may not have a positive effect on productivity. Flath (2011) uses the industry-level data produced by the *Census of Manufacturers* from 1961 to 1990, and demonstrates that there is a "U-shape" relation between market concentration measured by the Herfindahl index and technological growth, but has no relation to the Lerner index. Inui et al. (2012), based upon the firm-level data of roughly 35,000 observations between 1997 and 2003 produced by the *Basic Survey of Business Activities of Enterpises* (*BSBAE*), confirms whether the inverted-U shape theory does apply in the case of Japanese manufacturing firms following a study of Aghion et al. (2005). Controlling an endogeneity problem, this study shows not only that market competition measured by the Lerner index positively affects productivity growth, but also that there exists an inverted-U relation between them. Finally, Yagi and Managi (2013) also empirically find the inverted-U shape adopting instead the patent data as a dependent variable on the basis of the firm-level and industry-average data from 1964 to 2006.

Economists have yet to reach an overwhelming consensus, including studies conducted in Japan, mainly due to the difficulty in choosing the appropriate measurement variable of competition and identifying the causal relation. However, it seems that recent studies have found market competition to have a positive effect on productivity and innovative activity in manufacturing industries, resulting in disproportionate evidence against the Schumpeterian hypothesis.

3 Empirical Formulation

My empirical formulation of the relation between competition and productivity provides reference to, in particular, Okada (2005) and Inui et al. (2012). I focus on the industry-specific competition measure and TFP growth, and use the industry-level *JIP Database* (a detailed explanation is given in Section 4). It should be noted here that my empirical formulation differs from previous studies, in that it adds not only the index which indicates the degree of market competition (as measured by approximated industry-level Lerner index), but also other control variables such as the incremental research and development (R&D) stock ratio to output and the IT investment ratio to output that can directly affect the industrial productivities. As described later in this paper, all industries are split into the manufacturing and non-manufacturing industries so that the focus can be directed on specific characteristics prevalent in each industrial category. Further, by adding the quadratic term of the competition measure as other researchers do, I intend to test the idea proposed by Aghion et al. (2005) that the competition-innovation relation takes an inverted-U shape.

First, in order to simply test whether the effect of increased competition is positive or negative, the basic regression model is defined as follows:

$$tfpg_{it} = \alpha_i + \alpha_t + \beta_1 comp_{it-1} + \beta_2 \Delta rds_{it-2} + \beta_3 tit_{it-2} + \varepsilon_{it}, \tag{1}$$

where $tfpg$ is the annual TFP growth rate, $comp$ is the degree of competition, Δrds is the ratio of incremental R&D stock to output, tit is the ratio of total IT investment to output, i is the industry script, t is the time script, α_i is the industry fixed effects, α_t is the time fixed effects, vector β_j ($j = 1, 2,$ and 3) denotes the population coefficients, and ε_{it} is the serially uncorrelated random error terms. The variables used in this analysis are briefly summarized in Table 1.

I posit that the one-year lag of the competitive measure and the two-year lag of incremental R&D stock and IT investment affect present-time TFP growth. This premise of the one-year lag of the competition measure is the same as that posited by Inui et al. (2012). Although many other studies assume that TFP growth and the degree of competition are concurrently related, it seems more plausible that the effect of competition would be in force in due time, especially in the case of industrial analyses. Incremental R&D stock and total IT investment are also assumed to take a prolonged period of time to have any influence on productivity. The two-year lag of these two control variables are determined by investigating the correlation between these variables and TFP growth. [6]

If we assume that competition stimulates industries in improving productivity, β_1 will be positive. Inversely, β_1 being negative suggests that increasing market power may stimulate productivity improvement, which would lend support for the Schumpeterian hypothesis. As regards the coefficients of the incremental R&D stock ratio and the total IT investment ratio, it is generally expected that β_3 and β_4 are positive.

The following model that adds the quadratic term of the competition measure, $comp_{it-2}^2$, is also estimated to test the inverted-U shape theory:

$$tfpg_{it} = \alpha_i + \alpha_t + \beta_{11} comp_{it-1} + \beta_{12} comp_{it-1}^2 + \beta_2 \Delta rds_{it-2} + \beta_3 tit_{it-2} + \varepsilon_{it}. \tag{2}$$

Regarding the signs of the coefficients, β_{11} and β_{12} are expected to be positive and negative, respectively, according to this theory.

Within-group transformation of equations (1) and (2) is made to eliminate the industry fixed effects. [7] By this transformation, for example, equation (1) is modified as follows:

$$\begin{aligned} tfpg_{it} - \overline{tfpg}_i = (\alpha_t - \overline{\alpha}) + \beta_1(comp_{it-1} - \overline{comp}_i) + \beta_2(\Delta rds_{it-2} - \overline{\Delta rds}_i) \\ + \beta_3(tit_{it-2} - \overline{tit}_i) + (\varepsilon_{it} - \overline{\varepsilon}_i), \end{aligned} \tag{3}$$

where the "bar" notations denote the operation of taking mean over time. This formu-

[6] Although it is possible to assume that the further lags of the control variables can be included into equation (1), this has a drawback of decreasing observations that are used in estimations. Thus, considering the limited number of observations in my dataset, I do not include the further lags.

[7] The alternative way of estimating the model with fixed effects is to take a first difference. But the within estimation is usually favored in a static model as it is more efficient if ε_{it} is not serially correlated.

lation is called the fixed effects (FE) model, and it is a classical regression model that captures the unobservable individual fixed effects. One advantageous feature of the FE model is that, as long as the independent variables are uncorrelated with the error terms, ε_{it}, we can obtain consistent estimators even when the independent variables are correlated with the industry fixed effects.

We must, though, consider that an endogeniety problem can occur when we intend to run such a regression as the above equations. [8] It may be problematic estimating equations (1) and (2) based upon the simple FE model without using instrumental variables (IVs), because the degree of competition is likely to be correlated with the error term. In particular, reverse causalities, which trigger an endogeneity problem, seem to exist between the degree of competition and the annual TFP growth rate. If independent variables are correlated with the error term, estimators are generally biased and inconsistent. As Nickell (1996) and Okada (2005) stress, the reverse causality between competition and productivity is expected to generate the opposite sign. That is, the effect of productivity on competition (or market power) is likely to be negative (or positive). According to Okada (2005), if a positive relation between competition and productivity (or a negative relation between market power and productivity) is observed, competition would have a much stronger effect on productivity.

It is assumed in this study that the degree of competition is predetermined for one year before TFP grows. However, if this competition measure is serially correlated, then the one-year lag of the competition measure would be also correlated with the error term, as Inui et al. (2012) point out. As this may generate an endogeneity problem, we should employ IVs to alleviate it. [9] In contrast, as for endogeneity concerning incremental R&D

[8] Many recent studies have supported the viewpoint that competition (or market power) and innovative activity are simultaneously determined (Cohen 2010). For instance, Symeonidis (1996), who carefully surveys research conducted on market structures and innovation, summarizes: “Recent work in industrial economics suggests that market structure and RGD intensity are jointly determined by technology, demand characteristics, the institutional framework, strategic interaction and chance.”

[9] Aghion et al. (2005) find the policy instruments represented by the introduction of policy changes that generated exogenous variation in the degree of industry-wide competition. Instead of using such policy instruments, Nickell (1996) and Okada (2005) estimate their models based upon the Arellano-Bond GMM estimation (Arellano and Bond 1991) in the form of a dynamic panel data model.

stock and total IT investment, I assume that these two variables are exogenous at the industry level contrary to the firm-level analyses, and hence I presume that there occur no endogeneity problems in them. [10] Although I cannot completely deny the possibility of an endogeneity problem accruing to these control variables, unfortunately, I find it difficult to obtain in my dataset the IVs that allow us to appropriately estimate the model.

I employ the following variables as the IVs of the competition measure in $t-1$ ($comp_{it-1}$): the change of the competition measure from $t-2$ to $t-1$ ($\Delta comp_{it-1}$) and from $t-3$ to $t-2$ ($\Delta comp_{it-2}$), the ratio of household consumption to output in $t-2$ ($hcons_{it-2}$), and the ratio of export to output in $t-2$ (exp_{it-2}), all of which are calculated at the industry level. Note that different IVs are employed in equations (1) and (2) as shown in the notes of Tables 5-10. Here it is considered that these IVs affect only the competition measure, but not TFP growth. In particular, final demand of household consumption and export relative to output within industries seems to represent the market structures that can be related to the degree of competition. [11] In order to casually confirm whether the IVs are usable, I calculate the correlation coefficients between the independent variables and these potential IVs presented in Table 2. The result demonstrates that these IVs are largely correlated with the competition measure. Further, I also conduct the exogeneity, underidentification, weak identification, and overidentification tests in estimating the model to check the adequacy for conducting the FE-IV estimation. Finally, I report on the robust (Eicker-Huber-White) standard errors adjusted for small samples in all estimations.

[10] Ito and Lechevalier (2010) carefully address the reverse causality between R&D activity and TFP in the analysis of the Japanese firm-level data.

[11] Although the existing studies such as Inui et al. (2012) employ the import penetration ratio as an IV, I cannot construct the valid IV of this index obtained from my dataset.

4 Dataset

This section provides detailed explanations of how I construct the variables. Likewise Arai (2005), the primary indicators used in this study have been obtained from the *Japan Industrial Productivity (JIP) Database* produced jointly by the Research Institute of Economy, Trade and Industry (RIETI) and Hitotsubashi University. The *JIP Database* comprises various types of annual datasets that are necessary for the estimating sectoral TFP in 108 industries covering the Japanese economy as a whole. [12] The most recent *JIP Database 2012* is the primary source for the collecting of data on industry-specific TFP, output, intermediate, labor, and capital input costs, and final demand such as consumption and export.

The object of analysis in this study is the 86 industrial sectors listed in Table 3. Not only the 14 industrial sectors that are not based upon the market economy, such as social insurance/welfare, education, and medical, but also the 6 industrial sectors related to the primary industries such as agriculture, forestry, and fishing, are excluded from the sample. The reason is that the non-market and these primary sectors are not sufficiently exposed to market competition and are protected by measures, for example, regulations. The 2 industrial sectors, housing and the unclassified sectors, are also excluded. The period subject to estimation is the year units from 1980 to 2008. While my analysis is limited to this long-term period, I divide it into the two categorical periods: 1980-1994 and 1995-2008. As indicated in Figure 1 and 2, the Japanese economy experienced a drastic decline in GDP and TFP growth since 1990s caused by the bubble economy burst. Indeed, many economist reach an agreement that there were some structural changes within the Japanese industries around this time, such as more competitive economic environments at a global level. This is why I believe that it is meaningful to examine how the difference in productivity was generated by competition before and after the period.

[12] This brief explanation of the *JIP Database* is based upon the homepage of the RIETI website. See the following English page for details: http://www.rieti.go.jp/en/database/JIP2012/index.html.

4.1 Dependent Variable (TFP Growth)

The TFP growth rate is employed as a dependent variable that captures innovation. The data of industry-level TFP is easily available from the *JIP Database 2012*. [13] Although R&D expenditure or intensity was widely used as the measure of innovative activity in early studies, the use of such measures as productivity and innovation counts that allow us to directly comprehend the result of innovative activity has been more preferred (Cohen 2010). Indeed, for the purpose of robustness check, I conduct a preliminary regression analysis (the details are omitted), where real R&D investment growth rate is a dependent variable and where the one-year lag of the competition measure and the one-year lag of R&D stock ratio to output are independent variables. However, I cannot obtain from this regression substantially significant results of competition effects as I will find in the next section. This is because, in reality, many industries (firms) appear to make a long-term strategic R&D investment decision independently of the short-term change in market structures such as competition environments.

On the other hand, there is some question as to whether industry-level TFP is the appropriate indicator of testing the Schumpeterian hypothesis regarding innovation. In fact, industry-level TFP growth used in this study is decomposed into productivity dynamics comprising of the internal, distribution, entry, and exit effects, and the conventional Shumpeterian hypothesis generally views only the internal effect (that is, productivity improvement inside firms) as a result of innovative activity. However, because the internal effect is considered accounting for a large part of sectoral TFP growth, we can regard TFP growth as an approximate measure of innovation. [14] Or it may well be that we define the industry version of the Schumpeterian hypothesis as including all productivity dynamics that reflects industrial refreshment.

[13] See the RIETI homepage listed in footnote 12 or Fukao and Miyagawa (2008) for details on how to estimate industry-specific TFP.

[14] Using the financial data of Japanese listed companies, Kim et al. (2010) make it clear that an increase in TFP consistently resulted mainly from the internal effect since the 1980s including both the manufacturing and non-manufacturing industries and that the other effects were relatively minute.

4.2 Independent Variables and IVs

With regard to independent variables, the major indicator of competition is considered to be the Lerner index (the price-cost margin) used by numerous researchers (Nickell 1996, Okada 2005, Aghion et al. 2005, Arai 2005, Flath 2011, Inui et al. 2012). As Arai (2005) points out, although the conventionally popular measures of market competition in the context of the competition policy are the Herfindahl index and concentration ratio, they can appropriately reflect only the Cournot-type quantity competition where an increase in firms intensifies competition and not the Bertrand-type price competition where a decrease in firms coexists with fierce competition. Further, a practical predicament that the Herfindahl index and concentration ratio are available only for three years (1996, 2001 and 2006) in the *JIP Database 2012* prevents us from accumulating a sufficient number of observations. Therefore, in common with the above-mentioned existing studies, I employ the Lerner index as a measure of competition calculated for each industrial sector.

According to the basic definition, the Lerner index is defined as $(p - MC)/p$, where p is the price and MC is the marginal cost, and hence this index measures a certain type of monopoly rent or profitability that implies some market power. Because it is difficult to directly calculate the marginal Lerner index based upon this definition, I define the following industry-specific Lerner index as Arai (2005) does:

$$LI = \frac{output - intermediate\ input - labor\ input - capital\ service\ input}{output}, \tag{4}$$

where all variables are evaluated by nominal prices and all data is available from the *JIP Database 2012*. See Appendix 1 for the background of monopoly rent and the industry-specific Lerner index. Based upon the above construction of LI, the industry-level degree of competition can be simply defined as $comp = 1 - LI$, which means that the larger the value is, the more competitive the relevant industry is. In addition, since it is highly likely that the Lerner index (competition measure) fluctuates with business cycle either pro-cyclically or counter-cyclically, [15] year dummy variables are included as independent variables to control demand fluctuations.

I have obtained the basic R&D data from the *Estimation of the Industry-Level R&D Stock* edited by National Institute of Science and Technology Policy (NISTEP). This data accumulates long-run R&D stock at the industry level ranging from 1973 to 2008, and the classification of industrial sectors is adjusted to be the same as those of the *JIP Database*. Considering that flow of R&D affects TFP growth, I employ as an independent variable incremental R&D stock normalized by nominal output. Data regarding IT investment in each industrial sector between 1970 and 2008 is also provided by the *JIP Database 2012*. Finally, as regards the ratios of consumption and export to output at the industry level, the data can be obtained from final demand by sectors in the inter-industry relations table included in the *JIP Database 2012*.

4.3 Descriptive Statistics

Descriptive statistics of these variables such as the mean and standard deviation are provided in Table 4, where industries are categorized into all, manufacturing and non-manufacturing industries for each period. Although the degree of competition must theoretically take values ranging from 0 to 100 in percent figures, it actually takes values beyond 100 in the non-manufacturing industries due to the negative values of the Lerner index. There are some reasons for this. First, since total output and intermediate, labor and capital service inputs are separately estimated from the micro data and the estimation is not modified, the numerator of equation (4) (i.e. monopoly rent) may take negative values. Second, if firms hold excess labor and capital and they are slow to adjust, then there is a tendency for the estimates of labor and capital service input to have upward bias, and the Lerner index can be consequently negative. For these reasons, I simply use a

[15] Green and Porter (1984) demonstrate that the Lerner index moves in accordance with the business fluctuation, that is, it rises in economic booms and declines in recession (pro-cyclical). In contrast, Rotemberg and Saloner (1986) predict that the Lerner index moves in the opposing direction of the business fluctuation (counter-cyclical).

negative value of the Lerner index and the resultant degree of competition for estimations, instead of arbitrarily transforming negative values of the Lerner index to zero.

Table 4 reveals that the time grand mean over the industries of almost every variable, especially the TFP growth rate and the degree of competition, differ statistically between the manufacturing and non-manufacturing industries. Whereas the TFP growth rate achieved by the manufacturing industries is much higher than that of the non-manufacturing industries, the degree of competition in the manufacturing industries is lower than the non-manufacturing industries. This outcome seems to reflect the fact that, although the manufacturing industries have achieved a steady improvement in productivity along with satisfactory profits, the non-manufacturing industries have suffered low productivity and weak profits for a long period of time. Further, we can confirm the fact that the extent to which market environments got competitive for both the manufacturing and non-manufacturing industries is larger in the period of 1995-2008 than that of 1980-1994, as the change in the degree of competition indicates.

5 Results

Tables 5-8 show the results of the estimation formulated above. The dependent variable is the annual TFP growth rate. In addition to the independent variables listed in Table 1, year dummy variables are included in the formulation to control for business fluctuation, although they are omitted from the table to save space. Two types of specifications are estimated: the first including only *comp*, and the second including both *comp* and the quadratic term of *comp* (i.e. $comp^2$) to affirm the inverted-U shape theory. Also, all industries are divided into the manufacturing and non-manufacturing industries in order to develop a detailed view of the underlying differences between the two industrial categories. In Appendix 2, I briefly discuss the results based upon the different classification in terms of the industries (not) conducting R&D investment.

The results of both the FE and FE with IVs estimations are presented. Although the

FE (FE with IVs) estimation in general posits that the industry fixed effects are constant over years, it seems somewhat hard to believe that the characteristics intrinsic to industries are unchanged over time, and in particular, this assumption may be difficult to hold during the entire sample period of 1980-2008. Based upon the reason described before, I mainly focus on the two subdivided periods of 1980-1994 and 1995-2008, where there seems to be fewer changes in the industry fixed effects. We have to note the possibility that they may still change even in these subdivided periods, but I implicitly assume that industrial changes are relatively slow compared to those of firms due to the compound movements of firms. All the more, the reason why I do not further subdivide the period is that this industry-level panel data has small observations in the cross-sectional dimension and that, if I confine the sample to a shorter period, I cannot obtain an adequate number of observations to estimate significantly. In any case, the general FE estimations using a whole sample require us to recognize the limitation, and hence I treat them as a preliminary analysis.

5.1 Estimation Results in 1980-2008

Table 5 presents the results for the whole sample period: 1980-2008. Let me first look at the F-statistics of the exogenous test (Davidson-Mackinon test). This tests the null hypothesis that the FE-IV and FE estimations are both consistent, and the rejection implies the need for instrumenting. We can see that almost all estimations except (7) reject the null hypothesis and thus the FE-IV estimations are largely more robust to inconsistency. We also need to note the F-statistics and relative bias of the weak identification test (Stock-Yogo test). The null hypothesis is that the IVs are weak against the alternative that they are strong. Because the F-statistics in estimations (4), (8), and (12) (where we investigate the inverted-U shape theory) are fairly small, the finite-sample bias of these FE-IV estimations can be considerably large relative to those of the FE estimations. Thus, we prefer the simple FE estimators for these estimations. Finally, the overidentification test (Hansen J test) in these estimations cannot reject the null hypothesis that all IVs are valid. Hereafter, I will skip the detailed interpretations of these tests for descriptive simplicity. [16]

With these in mind, I first examine whether increased competition indicates a rise in TFP growth or not in each industrial category. As regards all industries, estimation (3) (FE-IV) shows a negative competition effect on the TFP growth rate, but the estimate is not significant at all ($p = 0.666$). Although the estimate of estimation (1) (FE) is slightly positive, it is significant only at the 10% level ($p = 0.070$). Hence, it is unclear whether the degree of competition affects TFP growth in all industries during this sample period. In the manufacturing industries, both estimations (5) (FE) and (7) (FE-IV) demonstrate that the one-year lag of the competition measure positively affects TFP growth at the 1% significance level. While estimation (5) is preferred on the basis of the exogeneity test, the relevant coefficient still takes a positive value, 0.151. In contrast, it is revealed that, in the non-manufacturing industries, the estimate of the competition measure is negative in estimation (11) (FE-IV), but the significance level is 10% ($p = 0.069$) and the relative bias is anywhere in the range of 10% to 20%. On the other hand, although the estimate is positive in estimation (9) (FE), this is not significant at the 10% level ($p = 0.167$). From these results, we have a rough idea that the degree of competition has a tendency to positively affect TFP growth in the manufacturing industries and negatively in the non-manufacturing industries.

As for the inverted-U shape theory, estimations (2) and (10) (i.e. the FE estimations of all and the non-manufacturing industries) show a very weak non-linear relation. [17] However, because we can hardly observe the inverted-U shapes in the other estimations, it does not seem that the inverted-U shape theory is considered so robust during this

[16] Additionally, I test the null hypothesis that the unreported coefficients of year dummy variables are jointly zero. The test statistics, for example, of (3) are 3.03 ($p = 0.000$), and hence they are considered significant. Although the year dummy variables may not necessarily control business fluctuations or demand shocks, I retain them in all formulations.

[17] Although these FE estimations are not preferred based upon the exogeneity test, the bias of the estimations (4) and (12) (i.e. the FE-IV estimations) can be relatively large.

sample period.

We can also see that an increase in R&D stock ratio has positive effects on all and the non-manufacturing industries at the 1% significance level and on the manufacturing industries at the 10% significance level. Interestingly enough, the estimates of the non-manufacturing industries (about 3.64) are much larger than those of the manufacturing industries (about 0.22) judging from estimations (7) and (11). Finally, it is shown that the total IT investment ratio is not significant at all in every industrial category.

5.2 Estimation Results in 1980-1994

Let me move on to the results obtained for 1980-1994 presented in Table 6. In view of all industries, we cannot reject the null hypothesis of the exogeneity test at the conventional 5% level. When we have a look at the competition measure in estimation (1) (FE), the estimate is positive at the 5% significance level ($p = 0.022$), but the numerical value, 0.051, is very small. Next, in the manufacturing industries, the estimate of the competition measure is positive, 0.206, at the 1% significance level in estimation (5) (FE), which is preferred rather than equation (7) (FE-IV) based upon the exogeneity test. We can also make sure that the relevant coefficient in estimation (7), 0.219, is very close to the above value although it is not significant. On the other hand, estimation (11) (FE-IV) in the non-manufacturing industries does not show any significant relation between the competition measure and TFP growth ($p = 0.669$). Estimation (9) (FE), which is not preferred based upon the exogeneity test, provides a positive figure at the 5% significance level, but the estimate, 0.041, is considerably small. Therefore, we can see that, while competition operates to improve TFP growth in the manufacturing industries, the competition effect is notably ambiguous in the non-manufacturing industries.

Taking a look at the result of estimation (2) (FE), we find that the competition measure and its quadratic term are significantly positive and negative, respectively, at the 1% significance level, which means that the inverted-U shape theory holds in all industries. Further, it is demonstrated that, in the non-manufacturing industries, the quadratic term of the competition measure is negative. But because the estimate of the quadratic term, -0.0004, is extremely small and significant at the 10% level ($p = 0.055$), the inverted-U shape does not seem so strong in the non-manufacturing industries.

Whereas an increase in the R&D stock ratio has a positive effect on TFP growth in the non-manufacturing industries, we cannot find any significant effect in all and the manufacturing industries. The total IT investment ratio is not significant in every industrial category, either.

5.3 Estimation Results in 1995-2008

Finally, Table 7 indicates the results in 1995-2008. As a composite effect, estimation (1) (FE) in all industries demonstrates that the degree of competition has a slightly positive effect on TFP growth. In the manufacturing industries, we can confirm from estimation (5) (FE) that not only the competition effect is still positive, 0.308, at the 1% significance level, but also the value gets larger than the estimated figure of 0.219 in 1980-1994. Moreover, equation (7) (FE-IV) also shows a positive value, 0.361 at the 1% significance level. Therefore, we can argue that the effect of competition in the manufacturing industries is likely to be robust over all the sample periods and that it gets stronger in the latter half of the sample than the former. In contrast to the manufacturing industries, estimation (11) (FE-IV) in the non-manufacturing industries, which passes the exogeneity test, reveals that the degree of competition has a slightly negative effect on TFP growth (the coefficient is -0.087) at the 10% significance level ($p = 0.064$). In other words, the Schumpeterian hypothesis may be seemingly applied in the non-manufacturing industries, although the negative effect of competition is neither large nor highly significant.

The inverted-U shape can be seen in all industries on the basis of estimation (2) (FE) in a similar fashion of the estimation in 1980-1995. However, there are no inverted-U shapes observed in the manufacturing and non-manufacturing industries.

As estimation (5) (FE) indicates, the incremental R&D stock ratio in the manufacturing industries is significant at the 1% level in contrast to the estimation in 1980-1994. But the relevant estimates in the non-manufacturing industries are insignificant in 1995-2008. Thus, there is a possibility that the manufacturing and non-manufacturing industries may have faced during the mid-1990s some structural changes that operated oppositely for these two industrial categories. Also, the total IT investment ratio is still insignificant in every industrial category. In order to probe these control variables in detail, I estimate the model for the period between 2000 and 2008, and the result is shown in Table 8. It indicates that almost all the estimates of the incremental R&D stock ratio achieve a degree of significance and the numerical values become much larger, especially in the non-manufacturing industries. Hence, some structural changes are likely to have occurred in around the year 2000 again with R&D activity contributing to TFP growth. Further, if we take a look at estimations (9) (FE) and (11) (FE-IV) in the non-manufacturing industries, the coefficients of the total IT investment ratio are both positive, although the p-values are 0.129 and 0.075, respectively. It seems that total IT investment may also have had a positive effect on TFP growth since around the year 2000, this result is not robust and needs to be further examined from other perspectives.

5.4 Summary and Discussion

The results derived from the above-mentioned analyses are summarized in what follows.

1. The competition effect on TFP growth in the manufacturing industries is positive over all the sample periods, 1980-2008, and it gets larger in the latter half of the sample period, 1995-2008. On the other hand, the competition effect in the non-manufacturing industries may be slightly negative in 1995-2008, which may suggest that the Schumpeterian hypothesis can be applied in this industrial category. As a result, the composite competition effect in all industries is slightly positive both

during 1980-1994 and 1995-2008.

2. There is a weak inverted-U shape relation between the competition measure and TFP growth observed almost exclusively in all industries to a limited extent.

3. While the incremental R&D stock ratio is significant for the non-manufacturing industries in 1980-1994, it is also the same for the manufacturing industries in 1995-2008. The estimates of the non-manufacturing industries are much larger than those of the manufacturing industries. Further, all the estimates including both the manufacturing and non-manufacturing industries in 2000-2008 are significant and become larger than in the previous periods.

As regards Result 1, that competition positively affects TFP growth in the manufacturing industries is consistent with many previous studies (Nickell 1996, Okada 2005, Inui et al. 2012). On the other hand, this result contradicts with that derived by Flath (2011) who insists that there is no relation between the Lerner index (price-cost margin) and innovation at the industry level. My opinion is, however, that the difference in the results between these two studies lies in the fact that, while Flath (2011) constructs the cross-sectional industry-level data and uses a time-average competition measure, I adopt the industry-specific panel data and employ the one-year lag of the competition measure as an independent variable assuming that the effect of competition in the industry level has a one-year lag.

I also discover a new result that competition may have negatively affected TFP growth in the non-manufacturing industries between 1995 and 2008, which no researchers have not comprehensively examined so far. How can these results be interpreted and what policy implications can be derived? But at the same time, we have to notice is that the inverted-U shape cannot be observed in the non-manufacturing industries. That is, while Aghion et al. (2005) point to the "Schumpeterian effect" such that increased competition would lower productivity growth only when the degree of competition is already sufficiently high, our finding does not indicate such a non-linear relation but shows a simple linear negative, though moderate, relation between competition and TFP growth. This causes a seemingly serious problem from the viewpoint of competition policies, since there seems to be hardly room to raise industrial productivity by promoting further competition. Although we may be tempted to conclude that overcompetition would be the main cause of stagnating TFP growth in the non-manufacturing industries and that eliminating overcompetition could provide benefits to the relevant industries, before making a conclusion, it would be wise to relate our finding to existing studies that explore why productivity of the non-manufacturing industries is relatively low in a way to complement our research. In what follows, I intend to briefly introduce the possible reasons that are considered associated with the negative competition effect on TFP growth.

First, regulations in the non-manufacturing industries could hinder competition in the industries from increasing TFP growth. According to the Cabinet Office of Japan (2006), indeed, the regulatory reforms have progressed steadily in the manufacturing industries rather than the non-manufacturing industries. [18] As many economists have pointed out, further regulatory reforms in the non-manufacturing industries need to be effectively implemented in such a manner to make the competition effect work accordingly, likewise in the manufacturing industries, and thus to raise TFP growth. [19] The second reason would be that, although they are not entailed in the rigorous definition of the Schumpeterian hypothesis and innovation, the distribution, entry, and exit effects mentioned in Section 4 are too weak to support the positive competition effect in the non-manufacturing industries. In particular, Kim et al. (2010), on the basis of the data of listed companies, show that the exit effect in the non-manufacturing industries was consistently negative between 1980

[18] The Cabinet Office of Japan (2006) reports the regulation index that indicates the progress of regulatory reforms in each industry based upon the classification of the *JIP Database* covering 1995-2005. The regulation index is normalized to 1 in 1995 if regulation exists in a particular industrial sector, and the closer the numerical value is to 0, the further regulatory reforms advance in comparison to 1995. The simple average values of this regulation index in the non-manufacturing industries in 1995 and 2008 are 0.971 and 0.600, while they are 0.635 and 0.273 in the manufacturing industries. Hence, more regulations have continued to exist in the non-manufacturing industries.

[19] Nakanishi and Inui (2007) investigate the effect of regulations using the *JIP Database* between 1970 and 2002. This study uncovers that regulations in the industries not conducting R&D investment, which are nearly the non-manufacturing industries, have a negative effect on both TFP and production growth.

and 2005. Then, the authors argue that high-productive firms fail to increase their market shares and that this absence of refreshment in industries stagnate TFP growth, which arguably backs up from another viewpoint our finding about the negative effect of competition on TFP growth. Thus, we can expect that, if the exit of low-productivity firms, mainly in service industries, is promoted by competition, the industrial TFP growth rate will rise. From these studies, therefore, it seems more important in the non-manufacturing industries to encourage sound competition to work through the measures such as regulatory reforms and industrial refreshment policies than to stifle competition simply based upon the observation about the linear negative relation. However, since I can only speculate these reasons for the application of the Schumpeterian hypothesis and the possible prescriptions for vitalizing the effect of competition in the non-manufacturing industries, additional research is required to make a close examination.

Result 2 is a bit different from other studies such as Inui et al. (2012) who find the inverted-U shape relation between the degree of competition and productivity using the data of manufacturing industries. One possible reason why my study displays a weak inverted-U shape almost exclusively in all industries, but not in other industrial categories, would be that whereas the firm-specific data used in existing studies has many observations being broadly distributed along with the competition measure and productivity growth as the theory predicts, the industry-specific data is accumulated from such small observations that we cannot detect a clear-cut relation because observations undergo little changes due to the rigidity of movements at the industrial level.

Finally, with regard to Result 3, the finding that an increase in the R&D stock ratio raises TFP growth in the period of 2000-2008 is the same as it is with previous studies conducted in Japan such as Kwon et al. (2010). But we are left with a lot to ponder about the difference in the impacts between the manufacturing and non-manufacturing industries. More precisely, it could be true from my result that R&D investments conducted by the non-manufacturing industries may be more closely connected to their productivity improvements than the manufacturing industries, and presumably, that the manufacturing industries may engage in more efforts to conduct basic research that does not directly improve their productivity. In the meanwhile, Kwon et al. (2010), who employ both the financial data from the manufacturing industries and the micro data of the *Report on the Survey of Research and Development* produced by NISTEP, find that the R&D intensity continues to be statistically significant between 1986-2005 and that the coefficient becomes larger over time. However, in contrast, our result is that an increase in the R&D stock ratio in the manufacturing industries is significant only in 1995-2008, but not in 1980-1994. Therefore, there is still much room for further discussion on the relation between R&D investment and productivity.

6 Concluding Remarks

This study mainly investigates the causal relation between the degree of competition, which is measured by the Lerner index, and the TFP growth rate on the basis of the Japanese industry-level panel data (*JIP Database*) from 1980 to 2008. The central finding indicates that, although a positive effect of competition on the TFP growth rate is clearly observable in the manufacturing industries throughout the sample period, such effect in the non-manufacturing industries may be slightly negative in the latter half of the sample period (1995-2008). This finding of a negative competition effect may lend support to the claim that the Schumpeterian hypothesis can be applied in the case of the non-manufacturing industries. Furthermore, a weak inverted-U shape relation between the competition measure and TFP growth proposed by Aghion et al. (2005) can be seen limitedly almost exclusively in all industries. An increaes in the R&D stock ratio stimulates TFP growth of the manufacturing industries in 1995-2008 and of the non-manufacturing industries in 1980-1995. However, we cannot observe any significant relation between the total IT investment ratio and TFP growth.

As I have already mentioned, we must bear in mind that, even if the Schumpeterian hypothesis seems applicable to the non-manufacturing industries, it never derives the simple conclusion that the market structures limiting competition, such as monopoly, are unequivocally desirable for productivity improvement and innovative activity in these industries. As the standard microeconomics theory indicates, monopoly usually causes inefficient resource allocation in the form of deadweight loss and transfers a portion of consumer surplus to producers. Furthermore, monopolists sometimes devote an abundance of energy to a rent-seeking activity in order to maintain their current monopoly rents and to exclude potential rivals from the markets. Indeed, certain monopoly power may have to be approved, for example, by awarding patents to firms that have innovated to compensate them for their R&D costs and efforts, but it is also of more importance to eliminate obstacles that prevent market competition from interacting well with productivity improvements, such as unnecessary regulations and stagnation of exit and entry in the industries as mentioned in Subsection 5.4. Therefore, it can be potentially dangerous to conclusively decide the course of action that competition or innovation policies should take toward restricting sound competition in the non-manufacturing industries based solely upon the results of this paper. In any event, I believe that allowing competition to work harmoniously in the non-manufacturing industries is the key to raising their productivity and thus restoring the Japanese economy.

The present study is subject to further debate. First, it needs to be proven whether the result that competition may imply a negative effect on TFP growth in the non-manufacturing industries is valid or not by using firm-level micro data. Thus, it is strongly desired to build firm-level datasets that allows for such an analysis to be carried out. Second, although this study regards some control variables as exogenous, the model specification can be further improved by implementing, for example, simultaneous equation models and by employing richer datasets. Finally, assuming that competition has some effects on productivity of industries, whether they are positive or negative, we need to conduct further study on the detailed mechanism in force within them, such as how and the extent to which innovative activity reacts to incentives.

Appendix 1 Industry-Specific Lerner Index

Existing studies such as Nickell (1996), Okada (2005), and Aghion et al. (2005) calculate the average Lerner index of firms as follows:

$$LI_F = \frac{sales - cost\ of\ sales + depreciation - rK}{sales}, \tag{5}$$

where r is the cost of capital and K is the capital stock. According to Fukao et al. (2008), the industry-specific Lerner index in industry i can be formally defined as follows:

$$LI_I = \frac{\Psi_i}{p_{Qi}Q_i} = \frac{p_{Qi}Q_i - p_{Mi}X_i - w_iL_i - r_iK_i}{p_{Qi}Q_i}, \tag{6}$$

where Ψ_i represents monopoly rents, and X_i, L_i, and K_i are the total amounts of intermediate, labor, capital service inputs, respectively. In addition, p_{Q_i}, p_{M_i}, w_i, and r_i denote the market prices for final output and intermediate input, wage rate, and capital costs, respectively. Because gross output measured by the factor costs is equivalent to the sum of the intermediate input, compensation of employment, operating profits, and consumption of fixed capital, the nominator in equation (6) (i.e. monopoly rent) should equal the sum of the operating profits and compensation of fixed capital minus the capital service input. Taking into account that the above operating profits corresponds to "sales − cost of sales" in equation (5), we can see that the interpretation of LI_I is the same as the average Lerner index of firms, LI_F. Hence, firms belonging to that industry would be expected to gain average profits in proportion to LI_I.

It should be noted that the above formulation of equation (6) is on the basis of the several simple assumptions, for example, perfect competition prevails in the factor production markets and the markup is constant over time. Therefore, it would be more feasible to regard the industry-specific Lerner index as a proxy for market power rather than accurate profitability.

Appendix 2 Estimation for Industries Conducting and Not Conducting R&D Investment

This appendix performs the same regression analysis as before dividing all industries into the industries conducting and not conducting R&D investment. While the 75 industries, composed of the most manufacturing industries and the part of the non-manufacturing industries, conduct R&D investment, the 11 industries, for example, eating/drinking and accommodation, do not invest in R&D. Note that because the observations of the industries not conducting R&D investment are fairly small, we need to interpret the following results in a careful manner.

Table 9 presents the results obtained for 1980-1994. For industries conducting R&D investment, estimation (7) (FE-IV), which passes the exogeneity test, indicates that the effect of the competition measure is negative but not significant at all. On the other hand, estimation (5) (FE) shows a significantly positive effect on TFP growth, but the numerical value, 0.092, is very small and close to zero. As regards the industries not conducting R&D investment, the competition effects are hardly observed, although estimation (11) (FE-IV) exhibits a slightly positive coefficient, 0.042, at the 10% significance level ($p = 0.081$). Further, a bit surprisingly, we can see that the increased R&D stock ratio has no significant effects on TFP growth in this sample period.

Let me turn to Table 10 that shows the results for 1995-2008. Contrasting to the previous results, it demonstrates from estimations (5) and (7) that increased competition has a significant larger impact on TFP growth in the industries conducting R&D investment. But for the industries not conducting R&D investment, the competition measures in equations (9) and (11) are not significant while the signs of the coefficients are slightly negative. In addition, it is revealed that an increase in the R&D stock ratio positively affects TFP growth in this latter half of the sample period. Finally, the total IT investment ratio may have positive impact on TFP growth for the industries not conducting R&D, although the estimate in equation (9) is only significant at around the 15% significance level ($p = 0.159$). This may suggest that the application of IT technologies is better promoted especially in the service industries. However, we need to note that the estimates of the total IT investment ratio are not so robust, as estimation (5) in the industries conducting R&D investment shows a highly significant and negative effect. Hence, the results concerning this variable should be carefully treated.

In conclusion, it seems that the industries conducting R&D investment not only improve their industrial productivity by being exposed to competition, but also make R&D investment more effective in the period of 1995-2008, namely after the bubble economy burst. To investigate further how competition affects (or does not affect) the incentives of industries and firms is an issue to be solved in the future.

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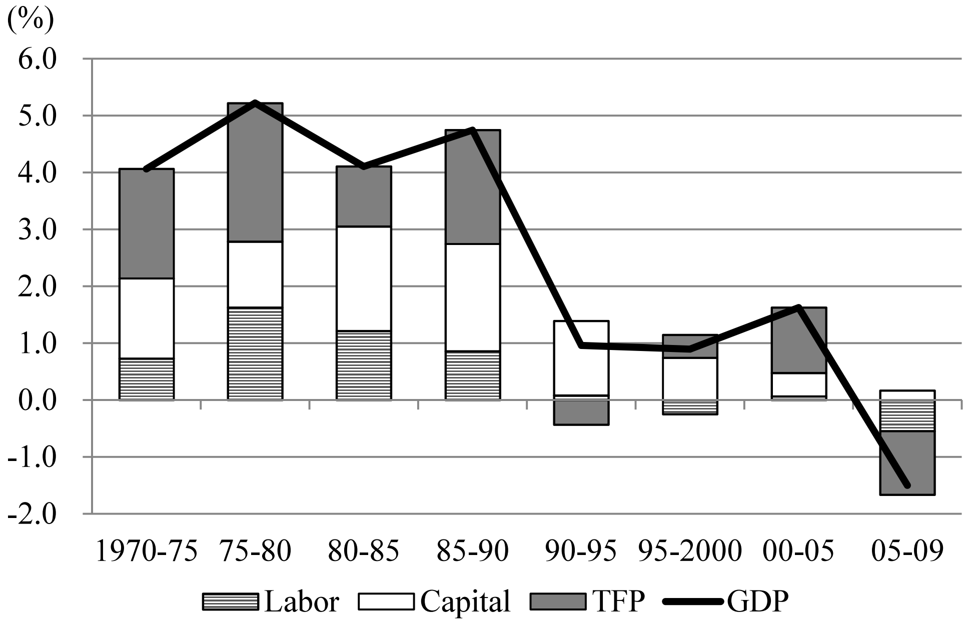
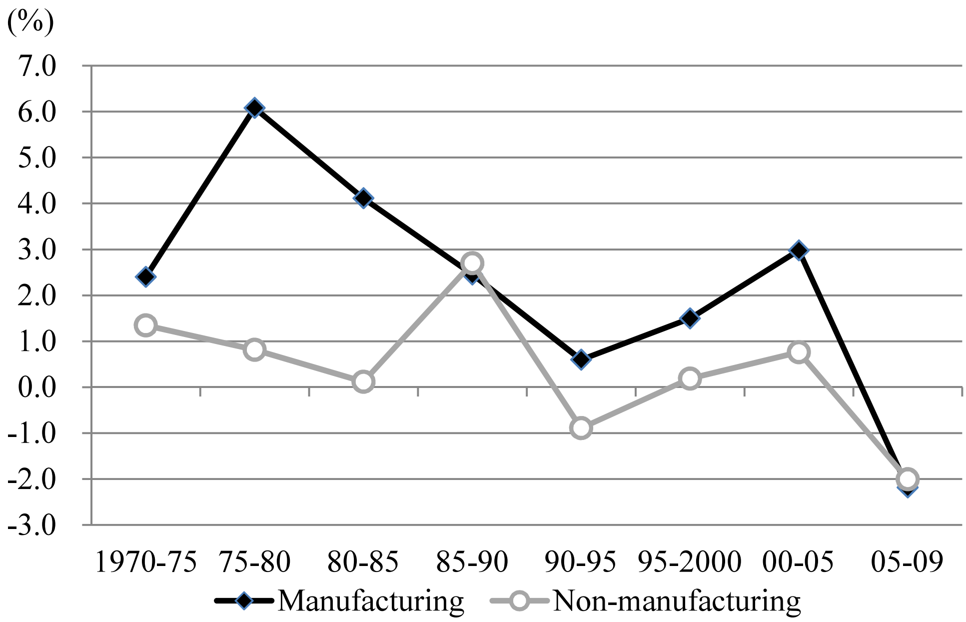
Figure 1　Average contribution to real GDP growth rate



Source: *JIP Database 2012*.

Figure 2　TFP growth rate of the manufacturing and non-manufacturing industries



Source: *JIP Database 2012*.

Table 1 Summary of variables

Variables	Definition
Dependent variables	
$tfpg$	Total factor productivity (TFP) annual growth rate (%)
Independent variable	
$comp$	Degree of competition (%) calculated by $1 - \textit{Lerner index}$ (%)
	Lerner index is calculated by
	$1 - (\textit{intermediate input} + \textit{labor input} + \textit{capital service input})/\textit{output}$
	(all values are evaluated by nominal prices)
$comp^2$	square of *comp*
rds	Ratio of nominal research and development (R&D) stock to nominal output (%)
tit	Ratio of nominal total IT investment to nominal output (%)
Instrumental variables	
$hcons$	Ratio of household consumption to nominal output (%)
	(obtained from final demand by sectors)
exp	Ratio of export to nominal output (%)
	(obtained from final demand by sectors)

Source: *JIP Database 2012* and *Estimation of Industry-Level R&D Stock*.

Table 2 Correlation between independent variables and instrumental variables

	$comp_{t-1}$	Δrds_{t-2}	tit_{t-2}
$\Delta comp_{t-1}$	0.059***		
	[0.005]		
$\Delta comp_{t-2}$	0.074***	0.132***	0.003
	[0.000]	[0.000]	[0.898]
$hcons_{t-2}$	−0.177***	−0.067***	−0.047**
	[0.000]	[0.002]	[0.024]
exp_{t-2}	0.037*	0.180***	−0.045**
	[0.075]	[0.000]	[0.029]

Note: 1. These correlation coefficients are calculated for the sample period between 1980 and 2008.
2. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.
3. The p-values are reported in the square parentheses

Table 3 Industry list

Index	M/NM	Industry name
7	NM	Mining
8	M	Livestock products
9	M	Seafood products
10	M	Flour and grain mill products
11	M	Miscellaneous foods and related products
12	M	Prepared animal foods and organic fertilizers
13	M	Beverages
14	M	Tobacco
15	M	Textile products
16	M	Lumber and wood products
17	M	Furniture and fixtures
18	M	Pulp, paper, and coated and glazed paper
19	M	Paper products
20	M	Printing, plate making for printing and bookbinding
21	M	Leather and leather products
22	M	Rubber products
23	M	Chemical fertilizers
24	M	Basic inorganic chemicals
25	M	Basic organic chemicals
26	M	Organic chemicals
27	M	Chemical fibers
28	M	Miscellaneous chemical products
29	M	Pharmaceutical products
30	M	Petroleum products
31	M	Coal products
32	M	Glass and its products
33	M	Cement and its products
34	M	Pottery
35	M	Miscellaneous ceramic, stone and clay products
36	M	Pig iron and crude steel
37	M	Miscellaneous iron and steel
38	M	Smelting and refining of non-ferrous metals
39	M	Non-ferrous metal products
40	M	Fabricated constructional and architectural metal products
41	M	Miscellaneous fabricated metal products
42	M	General industry machinery
43	M	Special industry machinery
44	M	Miscellaneous machinery
45	M	Office and service industry machines

Table 3 Industry list (continued)

Index	M/NM	Industry name
46	M	Electrical generating, transmission, distribution and industrial apparatus
47	M	Household electric appliances
48	M	Electronic data processing machines, digital and analog computer equipment and accessories
49	M	Communication equipment
50	M	Electronic equipment and electric measuring instruments
51	M	Semiconductor devices and integrated circuits
52	M	Electronic parts
53	M	Miscellaneous electrical machinery equipment
54	M	Motor vehicles
55	M	Motor vehicle parts and accessories
56	M	Other transportation equipment
57	M	Precision machinery and equipment
58	M	Plastic products
59	M	Miscellaneous manufacturing industries
60	NM	Construction
61	NM	Civil engineering
62	NM	Electricity
63	NM	Gas, heat supply
64	NM	Waterworks
65	NM	Water supply for industrial use
66	NM	Waste disposal
67	NM	Wholesale
68	NM	Retail
69	NM	Finance
70	NM	Insurance
71	NM	Real estate
73	NM	Railway
74	NM	Road transportation
75	NM	Water transportation
76	NM	Air transportation
77	NM	Other transportation and packing
78	NM	Telegraph and telephone
79	NM	Mail
81	NM	Research (private)
85	NM	Advertising
86	NM	Rental of office equipment and goods
87	NM	Automobile maintenance services
88	NM	Other services for businesses

Table 3 Industry list (continued)

Index	M/NM	Industry name
89	NM	Entertainment
90	NM	Broadcasting
91	NM	Information services and internet-based services
92	NM	Publishing
93	NM	Video picture, sound information, character information production and distribution
94	NM	Eating and drinking places
95	NM	Accommodation
96	NM	Laundry, beauty and bath services
97	NM	Other services for individuals

Note: 1. Index corresponds to that of *JIP Database 2012*.

2. M and NM denote the manufacturing and non-manufacturing industries, respectively.

Table 4 Descriptive statistics

	All	Mfr.	Non-mfr.	$t$value	p-value
Year: 1980-2008					
Number of observations (total)	2494	1508	986		
Number of industries (each year)	86	52	34		
Simple average across all observations					
TFP growth rate(%)	0.394	0.697	−0.069	3.626	0.000
	(5.173)	(5.473)	(4.641)		
Degree of competition (%)	99.064	94.134	106.606	−12.979	0.000
	(24.239)	(14.893)	(32.457)		
ΔDegree of competition (%)	0.044	0.151	−0.119	0.900	0.368
	(7.195)	(3.557)	(10.566)		
Ratio of R&D stock (%)	12.455	19.957	0.980	25.602	0.000
	(20.337)	(23.215)	(2.065)		
ΔRatio of R&D stock (%)	0.335	0.558	−0.008	6.616	0.000
	(2.070)	(2.633)	(0.209)		
Ratio of total IT investment (%)	2.378	1.355	3.943	−9.628	0.000
	(6.681)	(1.266)	(10.319)		
Ratio of household consumption (%)	23.870	18.761	31.684	−10.392	0.000
	(31.009)	(30.732)	(29.793)		
Ratio of export (%)	8.529	12.136	3.012	19.256	0.000
	(12.398)	(12.877)	(9.218)		

Table 4 Descriptive statistics (continued)

	All	Mfr.	Non-mfr.	$t$value	p-value
Year: 1980-1994					
Number of observations (total)	1290	780	510		
Number of industries (each year)	86	52	34		
Simple average across all observations					
TFP growth rate(%)	0.426	0.770	−0.100	2.722	0.007
	(5.627)	(5.844)	(5.238)		
Degree of competition (%)	99.913	93.674	109.455	−11.026	0.000
	(26.282)	(14.147)	(35.945)		
ΔDegree of competition (%)	−0.220	0.039	−0.615	1.428	0.153
	(7.767)	(3.430)	(11.598)		
Ratio of R&D stock (%)	9.589	15.212	0.988	19.095	0.000
	(14.812)	(16.722)	(2.243)		
ΔRatio of R&D stock (%)	0.352	0.593	−0.016	7.063	0.000
	(1.490)	(1.866)	(0.268)		
Ratio of total IT investment (%)	2.177	1.011	3.962	−7.523	0.000
	(7.034)	(1.155)	(10.862)		
Ratio of household consumption (%)	22.686	17.012	31.363	−9.014	0.000
	(28.816)	(26.757)	(29.705)		
Ratio of export (%)	7.462	10.593	2.672	13.735	0.000
	(10.840)	(10.740)	(9.111)		

Table 4 Descriptive statistics (continued)

	All	Mfr.	Non-mfr.	$t$value	p-value
Year: 1995-2008					
Number of observations (total)	1204	728	476		
Number of industries (each year)	86	52	34		
Simple average across all observations					
TFP growth rate(%)	0.359	0.618	−0.037	2.400	0.017
	(4.640)	(5.048)	(3.907)		
Degree of competition (%)	98.155	94.626	103.553	−7.084	0.000
	(21.812)	(15.648)	(27.963)		
ΔDegree of competition (%)	0.405	0.349	0.491	−0.345	0.730
	(6.706)	(3.749)	(9.611)		
Ratio of R&D stock (%)	15.525	25.041	0.971	18.926	0.000
	(24.572)	(27.703)	(1.858)		
ΔRatio of R&D stock (%)	0.359	0.594	0.001	3.775	0.000
	(2.583)	(3.300)	(0.120)		
Ratio of total IT investment (%)	2.594	1.724	3.923	−6.028	0.000
	(6.277)	(1.276)	(9.714)		
Ratio of household consumption (%)	25.139	20.635	32.028	−5.910	0.000
	(33.164)	(34.407)	(29.916)		
Ratio of export (%)	9.672	13.789	3.376	13.782	0.000
	(13.788)	(14.656)	(9.328)		

Note 1: The t-values represent statistics for the test of the difference in average between the manufacturing and non-manufacturing industries.
2. The standard deviations are reported in the round parentheses.
3. Some samples of the degree of competition (100 minus Lerner index) are over 100 because the Lerner index can be negative.

Table 5 Estimation of the competition effect: 1980-2008

Dependent variables: TFP growth rate

	All industries				Manufacturing industries				Non-manufacturing industries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FE	FE	FE-IV	FE-IV	FE	FE	FE-IV	FE-IV	FE	FE	FE-IV	FE-IV
$comp_{it-1}$	0.040*	0.167***	−0.013	1.478	0.151***	−0.020	0.236***	−2.148	0.030	0.128**	−0.073*	−0.105
	(0.022)	(0.041)	(0.030)	(1.126)	(0.031)	(0.164)	(0.088)	(1.987)	(0.021)	(0.047)	(0.040)	(0.531)
	[0.070]	[0.000]	[0.666]	[0.190]	[0.000]	[0.906]	[0.007]	[0.280]	[0.167]	[0.011]	[0.069]	[0.844]
$comp^2_{it-1}$		−0.0004***		−0.005		0.001		0.012		−0.0003**		0.0001
		(0.0001)		(0.004)		(0.001)		(0.010)		(0.0001)		(0.002)
		[0.000]		[0.197]		[0.302]		[0.226]		[0.014]		[0.952]
Δrds_{it-2}	0.278**	0.268**	0.292***	0.171	0.232*	0.233*	0.217*	0.246*	3.076***	3.011***	3.638***	3.666***
	(0.108)	(0.110)	(0.113)	(0.153)	(0.119)	(0.119)	(0.124)	(0.129)	(0.948)	(0.899)	(0.988)	(1.080)
	[0.011]	[0.017]	[0.010]	[0.262]	[0.057]	[0.056]	[0.080]	[0.056]	[0.003]	[0.002]	[0.000]	[0.001]
tit_{it-2}	−0.031	−0.032	0.054	0.026	−0.143	−0.165	−0.283	−0.484	−0.003	0.001	0.159	0.159
	(0.072)	(0.057)	(0.100)	(0.176)	(0.271)	(0.275)	(0.372)	(0.401)	(0.085)	(0.072)	(0.115)	(0.116)
	[0.666]	[0.584]	[0.589]	[0.884]	[0.600]	[0.551]	[0.447]	[0.228]	[0.969]	[0.985]	[0.167]	[0.170]
year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	2236	2236	2236	2236	1352	1352	1352	1352	884	884	884	884
# of indus.	86	86	86	86	52	52	52	52	34	34	34	34
F	4.902	5.724	3.680	2.261	9.235	9.158	3.402	3.257	42.228	81.347	2.207	2.142
Exogeneity test (Davidson-Mackinnon test)												
F			4.532	7.099			2.544	4.025			16.738	7.810
			[0.033]	[0.000]			[0.111]	[0.018]			[0.000]	[0.000]
Underidentification test (Kleibergen-Paap rk LM test)												
χ^2			31.154	8.210			95.828	12.623			17.679	2.258
			[0.000]	[0.042]			[0.000]	[0.006]			[0.001]	[0.521]
Weak identification test (Stock-Yogo test)												
F			16.819	2.346			61.062	2.073			8.071	0.456
Relative bias			<5%	>30%			<5%	>30%			10–20%	>30%
Overidentification test (Hansen J test)												
χ^2			3.763	0.021			1.240	0.416			0.235	0.245
			[0.152]	[0.989]			[0.538]	[0.812]			[0.889]	[0.885]

Note: 1. $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$ are used as IVs for (3), (7), (11), and $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$, exp_{it-2} for (4), (8), (12).
2. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.
3. The robust (Eicker-Huber-White) standard errors adjusted for small samples and p values are reported in the round and square parentheses, respectively.
4. The relative bias of the weak identification test represents the largest relative bias of the FE-IV estimators relative to the FE estimators.

Table 6 Estimation of the competition effect: 1980-1994

Dependent variables: TFP growth rate

	All industries				Manufacturing industries				Non-manufacturing industries			
	(1) FE	(2) FE	(3) FE-IV	(4) FE-IV	(5) FE	(6) FE	(7) FE-IV	(8) FE-IV	(9) FE	(10) FE	(11) FE-IV	(12) FE-IV
$comp_{it-1}$	0.051**	0.220***	−0.001	0.950	0.206***	−0.322	0.219	−4.548	0.041**	0.174**	−0.015	0.107
	(0.022)	(0.065)	(0.038)	(1.211)	(0.044)	(0.395)	(0.221)	(4.741)	(0.018)	(0.079)	(0.036)	(0.234)
	[0.022]	[0.001]	[0.978]	[0.433]	[0.000]	[0.419]	[0.323]	[0.338]	[0.027]	[0.034]	[0.669]	[0.649]
$comp^2_{it-1}$		−0.001***		−0.003		0.003		0.024		−0.0004*		−0.0004
		(0.0002)		(0.004)		(0.002)		(0.024)		(0.0002)		(0.001)
		[0.002]		[0.434]		[0.171]		[0.310]		[0.055]		[0.597]
Δrds_{it-2}	0.266	0.269	0.278	0.290	0.258	0.267	0.258	0.338	4.377***	4.186***	4.615***	4.444***
	(0.241)	(0.249)	(0.359)	(0.376)	(0.303)	(0.305)	(0.394)	(0.399)	(1.418)	(1.146)	(1.376)	(1.290)
	[0.272]	[0.284]	[0.438]	[0.440]	[0.398]	[0.385]	[0.513]	[0.398]	[0.004]	[0.001]	[0.001]	[0.001]
tit_{it-2}	0.035	0.015	0.130	0.003	−0.084	−0.185	−0.103	−0.748	−0.016	−0.031	0.100	0.089
	(0.063)	(0.060)	(0.137)	(0.243)	(0.392)	(0.349)	(0.650)	(0.847)	(0.054)	(0.055)	(0.139)	(0.142)
	[0.578]	[0.805]	[0.343]	[0.992]	[0.832]	[0.597]	[0.874]	[0.378]	[0.775]	[0.572]	[0.472]	[0.532]
year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	1032	1032	1032	1032	624	624	624	624	408	408	408	408
# of indus.	86	86	86	86	52	52	52	52	34	34	34	34
F	3.902	5.645	3.150	2.665	10.368	11.883	2.126	1.816	7.678	11.248	3.799	3.787
Exogeneity test (Davidson-Mackinnon test)												
F			2.728	2.541			0.019	1.477			4.043	2.178
			[0.099]	[0.079]			[0.890]	[0.229]			[0.045]	[0.115]
Underidentification test (Kleibergen-Paap rk LM test)												
χ^2			22.895	10.135			35.015	7.024			22.068	11.104
			[0.000]	[0.018]			[0.000]	[0.071]			[0.001]	[0.011]
Weak identification test (Stock-Yogo test)												
F			10.391	2.393			23.956	1.484			10.699	2.268
Relative bias			5–10%	>30%			<5%	>30%			5–10%	>30%
Overidentification test (Hansen J test)												
χ^2			0.313	1.025			1.632	0.589			1.768	2.077
			[0.855]	[0.599]			[0.442]	[0.745]			[0.413]	[0.354]

Note: 1. $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$ are used as IVs for (3), (7), (11), and $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$, exp_{it-2} for (4), (8), (12).
2. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.
3. The robust (Eicker-Huber-White) standard errors adjusted for small samples and p values are reported in the round and square parentheses, respectively.
4. The relative bias of the weak identification test represents the largest relative bias of the FE-IV estimators relative to the FE estimators.

Table 7 Estimation of the competition effect: 1995-2008

Dependent variables: TFP growth rate

	All industries				Manufacturing industries				Non-manufacturing industries			
	(1) FE	(2) FE	(3) FE-IV	(4) FE-IV	(5) FE	(6) FE	(7) FE-IV	(8) FE-IV	(9) FE	(10) FE	(11) FE-IV	(12) FE-IV
$comp_{it-1}$	0.079**	0.278**	0.090*	0.397	0.308***	0.352	0.361***	−5.508	−0.003	−0.027	−0.087*	−0.794
	(0.036)	(0.109)	(0.047)	(0.964)	(0.061)	(0.378)	(0.096)	(5.321)	(0.018)	(0.091)	(0.047)	(0.575)
	[0.031]	[0.012]	[0.058]	[0.681]	[0.000]	[0.355]	[0.000]	[0.301]	[0.863]	[0.765]	[0.064]	[0.168]
$comp^2_{it-1}$		−0.001**		−0.001		−0.0002		0.030		0.0001		0.003
		(0.0004)		(0.004)		(0.002)		(0.027)		(0.0004)		(0.002)
		[0.029]		[0.769]		[0.902]		[0.270]		[0.784]		[0.234]
Δrds_{it-2}	0.325***	0.316***	0.323***	0.307***	0.282***	0.281**	0.275***	0.347***	2.493	2.509	3.426	3.670
	(0.098)	(0.098)	(0.096)	(0.106)	(0.101)	(0.101)	(0.098)	(0.121)	(2.922)	(2.919)	(2.367)	(2.536)
	[0.001]	[0.002]	[0.001]	[0.004]	[0.007]	[0.007]	[0.005]	[0.004]	[0.400]	[0.396]	[0.149]	[0.149]
tit_{it-2}	−0.062	0.005	−0.073	0.018	−0.489	−0.481	−0.570	−1.538	0.013	0.005	0.079	−0.174
	(0.043)	(0.059)	(0.160)	(0.429)	(0.331)	(0.348)	(0.710)	(1.080)	(0.041)	(0.051)	(0.161)	(0.300)
	[0.154]	[0.931]	[0.648]	[0.966]	[0.146]	[0.173]	[0.422]	[0.155]	[0.753]	[0.921]	[0.625]	[0.561]
year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	946	946	946	946	572	572	572	572	374	374	374	374
# of indus.	86	86	86	86	52	52	52	52	34	34	34	34
F	5.707	5.327	4.143	4.107	8.435	8.042	5.565	4.044	1.135	1.135	1.194	1.184
Exogeneity test (Davidson-Mackinnon test)												
F			0.088	0.236			0.849	3.734			3.979	3.702
			[0.767]	[0.790]			[0.357]	[0.025]			[0.047]	[0.026]
Underidentification test (Kleibergen-Paap rk LM test)												
χ^2			48.034	6.370			72.171	6.266			23.053	5.924
			[0.000]	[0.095]			[0.000]	[0.099]			[0.000]	[0.115]
Weak identification test (Stock-Yogo test)												
F			34.213	1.659			69.125	1.442			15.901	1.858
Relative bias			<5%	>30%			<5%	>30%			<5%	>30%
Overidentification test (Hansen J test)												
χ^2			3.507	6.130			0.618	0.544			2.120	0.454
			[0.173]	[0.047]			[0.734]	[0.762]			[0.347]	[0.797]

Note: 1. $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$ are used as IVs for (3), (7), (11), and $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$, exp_{it-2} for (4), (8), (12).
2. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.
3. The robust (Eicker-Huber-White) standard errors adjusted for small samples and p values are reported in the round and square parentheses, respectively.
4. The relative bias of the weak identification test represents the largest relative bias of the FE-IV estimators relative to the FE estimators.

Table 8 Estimation of the competition effect: 2000-2008

Dependent variables: TFP growth rate

	All industries				Manufacturing industries				Non-manufacturing industries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FE	FE	FE-IV	FE-IV	FE	FE	FE-IV	FE-IV	FE	FE	FE-IV	FE-IV
$comp_{it-1}$	0.228***	0.276	0.272**	−4.158	0.399***	0.604	0.513***	−5.345	0.060	−0.080	−0.096	−2.994
	(0.068)	(0.243)	(0.120)	(8.738)	(0.108)	(0.737)	(0.126)	(5.019)	(0.048)	(0.207)	(0.076)	(7.684)
	[0.001]	[0.259]	[0.024]	[0.634]	[0.001]	[0.416]	[0.000]	[0.288]	[0.220]	[0.701]	[0.210]	[0.697]
$comp^2_{it-1}$		−0.0002		0.021		−0.001		0.030		0.001		0.013
		(0.001)		(0.042)		(0.004)		(0.025)		(0.001)		(0.034)
		[0.828]		[0.615]		[0.776]		[0.244]		[0.496]		[0.701]
Δrds_{it-2}	0.362***	0.361***	0.352**	0.476	0.313***	0.310***	0.291**	0.400**	11.182***	11.299***	11.590**	14.173*
	(0.071)	(0.071)	(0.119)	(0.300)	(0.079)	(0.079)	(0.119)	(0.174)	(3.363)	(3.402)	(4.665)	(8.081)
	[0.000]	[0.000]	[0.003]	[0.114]	[0.000]	[0.000]	[0.015]	[0.022]	[0.002]	[0.002]	[0.014]	[0.081]
tit_{it-2}	0.015	0.034	−0.030	−1.579	−0.956	−0.913	−1.106	−2.331*	0.311	0.258	0.471*	−0.525
	(0.292)	(0.353)	(0.386)	(3.282)	(0.848)	(0.891)	(0.821)	(1.372)	(0.200)	(0.260)	(0.263)	(2.506)
	[0.959]	[0.924]	[0.938]	[0.631]	[0.265]	[0.310]	[0.179]	[0.91]	[0.129]	[0.330]	[0.075]	[0.834]
year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	516	516	516	516	312	312	312	312	204	204	204	204
# of indus.	86	86	86	86	52	52	52	52	34	34	34	34
F	11.652	10.738	4.959	2.601	12.004	10.800	5.818	3.952	3.153	6.943	2.117	0.906
Exogeneity test (Davidson-Mackinnon test)												
F			0.236	0.457			1.686	4.137			2.103	1.018
			[0.627]	[0.633]			[0.195]	[0.017]			[0.149]	[0.364]
Underidentification test (Kleibergen-Paap rk LM test)												
χ^2			26.717	0.701			33.646	5.476			7.357	0.310
			[0.000]	[0.873]			[0.000]	[0.140]			[0.061]	[0.958]
Weak identification test (Stock-Yogo test)												
F			5.829	0.201			42.982	1.373			2.74	0.074
Relative bias			20–30%	>30%			<5%	>30%			>30%	>30%
Overidentification test (Hansen J test)												
χ^2			0.423	1.009			1.024	0.864			2.080	0.573
			[0.809]	[0.604]			[0.599]	[0.649]			[0.353]	[0.751]

Note: 1. $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$ are used as IVs for (3), (7), (11), and $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$, exp_{it-2} for (4), (8), (12).
2. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.
3. The robust (Eicker-Huber-White) standard errors adjusted for small samples and p values are reported in the round and square parentheses, respectively.
4. The relative bias of the weak identification test represents the largest relative bias of the FE-IV estimators relative to the FE estimators.

Table 9 Estimation of the competition effect: 1980-1994

Dependent variables: TFP growth rate

	All industries				Industries conducting R&D				Industries not conducting R&D			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FE	FE	FE-IV	FE-IV	FE	FE	FE-IV	FE-IV	FE	FE	FE-IV	FE-IV
$comp_{it-1}$	0.051**	0.220***	−0.001	0.950	0.092**	0.294***	−0.023	3.987	0.002	0.119	0.042*	0.289
	(0.022)	(0.065)	(0.038)	(1.211)	(0.040)	(0.111)	(0.085)	(4.623)	(0.009)	(0.087)	(0.024)	(0.306)
	[0.022]	[0.001]	[0.978]	[0.433]	[0.023]	[0.010]	[0.791]	[0.389]	[0.821]	[0.203]	[0.081]	[0.348]
$comp^2_{it-1}$		−0.001***		−0.003		−0.001**		−0.015		−0.0003		−0.001
		(0.0002)		(0.004)		(0.0003)		(0.018)		(0.0002)		(0.001)
		[0.002]		[0.434]		[0.027]		[0.390]		[0.166]		[0.454]
Δrds_{it-2}	0.266	0.269	0.278	0.290	0.284	0.284	0.296	0.307				
	(0.241)	(0.249)	(0.359)	(0.376)	(0.250)	(0.257)	(0.362)	(0.434)				
	[0.272]	[0.284]	[0.438]	[0.440]	[0.260]	[0.272]	[0.413]	[0.481]				
tit_{it-2}	0.035	0.015	0.130	0.003	−0.022	0.025	0.175	1.150	0.183	0.031	−0.346	−0.737
	(0.063)	(0.060)	(0.137)	(0.243)	(0.094)	(0.069)	(0.194)	(1.440)	(0.659)	(0.735)	(0.860)	(0.903)
	[0.578]	[0.805]	[0.343]	[0.992]	[0.813]	[0.715]	[0.367]	[0.425]	[0.786]	[0.968]	[0.688]	[0.417]
year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	1032	1032	1032	1032	900	900	900	900	143	143	132	132
# of indus.	86	86	86	86	75	75	75	75	11	11	11	11
F	3.902	5.645	3.150	2.665	4.143	5.007	2.702	0.790	–	–	1.383	1.703
Exogeneity test (Davidson-Mackinnon test)												
F			2.728	2.541			4.016	5.818			0.756	1.021
			[0.099]	[0.079]			[0.045]	[0.003]			[0.386]	[0.364]
Underidentification test (Kleibergen-Paap rk LM test)												
χ^2			22.895	10.135			21.045	3.166			11.658	3.622
			[0.000]	[0.018]			[0.000]	[0.367]			[0.009]	[0.305]
Weak identification test (Stock-Yogo test)												
F			10.391	2.393			9.429	0.816			7.589	0.956
Relative bias			5–10%	>30%			5–10%	>30%			10–20%	>30%
Overidentification test (Hansen J test)												
χ^2			1.010	1.025			1.010	0.440			8.311	13.676
			[0.855]	[0.599]			[0.604]	[0.803]			[0.016]	[0.001]

Note: 1. $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$ are used as IVs for (3), (7), (11), and $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$, exp_{it-2} for (4), (8), (12).
2. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.
3. The robust (Eicker-Huber-White) standard errors adjusted for small samples and p values are reported in the round and square parentheses, respectively.
4. The relative bias of the weak identification test represents the largest relative bias of the FE-IV estimators relative to the FE estimators.

Table 10 Estimation of the competition effect: 1995-2008

Dependent variables: TFP growth rate

	All industries				Industries conducting R&D				Industries not conducting R&D			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FE	FE	FE-IV	FE-IV	FE	FE	FE-IV	FE-IV	FE	FE	FE-IV	FE-IV
$comp_{it-1}$	0.079**	0.278**	0.090*	0.397	0.173***	0.418***	0.156**	1.541	−0.017	−0.274**	−0.095	−0.872
	(0.036)	(0.109)	(0.047)	(0.964)	(0.048)	(0.131)	(0.064)	(2.898)	(0.029)	(0.097)	(0.061)	(0.779)
	[0.031]	[0.012]	[0.058]	[0.681]	[0.001]	[0.002]	[0.015]	[0.595]	[0.569]	[0.018]	[0.124]	[0.266]
$comp^2_{it-1}$		−0.001**		−0.001		−0.001**		−0.007		0.001**		0.003
		(0.0004)		(0.004)		(0.001)		(0.014)		(0.0003)		(0.003)
		[0.029]		[0.769]		[0.033]		[0.641]		[0.019]		[0.321]
Δrds_{it-2}	0.325***	0.316***	0.323***	0.307***	0.302***	0.294***	0.305***	0.254*				
	(0.098)	(0.098)	(0.096)	(0.106)	(0.098)	(0.098)	(0.094)	(0.143)				
	[0.001]	[0.002]	[0.001]	[0.004]	[0.003]	[0.004]	[0.001]	[0.076]				
tit_{it-2}	−0.062	0.005	−0.073	0.018	−0.159***	−0.030	−0.144	0.531	1.324	1.498*	1.775***	2.107***
	(0.043)	(0.059)	(0.160)	(0.429)	(0.056)	(0.101)	(0.169)	(1.553)	(0.871)	(0.759)	(0.679)	(0.789)
	[0.154]	[0.931]	[0.648]	[0.966]	[0.005]	[0.771]	[0.395]	[0.732]	[0.159]	[0.077]	[0.010]	[0.009]
year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	946	946	946	946	825	825	825	825	132	132	121	121
# of indus.	86	86	86	86	75	75	75	75	11	11	11	11
F	5.707	5.327	4.143	4.107	6.524	6.442	4.522	4.433	–	–	1.015	0.891
Exogeneity test (Davidson-Mackinnon test)												
F			0.088	0.236			0.164	0.116			1.556	1.029
			[0.767]	[0.790]			[0.686]	[0.891]			[0.215]	[0.361]
Underidentification test (Kleibergen-Paap rk LM test)												
χ^2			48.034	6.370			104.721	2.840			16.777	4.258
			[0.000]	[0.095]			[0.000]	[0.417]			[0.001]	[0.235]
Weak identification test (Stock-Yogo test)												
F			34.213	1.659			89.105	0.671			8.181	0.918
Relative bias			<5%	>30%			<5%	>30%			10–20%	>30%
Overidentification test (Hansen J test)												
χ^2			3.507	6.130			0.877	3.617			2.415	1.007
			[0.173]	[0.047]			[0.645]	[0.164]			[0.299]	[0.604]

Note: 1. $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$ are used as IVs for (3), (7), (11), and $\Delta comp_{it-1}$, $\Delta comp_{it-2}$, $hcons_{it-2}$, exp_{it-2} for (4), (8), (12).
2. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.
3. The robust (Eicker-Huber-White) standard errors adjusted for small samples and p values are reported in the round and square parentheses, respectively.
4. The relative bias of the weak identification test represents the largest relative bias of the FE-IV estimators relative to the FE estimators.