Competition, R&D and Productivity in Japanese Manufacturing Industries

Yosuke Okada

Graduate School of Economics

Hitotsubashi University

December 2004

I would like to thank Hiroyuki Chuma, Akira Goto, Masaharu Hanazaki, Hideshi Itoh, Daiji Kawaguchi, Tatsuya Kikutani, Fukunari Kimura, Yukinobu Kitamura, Hyeong Ug Kwon, Tsutomu Miyagawa, Kazuyuki Motohashi, Sadao Nagaoka, Takanobu Nakajima, Hiroyuki Odagiri, Kotaro Suzumura and other seminar participants at the JEA spring meeting, Hitotsubashi University and the Japan Development Bank for their helpful comments. This study is based on the author's work in the research project on *Changing Corporate Governance and its Effects on Productivity in Japan* in the collaboration with the Research and Statistics Department of the Ministry of Economy, Trade and Industry (METI). I would like to thank to METI and the Ministry of Public Management, Home Affairs, Posts and Telecommunications for enabling me to use data of *The Basic Survey of Business Structure and Activity*. Financial support was provided by the Ministry of Education, Culture, Sports, Science and Technology for the 21st Century COE Program (Normative Evaluation and Social Choice of Contemporary Economic Systems). The usual disclaimer applies.

Abstract

Using a newly available panel data on around ten thousand firms in Japanese manufacturing for the years 1994-2000, I provide some empirical evidence that competition, as measured by lower level of industrial mark-ups, enhances productivity growth, controlling for R&D and other industrial characteristics. R&D competition, as measured by increased numbers of R&D doers, is also positively associated with a higher rate of productivity growth. Moreover, market power, as measured by either market share or price-cost margin, has negative impact on productivity level for R&D performing firms.

Key words: competition, R&D, productivity, manufacturing, GMM, dynamic panel data model
JEL classification: L11, L60, O30

Correspondence:
Yosuke Okada
Graduate School of Economics
Hitotsubashi University
Naka 2-1, Kunitachi, Tokyo, 186-8601 Japan
E-mail: yookada@econ.hit-u.ac.jp

I. Introduction

Does competition improve productivity? There is some theoretical basis that competition enhances productivity. But the empirical basis is not, as yet, strong enough. Although this general belief in the importance of competition is not fully supported by a series of solid empirical evidence in its favor, a feeling of the desirability of competition is quite strong in the policy arena ranging from deregulation, re-regulation to competition policy. By using a dynamic panel data model, this paper analyzes the determinants of productivity in Japanese manufacturing industries, looking particularly at the impact of both product market competition and R&D competition on productivity[1]. In addition, I consider the impact of R&D stock on productivity using a standard production function framework.

In the structure-conduct-performance (SCP) tradition since the seminal work by Bain (1951, 1956), there have been a lot of studies suggesting cross-sectional impact of market power on productivity. A cross-section analysis is very tricky, however, because it is subject to various sources of misspecification due to simultaneity of R&D, heterogeneity and endogeneity of individual product prices, heterogeneity of the underling production functions, and industrial characteristics such as demand growth and spillovers (Bresnahan 1989, Schumalensee 1989, Cohen and Levin 1989, Griliches 1992, Cohen 1995).

I utilize an exceptionally valuable panel data at the firm level. The Ministry of Economy, Trade and Industry (METI) has conducted the comprehensive survey about real-world activities of Japanese firms - *Basic Survey of Business Structure and Activities* (*BSBSA*) - since 1991. The BSBSA has been conducted annually since the second survey in 1994, and I am able to examine firm level data consecutively since 1994 to the present. The BSBSA covers all the firms with no less than 50 employees or greater than 30 million yen capitalization in mining, manufacturing, wholesale and retail trade.[2]

The most valuable character of this survey is that it has been conducted by firm-unit of observation with a permanent identification code. Establishment data from *Census of Manufacturers* are also available in many countries, but price setting, investment, diversification, and R&D activities, to name but a few, are rarely determined by the unit of establishment as managerial decisions. In this respect, the BSBSA provides valuable information to accomplish empirical studies on firms' behaviors.

The available dataset consists of an unbalanced panel with a large number of

---

[1] Baltagi (2001), Wooldridge (2001), Arellano and Honoré (2001), Bond (2002), and Arellano (2003) concisely explain recent developments of dynamic panel data models. The following description of econometric issues heavily depends on these studies.

[2] The survey also covers firms in agriculture, construction, and various service sectors, so long as they also engage at least partly in one of mining, manufacturing, wholesale and retail trade or restaurant activities.

cross-section units of manufacturing firms (more than 13000 firms classified by 59 industry codes in manufacturing), each observed for a small number of time periods (for the years 1994-2000 at most). This situation is typical of micro panel data, and calls for an estimation method that does not require the time dimension to become large in order to obtain consistent parameter estimates.

In the analysis of micro panel data, assumptions about the properties of initial condition play an important role, because the influence of the initial observations on each subsequent observation cannot safely be ignored when the time dimension is short. Identification then depends on limited serial correlation in the error term, which leads to use a convenient and widely used class of generalized method of moments (GMM) estimators, i.e. the Arellano-Bond dynamic panel data model (Arellano and Bond 1991). This estimator optimally exploits all the linear moment restrictions that follow from the assumption of no serial correlation in the error terms. This method has been widely used in the empirical industrial organization literature (Geroski et al. 1993, 1997; Nickel 1996; Nickel et al. 1997; Blundell et al. 1995, 1999; Klette 1999; Aghion et al. 2002).

The empirical results reported here provide some support for the view that competition, as measured by lower level of industrial mark-up, enhances productivity *growth*, controlling for various firm specific and industry specific characteristics. R&D competition, as measured by increased numbers of R&D doers, is also associated with a higher rate of productivity growth. In addition, substantial part of productivity growth can be attributed to R&D activity. Market power, as measured by either market share or price-cost margin, has negative impact on productivity *level* in R&D performing firms.

The rest of the paper is structured as follows. Section II gives a literature review concerning competition, R&D and productivity. Section III lays out empirical formulations. Section IV explains variable construction and measurement issues. Section V presents empirical findings. Section VI concludes the paper.

II. Literature

In the *Schumpeterian* tradition, key features of market structure which would determine innovation and productivity are *firm size* and *market power*. There is a broad range of both theoretical and empirical literatures on the relationship between competition and productivity[3].

First, there have been a lot of studies in line with a *neoclassical model of firms*. If

---

[3] The literature survey hereafter is greatly indebted to Cohen and Levin (1989), Scherer and Ross (1990), Cohen (1995), Nickel (1996), Geroski (1995, 1999), Aghion and Howitt (1998), Klette and Griliches (2000), Aghion et al. (2001, 2002), and Nishimura et al. (1999, 2003).

firms have market power, then their optimum size may differ from minimum cost position, and if economies of scale and/or scope exist, such differences may be more noticeable. Recent *game-theoretic* arguments have suggested that the degree to which costs are sunk and the resulting intensity of potential competition may be important determinants of firm size and market structure (Sutton 1991, 1998).

Second, *transaction cost economics* and *contract theory of firms* provide various theoretical predictions. Holmstrom (1982), Hart (1983) and Mayer and Vickers (1997) present models of managerial incentives that demonstrate explicitly how competition among firms may sharpen efficiency incentives. On the other hand, Martin (1993) provides a model in which competitive forces in the product market may raise the sensitivity of profits to the action of managers. He finds that increased competition tends to be negatively associated with managerial effort. Furthermore, financial pressure may play some role in motivating organizational efficiency and growth, as pointed out by Jensen (1986, 2000), Nickel et al. (1997), and Aghion et al. (1999)[4].

Third, *endogenous growth theory* (hereafter EGT) provides an alternative theoretical basis of the relationship between competition and productivity (Grossman and Helpman 1991, Aghion and Howitt 1992, Caballero and Jaffe 1993, Jones 1995, Aghion and Howitt 1998, Aghion et al. 2001). EGT generates various predictions as to the relationship between competition, innovation and productivity. For instance, Aghion et al. (2002) predicts theoretically and then examine empirically the relationship between product market competition and the number of successful patents. They find an *inverted-U* relationship between them as in line with earlier empirical findings by Scherer (1967) and Levin et al. (1985, 1987).

Fourth, there are a lot of attempts to identify life cycles of firms. Geroski (1999) describes the literature as *stage theories of growth* (Jovanovic 1982, Hopenhayn 1993, Klepper 1996). Several case studies using relatively long time-series data provide appealing empirical findings which are consistent with some predictions of the theoretical models (Jovanovic and MacDonald 1994, Pakes and Ericson 1998, Klepper and Simon 2000).

Finally, there is a growing body of the literature concerning *Penrosian* models of *organizational capabilities* (Penrose 1959, Slater 1980, Clark and Fujimoto 1991, Teece et al. 1997, Dosi et al. 2000). Penrose thought of firms as bundles of managerial resources which were bound together by a set of organizational capabilities. In the spirit of this theory, firms compete in constructing organizational capability (or *core competence*), rather than simply setting price or quantity. R&D competition seems to be relevant to this view. Of course R&D is not the only method to build up organizational capability. There are a lot of other aspects of a

---

[4] Empirical findings by Aghion et al. (2002) suggest that firms with higher financial pressures innovate more for any level of product market competition.

firm's organizational capability, such as managerial skill, product market strategies, experiences (learning by doing or *practiced routines*), and IT investment.

There are several empirical studies which confirm competition effects on the *level* of productivity, such as Geroski (1990, 1995), Caves et al. (1992), Nickel et al. (1992) and Torii (2001). On the other hand, Nickel (1996), Geroski et al. (1997), Nickel et al. (1997), Blundell et al. (1995, 1999), and Aghion et al. (2002) utilize *dynamic* panel data models, and suggest that market power reduce the *growth* of productivity and/or innovation. For example, Nickel (1996) presents evidence that competition, as measured by lower levels of rents, is associated with a significantly higher rate of total factor productivity in UK manufacturing.

In general, productivity estimates would be biased upward by imperfect competition without careful treatment of endogeneity of market structure. It is almost impossible to negate that a lot of important manufacturing sectors are subject to imperfect competition (Hall 1988, Bresnahan 1989). Moreover, joint consideration of the impact of R&D and competition toward productivity needs additional care about the Schumpeterian dynamics in market structure, since innovation incentive depends not only on post-innovation rents, but also on the differences between post-innovation and pre-innovation rents (Arrow 1962, Geroski 1995, Geroski et al. 1997, Hall 1999, Aghion et al. 2002). Competition may increase the incremental profit from innovation because it may reduce a firm's pre-innovation rents by more than it reduces its post-innovation rents. Competition thereby encourages R&D investments, which may lead to higher productivity growth.

Concerning the relationship between product market competition and innovation, a standard industrial organization theory predicts that innovation should decline with competition, as more competition reduces the monopoly rents that reward successful innovators (Dasgupta and Stiglitz 1980, Aghion and Howitt 1992)[5]. A lot of empirical studies, however, show that there is a positive correlation between product market competition and innovative output (Geroski 1995; Blundell et al. 1995, 1999; Aghion et al. 2002).

Overall, there is some theoretical basis that competition drives productivity improvements forward. Indeed, there have been several empirical studies which confirm competition effect on productivity. The impact of product market competition on productivity should be the main concern about competition policy, but there are few solid empirical studies especially for the Japanese industries. On the other hand, there is a growing body of empirical

[5] A recent game theoretic analysis by Vives (2004) shows that increasing the number of firms still tend to reduce R&D effort, whereas increasing the degree of product *substitutability* increase R&D effort provided that the total market for varieties does not shrink. This indicates that it is an important role of innovation to expand the set of new products, which would change resulting market structure. See also Klette and Griliches (2000) which give an alternative explanation to new product innovation by using a quality ladder model.

studies showing that product market competition enhances R&D and innovation, which may lead to a higher rate of productivity growth.

III. Empirical Formulation

In an excellent study, Nickel (1996) suggests that market power reduce the productivity growth in manufacturing sectors in the UK. I utilize his econometric framework as a basic model with a slightly different specification. Furthermore, I expand the basic model with an additive term of R&D activity using the conventional specification of the literature (Griliches 1979, 1986). Following Griliches (1979, 1986) and Nickel (1996), I define a productivity equation utilizing a Cobb-Douglas production function as follows:

$$y_{it} = \beta_i + \beta_t + \lambda\, y_{i,t-1} + (1-\lambda)\,\alpha\, l_{it} + (1-\lambda)\,(1-\alpha)\, c_{it} + \gamma\, k_{it} + \delta\, h_{it} + \varsigma\, s_{it} + \xi\, comp_j t + \varepsilon_{it}$$

where y_{it} is log real output, l_{it} is log employment, c_{it} is log capital stock, k_{it} is log R&D stock, h_{it} is a cyclical component, s_{it} reflects the impact of market power on the *level* of productivity, $comp_j$ represents a cross-sectional impact of product market competition on productivity *growth* at the industry level, i is the firm subscript, j is the industry subscript, t is the time subscript, β_i is firm fixed effects, β_t is time effects, and ε_{it} is serially uncorrelated error terms. I assume that the production function exhibit constant-returns to conventional inputs (l_{it}, c_{it}) and therefore increasing-returns to the basic three arguments (l_{it}, c_{it}, k_{it}), following the EGT literature.

It is worth noting that the present formulation does not make any explicit assumption of profit maximization, reflecting various predictions of firms' behavior in the literature. Put it differently, the model allows for the possibility that inputs (especially knowledge stock) are not fully adjusted to their equilibrium values, but are considered quasi-fixed while the firm solves its short run profit maximization problem. As Griliches (1986, p.152) indicated, "while it is likely that major divergences among firms in rate of return to R&D would be eliminated or reduced in the long run, the relevant runs can be quite long."

To eliminate the firm fixed effects, I simply difference the production function to obtain, after rearrangement,

$$\Delta(y_{it} - c_{it}) = \Delta\beta_t + \lambda\Delta(y_{it-1} - c_{it}) + (1-\lambda)\alpha\Delta(l_{it} - c_{it}) + \gamma\,\Delta k_{it} + \delta\,\Delta h_{it} + \varsigma\,\Delta s_{it} + \xi\, comp_j + \Delta\varepsilon_{it}.$$

To avoid the corruption of parameter estimates, y_{it}, l_{it}, c_{it}, k_{it}, s_{it} and some other control variables (which are explained in the next section) are treated as *endogenous*, in that they are correlated with ε_{it} and earlier shocks, but is uncorrelated with ε_{it+1} and subsequent shocks, i.e., the endogenous variables are treated symmetrically with the dependent variable y_{it} [6]. Furthermore, after differencing, $y_{i,t-1}$ is correlated with the equation error $\Delta\varepsilon_{it}$. As long as the basic error term ε_{it} is serially uncorrelated, however, all lags on y_{it}, l_{it}, c_{it}, k_{it}, s_{it} beyond $t-1$ are valid instruments.

I estimate the model using orthogonality assumptions between $\Delta\varepsilon_{it}$ and the set of instruments Z_{is}:

$$E(\Delta\varepsilon_{it} Z_{is}) = 0$$

where Z_{is} is a vector of instruments dated $s \le t-2$ $(i = 1,2,\ldots,N; t = 3,4,\ldots,T)$ and $\Delta\varepsilon_{it} = (\Delta\varepsilon_{i3}, \Delta\varepsilon_{i4}, \ldots, \Delta\varepsilon_{iT})'$. Instrumental variables estimators based on this fact is essentially a generalized method of moment estimators (GMM), making use of the moment restrictions generated by the serially uncorrelated errors (Arellano and Bond 1991).

GMM provides the optimal way to combine the set of orthgonality conditions. The asymptotically efficient GMM estimator based on the set of moment conditions minimizes

$$J = \left(\frac{1}{N} \sum_{i=1}^{N} \Delta\varepsilon_i' Z_i \right) W_{2N} \left(\frac{1}{N} \sum_{i=1}^{N} Z_i' \Delta\varepsilon_i \right)$$

by using the weight matrix

$$W_{2N} = \left(\frac{1}{N} \sum_{i=1}^{N} \left(Z_i' \,\hat{\Delta\varepsilon}_i\, \hat{\Delta\varepsilon}_i'\, Z_i \right) \right)^{-1}$$

where $\hat{\Delta\varepsilon}_i$ is consistent estimate of the first-differenced residuals obtained from a preliminary consistent estimator, N is the total number of firms, and W_{2N} is a consistent estimator of the covariance matrix of $(Z_i'\Delta\varepsilon_i)$. This is a *two-step* GMM estimator. Under homoskedasticity of the ε_{it} disturbances, the particular structure of the first-differenced model implies that an asymptotically equivalent GMM estimator can be obtained through a *one-step* procedure, replacing the weight matrix to

$$W_{1N} = \left(\frac{1}{N} \sum_{i=1}^{N} Z_i' H Z_i \right)^{-1}$$

[6] According to the usual terminology of the dynamic panel data analysis, x_{it} series is *endogenous* if x_{it} is correlated with ε_{it} and earlier shocks although x_{it} is uncorrelated with ε_{it+1} and subsequent shocks. On the other hand, if x_{it} and ε_{it} is also uncorrelated but still correlated with $\varepsilon_{i,t-1}$ and earlier shocks, the variable x_{it} series are called *predetermined*.

where H is a square matrix with twos on the main diagonal, minus ones on the first off-diagonals and zeros otherwise (see Arellano and Bond 1991 in more detail). This method crucially depends on the absence of serial correlation in ε_{it}. Absence of serial correlation is assisted by the inclusion of dynamics in the form of a lagged dependent variable. I use serial correlation tests developed by Arellano and Bond (hereafter A-B test), as well as a standard instrument validity test (i.e. Sargan test).

I will mainly report the one-step GMM estimators' results since the standard errors associated with the two-step estimators tends to be seriously downward biased, as noticed by Arellano and Bond (1991). This is because the dependence of the two-step weight matrix on estimated parameters makes the usual asymptotic distribution approximations less reliable for the two-step estimators (Blundell and Bond 1998, Bond 2002).

Generally, estimators which rely on first-differencing or related transformations to eliminate unobserved fixed-effects, and then use lagged values of endogenous variables as instruments for subsequent first-differences, can be expected to perform poorly in situations where the series are close to being random walks, so that their first-differences are close to being innovations, and will not identify parameters of interest in some limiting cases (Blundell and Bond 1998). Firms' growth rate might be subject to Gibrat's Law, and more generally identification may be weak when the series are near unit root processes. Thus the A-B tests are crucial to examine whether estimates are spurious statistical artifacts or not.

An important implication of a standard fixed effect model is that in the cross-sectional dimension (between) differences in levels explain differences in levels, while in the time dimension (within) differences in growth rates explain differences in growth rate. It is worth noting that, in the context to the present model, the attempt to isolate the impact of competition on the *level* of productivity is essentially a search for a time-series effect. It is clear from the estimation equation that what is concerned is the impact of changes in the level of market power (Δs_{it}) on changes in productivity. On the other hand, the impact of competition on productivity *growth* is represented by the cross-sectional correlation between industrial competition index ($comp_j$) and productivity growth. In other words, the coefficient of competition variables either represents growth effect (cross-section effect) or level effect (time-series effect), depending on the variable construction of the competitive measures.

A new semi-parametric approach to market turbulence is presented by Olley and Pakes (1996). They deal with both selectivity and simultaneity in an intertwined fashion. I adopt another approach in the present study which leans more heavily on assumptions about lags in the transmission of the disturbances to the other decision variables and use lagged values as instrumental variables in estimation (Blundell and Bond 1998). Thus although I treat simultaneity biases and serial correlations explicitly, selectivity problem is still hardly avoidable in the present study. I will discuss this issue further in later sections.

IV. Variable Construction and Measurement Issues

Real Output, Real Input of Labor and Capital

Variable definitions are summarized in Table 1. Output is measured by deflated sales and input of labor is defined by the total number of employees. Since there is no accurate information on material or the number of hours worked in the dataset, I have to define value-added as follows: sales - operating cost + wage + depreciation + interest payments. Concerning capital stock, making consecutive time-series data from BSBSA is virtually impossible, because the BSBSA has considerable numbers of samples with null investment as well as the dataset is unbalanced. Thus a standard perpetual inventory method is not applicable here[7]. Therefore capital stock is represented by the book value of tangible fixed asset deflated by real price of capital goods. This misspecification would introduce substantial measurement errors, especially in capital and labor coefficients in regressions.

As is suggested by Nickel (1996, p738), freely estimated on these parameters, the data tends to push the coefficients strongly toward diminishing returns, which is not unusual in a dynamic time-series context. Nickel indicates that this is because of inadequately controlled measurement error in labor and capital, strongly accentuated by differencing. Hence for the purposes of investigating total factor productivity effects, it is better to impose constant returns[8]. The present specification attempts to alleviate the simultaneity bias in the determination of employment, capital and output by using lagged variables as instruments. Thus, although the coefficients of labor and capital are not the primary concern at the present study, the ultimate directions of biases are not known a priori.

Product Market Competition

Main indicator of product market competition is price-cost margin. The conventionally used measures are concentration ratio, Herfindahl index, and market share. However, these measures tend to be misleading because they neglect both potential and international competition.

---

[7] Nishimura et al. (2003) construct time-series data on capital stock from the BSBSA. Their method is crucially dependent upon the assumption that positive increments of book values are net investments. I do not apply the same method here because the sample clean-up procedure would be problematic for this method, as explained below.

[8] By using establishment data, Nakajima et al. (1998) find that, while significant scale economies exist in many manufacturing industries, the TFP growth is attributable primarily to technical progress. They suggest that this finding validates the current practice of assuming constant returns to scale production functions. Klette (1999) shows that there is little scale effect on price-cost margins and productivity using establishment data in Norwegian manufacturing. I utilize *firm-level* data, thereby it remains to be seen that scale effect has some significant effect on productivity growth.

Furthermore, they are crucially dependent on the definition of market boundary and possible market turbulence effect as depicted by Nishimura et al. (2003).

Unfortunately, I cannot address the market turbulence effect fully due to data limitation. That is, to make a dynamic panel data model estimable and particularly to be testable for serial correlation, I have to eliminate those observations with the number of consecutive periods for which data are held is less than five years. Hence it is problematic to use the traditional market competition measures alone. Therefore, I explore the impact of competition on productivity growth by using price-cost margin as an alternative competition measure.

There are several prior studies applying this treatment. Boone (2000) provides a convincing argument that any parameter increase that would result in increasing the relative profit shares of firms would be a suitable measure of product market competition. Nickel (1996) defines a competitive measure by average rents normalized on value-added. Aghion et al. (2002) uses the Lerner Index which is defined by operating profit minus financial cost divided by sales. Klette (1999) shows that simultaneous estimation of price-cost margins, scale economies and productivity reveals statistically significant, but quite small margins between price and marginal costs in most manufacturing industries. That is, problems with market power and unexploited scale economies seem to be small on average across manufacturing. Furthermore, Nishimura et al. (1999) shows that there is a negative correlation between international competitiveness and markup. Its sensitivity is uniform within an industry though skewness may be problematic in estimation. Overall there is a sound theoretical basis and empirical support for price cost margin or other form of rents to use as a product market competition measure.

I define individual firm's average price cost margin as follows:

$$pcm = \frac{sales - cost\ of\ sales + depreciation - rK}{sales}$$

where r is cost of capital and K is capital stock. Cost of capital is defined by

$$r = (\rho + \delta - \pi_K^e) \times (\frac{1-\tau\, d}{1-\tau}) p_K$$

where ρ is cost of fund (inter-bank prime rate), δ is economic rate of depreciation (assuming δ=0.09), π_K^e is expected rate of inflation of capital goods (approximated by the past 3-year moving average of the real price of capital goods, Bank of Japan), τ is an effective corporate tax rate (Cabinet Office), d denotes the present value of the depreciation deduction on unit nominal investment[9], and p_K is a investment goods deflator (SNA private

[9] I simply define d as $\delta/(\delta + \rho + \pi_K^e)$ following Auerback (1979).

non-residential investment deflator, Cabinet Office). Using this price-cost margin index, I define industry aggregate competition measure, following Aghion et al. (2002), as follows:

$$comp_j = 1 - \frac{1}{N_j} \sum_i pcm_{ij}$$

where i indexes firms, j indexes industry, and N_j is the number of firms in industry j.

These competitive measures may contain several misspecification biases. The most important appears to be: (i) mark-ups would fluctuate either pro-cyclically or counter-cyclically; and (ii) estimates of the competition index would suffer from endogeneity bias. The first point has been examined extensively in the industrial organization literature. Green and Porter (1984) show theoretically that markups will be pro-cyclical under imperfect information. On the other hand, Rotenberg and Saloner (1986) show markups will be counter-cyclical under perfect information. Both of the theoretical analyses assume implicit collusion among firms. As for empirical findings, Odagiri and Yamashita (1987) and Nishimura et al. (1999) find pro-cyclical mark-ups in Japanese manufacturing industries. Domowitz et al. (1986), Machin and Van Reenen (1993), Chirinko and Fazzari (1994), and Ghosal (2000) also find similar pro-cyclicality in manufacturing industries in UK or US. Thus I include growth rates of both industrial sales and import penetration in regressions to control possible cyclicality of industrial demand.

Concerning the second issue, I treat the individual firm's price-cost margin or market share as endogenous. That is, the firm specific competition variable (Δs_{it}) is expected to measure time-series competitive effect on productivity *level*. On the other hand, the industrial competition measure ($comp_j$) is assumed to be exogenous, and their identification comes from variation across industries over time. This means that, although $comp_j$ is assumed to be time-invariant in the empirical formulation and this is virtually in accordance with the actual data, there still remains some endogeneity bias. To alleviate possible endogeneity bias in the industrial competitive measure, I contain several cross-sectional control variables in regressions which will be explained below.

R&D Competition

Unlike product market competition, R&D competition was "explicitly advocated by Schumpeter as unambiguously good for innovation and growth" (Aghion and Howitt 1998, p.205). The effect of R&D competition upon productivity has been extensively examined in the theoretical literature, but empirical studies are disappointingly scarce. I define the measure of R&D competition as follows:

$$rd\_herf_{jt} = \sum_i (R_{ijt} / \sum_l R_{ilt})^2$$

where R is R&D expenditure, i indexes firms, and j indexes industry. This measure is the Herfindahl Index of R&D investment. Larger industries would contain more R&D doers and thus tend to have lower values of rd_herf_{jt}, nonetheless, some of smaller industries have a lot of R&D performers: some industries would evenly spread R&D expenditure among firms whereas some other industries may concentrate R&D on a few large firms.

This index is accompanied by the similar caveats to the measure of product market competition. The most salient point appears to be: (i) international R&D competition; (ii) economies of scale and scope in R&D; (iii) gestation lag between R&D investment and productivity gain; and (iv) knowledge spillovers among firms. While the measure is an industry level aggregate, its estimate may be still suffered from some endogeneity bias. Accordingly there would be some reservations about this crude variable formulation. Nonetheless it is the first attempt, as far as I know, to measure R&D competition directly in the cross-industry productivity literature.

R&D Stock

The effect of R&D stock is measured by γ that is allowed to vary across firms. Estimation of γ would require data on the growth of R&D stock. But if investment in R&D does not depreciate, then data on R&D intensity can be used to capture the R&D effect. That is, $\Delta k_{it} \cong R_{it} / K_{it}$ and $\gamma \Delta k_{it} \cong \rho (R_{it} / Y_{it})$ where ρ is the marginal product of R&D, Y is output, R is R&D expenditures, and K is R&D stock. This implies that the rate of growth in productivity depends on the intensity of R&D investment (Griliches 1986, 1998) [10]. Thus the impact of R&D intensity on productivity growth can be regarded as time-series effects, i.e. the impact of R&D stock on the *level* of productivity.

R&D would possibly enhance productivity (Griliches 1998). However, almost the same caveats to R&D competition are applied in exploring the relationship between R&D and productivity as suggested before. For example, there would be sample selection biases (a lot of zero-reporting firms in R&D as is emphasized by Griliches 1994), long gestation lag in R&D activity, the role of public research (spillovers) etc. In the following econometric analyses, I employ regressions by using separate samples of R&D performers and non-performers, but sample selection bias may still affect the estimates. Furthermore, a large portion of R&D is personnel cost, and tacit knowledge would be accumulated as human capital within a firm. R&D stock bears thereby a considerable adjustment cost. Hence I treat R&D stock as an endogenous variable in regressions.

[10] If R&D investments depreciate, as they likely do, the estimated coefficient may contain some downward bias. However, this assumption of zero depreciation is somewhat standard in the productivity literature. Griliches and Lichtenberg (1984) and Hall and Mairesse (1995) find that point estimates rise with the assumed rate of depreciation but that the specification's fit is best with zero rate of depreciation.

Market Share and Diversity Index

Although market share is conventionally used as an index of market power, there are a lot of reservations to use (Nickel 1996, p.733): (i) collusion depends not only on the size of the various firms involved relative to the market but also on other factors that are hard to control; (ii) potential as well as actual competition influences market power; (iii) market share does not fully reflect foreign competitors; (iv) market share uses industrial sales as the denominator, but it is not certain that this represents the actual *market*. Thus, the estimates of market share would have little value as a *cross-section* measure of market power. However, if the measure is used as a *time-series* measure, the problems above are less serious (Nickel 1996, pp.733-4). The reason is as follows. There are two types of possible causality: (i) competition to firm growth and productivity growth; (ii) firm growth and productivity growth to competition. Reverse causality yields the opposite sign. Thus if there is a positive relationship between productivity growth and competition (or negative relationship between market share and productivity growth), I might argue that the true relationship is much stronger.

Furthermore, in order to alleviate the above mentioned issues, I define weighted average market share following Crépon et al. (1998). By using their definition, it is also possible to define diversity index of firms. Let $S_{i,k}$ be the sales of firm i for its product k in the industry segment or market k (time subscripts are suppressed), then

$$S_i = \sum_k S_{i,k} \quad \text{and} \quad S_k = \sum_i S_{i,k}$$

are respectively the overall sales of firm i (over all its products) and the overall sales on market k (over all firms). The market share $s_{i,k}$ of firm i on market k and the share of product k in firm i total sales are thus equal to:

$$s_{i,k} = S_{i,k} / S_k \quad \text{and} \quad b_{i,k} = S_{i,k} / S_i \, .$$

Note that $\sum_k b_{i,k} = 1$ for each firm i. Then for diversified firm i the weighted average market share s_i^w and the diversification index ($diversity_i$) are calculated as follows:

$$s_i^w = \sum_k b_{i,k} \times s_{i,k} \quad \text{and} \quad 1/diversity_i = \sum_k b_{i,k}^2 \, .$$

For a non-diversified firm, I have $s_i^w = s_i$ and $diversity_i = 1$. To calculate these indices, I fully utilize individual firm's sales data by industry in the BSBSA: agriculture, construction, mining, manufacturing, wholesale and retail trade, and remaining service sectors. The total number of industries is 135 in which manufacturing sector consists of 59 industries[11]. Thus the

[11] The industry classification in manufacturing as well as the corresponding number of firms in both full

weighted market share and diversity index likely reflect the extent of vertical (as well as horizontal) diversification.

Other Control Variables

I include additional control variables in regressions as shown in Table 1. Although it is very difficult to incorporate a broad range of real business activities into a single empirical formulation, I attempt to trace not only R&D activity but also some other related aspects of industrial characteristics[12].

First, to control market demand fluctuation, I include growth rates of both industrial sales and import penetration in regressions. These variables as well as year dummies are expected to control the cyclical components of price-cost margin.

Second, in order to control a firm specific appropriability condition which may affect individual firm's productivity, I also contain a technology trade variable ($tech\_trade_{it}$) in regressions which is defined by technology trade turnovers (revenue + expenditure) divided by sales. The sum of revenues and expenditures of the whole category of technology (patents, utilities, design, copyrights, trademarks, and know-how) are used in calculation. This variable is expected to condition appropriability of R&D in a comprehensive manner (Levin et al. 1987, Cohen 1995). That is, an active firm in technology transaction is able to retain more profit from R&D investment, thus such a firm would be more productive.

Third, I contain debt-asset ratio in regressions as a financial constraint variable. As is well known, the macro economy since the latter half of 90s in Japan has been suffered from severe financial predicament and debt-deflationary pressure. Note that diversity index, debt-asset ratio and technology trade are all included in levels. Hence these variables are expected to control the cross-sectional correlates of productivity *growth*. I also treat these variables as endogenous.

Data Issues and Selectivity Bias

To eliminate apparent outliers (due to missing data, erroneous data and possible erroneous matches) without using arbitrary imputation procedures, I computed the sales/asset ratio and eliminated those observations outside the 95 percentile (i.e. 2.5% on both side). I also eliminated those observations whose price-cost margins were more than unity. Using these

---

sample and estimation sample is shown in Table A1.

[12] Some related data which would be expected to reflect organizational capabilities are actually collected in the BSBSA, such as the usage of IT technology between and within firms. But it is impossible to use these data consecutively and consistently at the present study since most of these questionnaires are conducted every three years and the questionnaires themselves have been significantly changed through the surveys.

procedures, the observations decreased by 5.05%. To make the dynamic panel data model estimable, I further eliminated those observations with the number of consecutive periods for which data were held was less than five years. By this procedure, the observations decreased by 27.40% (see Tables 2 and A).

The summary statistics are presented in Tables 2 and 3. Number of observations and basic statistics of R&D performers and non-performers are shown in Table 2. According to the Student's t-values, almost all key variables, such as sales growth rate, price-cost margin, debt-asset ratio and real value added per employee, are statistically different between R&D performers and non-performers. Employment adjustment rate is the sole variable which is not statistically different between the two sub-samples.

The sample selectivity problem may be quite serious for a dynamic panel data model. If observations are not missing at random, estimates that are based on cleaned sub-samples could be badly biased. A negative correlation between estimated productivity shocks and future probabilities of exit would induce a negative correlation between an error term and the stock of capital among the surviving firms and bias the estimated capital coefficient downward in such sample. Moreover, sample selection bias due to zero-R&D reporting or less-R&D reporting is hardly avoidable.

Unfortunately, entry, exit, and mergers are often neglected in the productivity literature[13]. In a recent careful study, Nishimura et al. (2003) shows that there are no evidence to demonstrate natural selection mechanism of economic Darwinism works even in severe recession periods in Japan. They explore a firm's entry, survival, and exit and its relationship with total factor productivity using the BSBSA data. Their empirical results show that efficient firms in terms of total factor productivity quit while inefficient ones survived in the banking-crisis period 1996-1997. Their study strongly suggests that entry barriers to new competition due to a financial predicament as well as strict government regulations (especially in service sectors) are crucial determinants of productivity.

The comparison between the full sample and the estimation sample in Table 2 suggests that firm size (permanent employee and real sales) in the estimation sample is slightly larger than in full sample, whereas sales growth rate in estimation sample is relatively lower than in full sample. This indicates that some new growing firms are omitted in our estimation sample, in other words, the coefficients of the competition measures would be underestimated due to sample selection bias.

It is difficult to eliminate selectivity bias by the current empirical specification. But if I adopt price-cost margin as an alternative competition measure, I expect that the above

[13] The recent careful studies which treat market turbulence effect explicitly are, for example, Hopenhayn (1993), Nishimura et al. (2003), and Disney et al. (2003).

mentioned sampling bias would be, at least partially, alleviated. Price-cost margin would reflect some potential as well as international competition and there are no significant differences in price-cost margin between the two sub-samples[14]. The present dataset from the BSBSA arguably covers smaller non-listed firms much more comprehensively than other firm-level data source such as financial statements[15]. Hence I expect that this sort of selection bias would be less serious than the conventionally used firm level data set which contains listed companies alone.

V. Results

The results of the basic specification are presented in Table 4. The dependent variable is log real sales. The number of consecutive periods for which data are held is at least five years. Since some observations for market share and price-cost margins are differently missing due to erroneous data and possible erroneous matches, the number of observations for market share is not necessarily identical with that for price-cost margin. Constant-returns-to-scale in labor and capital is imposed in all regressions. All equations are estimated in first differences and include both year dummies and industry dummies. To save space the coefficients of these dummies are omitted.

A-B test statistics that average auto-covariance in residuals of order 1 and 2 is zero are shown by the rows denoted by m_1 and m_2 respectively. The pattern of serial correlation in the first-differenced residuals is consistent with the assumption that the ε_{it} disturbances are serially uncorrelated, so that $\Delta\varepsilon_{it}$ should have significant negative first-order serial correlation but no significant second-order serial correlation. There is also some evidence that the AR(1) model is well specified for the data series as is shown by the significant coefficients of the lagged dependent variable. The estimates, however, are quite small and *negative*. This suggests that there may be some weak tendency to *mean reversion* which has been pointed out by the literature on Gibrat's Law (Sutton 1997).

As the empirical model is over-identified, it is appropriate to use Sargan statistics to test the validity of the over-identifying restrictions. Consistent with the evidence from the serial correlation tests, the null that these moment conditions are invalid is not rejected at any conventional significance level in columns (1) and (3). The Sargan statistic from the one-step homoskedastic estimator in column (2) marginally rejects the null that the over-identifying

[14] The BSBSA data is truncated by the threshold of 50 employees or 30 million capitalizations. Thus new small entrants are not likely to be covered in the survey. Moreover some firms are occasionally classified in a different industrial sector from the previously classified one. Thus entry and exit through inter-industry move would cause possible another sampling bias.

[15] The BSBSA is one of the *government-specified* statistics, which means that all the relevant respondents have legal obligations to respond to them, as is the case in the National Census.

restrictions are valid. This could be due to heteroskedasticity. However, the two-step Sargan test may be better for inference on model specification. Sargan $\chi^2(98)$ is 80.51 (p=0.901) in column (2) using two-step homoskedastic estimator. In addition, the two-step standard errors tend to be biased downward in small samples. For this reason, Arellano and Bond (1991) recommend the one-step results for statistical inferences. Thus I report the one-step results in column (2).

The estimation result in columns (1) through (3) show that both of the industrial competitive measures ($comp_{jt}$ and rd_herf_{jt}) are strongly significant[16]. Industrial competitive measure ($comp_{jt}$) has a positive and significant effect. This reveals a strong impact of competition on productivity *growth*, controlling for various firm and industry specific characteristics. The coefficients of R&D concentration index (rd_herf_{jt}) is negative and significant. This suggests that spreading R&D expenditures among firms has positive impact on productivity growth. Although whether this R&D concentration index can be regarded as an R&D competitive measure and as an exogenous variable remains to be questionable, it is an interesting finding to be interpreted in the context of Schumpeterian dynamics, as discussed by Aghion et al. (2002)[17].

In columns (2) and (3), the time-series measures of product market competition ($share_{it}$ or pcm_{it}) have negative sign as expected but not statistically significant. These variables are entered in growth rate, thus there are no significant impact of competition on productivity *level*. This non-significance may be partly due to small within variation in the data with at most seven-year periods.

It should be noted that several control variables have also significant coefficients. First, cyclical time-series factors such as industrial growth and import penetration are positive and significant. Unreported coefficients of either industry dummies or year dummies are also jointly significant respectively. Thus it is arguable that industrial demand fluctuation is well controlled in the basic specification. Second, debt asset ratio has significantly negative impact on productivity. Third, product diversity and technology trade has positive signs although statistical significances are quite weak.

Next, in order to see whether or not R&D affects productivity growth, I expand the basic specification to include R&D stock measures. Table 5 shows that the positive impact of R&D intensity (*rd_intensity*) on productivity growth is highly significant. If R&D intensity can be regarded as R&D stock measure as is explained before, substantial part of productivity growth can be attributable to R&D stock. The parameter estimates (0.48 to 0.61) are virtually comparable to but slightly higher than the estimates of the prior studies in Japan, such as

---

[16] In unreported regressions, each variable is still strongly significant even if the other variable is dropped.
[17] Aghion et al. (2002) found that the equilibrium degree of technological 'neck-and-neckness' among firms should decrease with product market competition.

Odagiri and Iwata (1986) and Goto and Suzuki (1989). The possible reason for the higher estimates would be the omission of knowledge spillovers (Griliches 1992, Goto and Suzuki 1989). The coefficients may be thereby over-estimated due to the omitted variable bias.

As for the remaining explanatory variables, I obtain virtually similar results to the previous ones. The time-series effect of market power ($share_{it}$ or pcm_{it}) is negative as expected but not significant. The industrial competitive variables are still highly significant. Debt-asset ratio is negative and technology trade is positive coefficients and both variables are statistically significant.

In Table 6, I employ regressions by using separate samples of R&D performers and non-performers. R&D performers are defined as firms reporting non-zero R&D expenditures and non-performers reporting no R&D expenditures within observation periods. In this case, the time-series competition effect ($share_{it}$ or pcm_{it}) has negative signs and is statistically significant for R&D performers, whereas they are not statistically significant for non-R&D performers. This suggests that market power, as measured by market share or by higher level of individual mark-up, has negative impact upon productivity *level* in R&D performing firms. Industrial competitive effects are virtually preserved in Table 6. Thus it is likely that industrial competitive effects have a robust cross-sectional impact on productivity growth.

R&D intensity has still positive and significant effect on productivity level, but the coefficients (0.23 to 0.24) become slightly lower than the previous estimates. The possible reason would be the negligence of knowledge spillovers which have the estimated coefficients downward biased. R&D performers would have better absorptive capacity and could obtain external knowledge more effectively than non-R&D-performers, as is suggested by Cohen and Levinthahl (1989). But the magnitude of this effect is virtually comparable to the estimates of the previous studies such as Goto and Suzuki (1989).

Other salient feature in the estimated results in Table 6 is as follows. First, the coefficients of debt-asset ratio are negative and still highly significant for non-R&D performers, but no longer significant for R&D performers. As is well known, in the latter half of 1990s, the Japanese economy suffered severe debt-deflationary pressure which possibly damaged the firms with stricter financial constraint. The estimates suggest that this financial predicament damaged more the non-R&D performers than the R&D-performers[18].

Second, concerning the technology trade variable, Table 5 produces positive and significant result at the 5% significance level. In table 6, however, the *tech_trade* variable is not statistically significant for R&D performers, but slightly significant for non-R&D performers (at

[18] The estimation results which are obtained by using separate samples between large and small firms are shown in Table A2. The specification's fit is relatively weak due to serial correlation or invalid over-identification, but the coefficients of debt-asset ratio are significant in both samples. This may be due to the fact that non-R&D performers are not necessarily small and medium sized firms.

5 to 10% significance level). The possible reasons for the differences between R&D performers and non-performers appear to be that (i) R&D performers may tend to appropriate their R&D outcome through in-house production; (ii) some industries with many non-R&D performers are likely to be doing relatively more informal R&D, reporting less of it, and hence providing the appearance of more productivity gain from technology transaction. Thereby the relevant R&D expenditure is measured with error due to less-reporting bias and the estimated coefficients for technological trade may be upward biased. Unfortunately this sort of bias is hardly avoidable.

VI. Concluding Remarks

Our findings suggest that both product market competition and R&D competition enhance productivity growth (cross-section effect). R&D stock is also positively associated with productivity growth (cross-section effect). Market power may have some negative impact upon productivity level in R&D performing firms (time-series effect). Furthermore, debt-asset ratio has a negative impact on productivity growth in non-R&D performing firms. The empirical findings provided here are subject to a number of reservations. Nevertheless, they do raise the issue that suppressing competition may turn out to have been very costly to the economy in terms of foregone growth opportunities.

The present study opens up a number of questions for further study. First, the analysis should have controlled for *product differentiation* because most products in manufacturing consist of a number of different level of quality and varieties. However, empirically useful measures of product differentiation and appropriate *deflators* adjusted for quality are difficult to derive even in principle, not to mention the practical problems with data availability.

Second, I construct the R&D competition measure by using the R&D expenditures *at the firm level*. But firm-level R&D data may not be adequate enough for the purpose of investigating R&D competition, since some portion of manufacturing firms in Japan are integrated into interlocking groups[19]. Economies of scope and spillovers in R&D may have also caused possible estimation biases. Furthermore, R&D outsourcing and joint R&D cooperation is more noticeable in the late 90s in Japan. Ownership structure and R&D cooperation, especially in high-tech sectors, would be very important issues to explore the cause and effect of R&D competition in future research. Patent data would be a possibly beneficial source of information to investigate R&D competition, cooperation and spillovers (Jaffe and Trajtenberg 2002).

Third, Griliches and his colleagues show that there are substantial heterogeneity and instability in the coefficients of the estimated Cobb-Douglas production function (Griliches 1998). This indicates that a more flexible specification of technology would be desirable, as

[19] See Klette (1996) concerning scope economies, interlocking group and R&D performance.

suggested by Klette (1999) and Nishimura et al. (1999). The parameter estimates at the present study are still likely to be suffered from some instability, especially in the input coefficients of labor and capital. Furthermore, dynamic panel data models are in a developing area of research because in many cases GMM for panel data perform poorly in finite samples. I have used a large panel dataset and luckily obtained meaningful estimates, although the GMM on first differences still may produce imprecise estimates.

Finally, we should view this research as a small part of broader investigations in Japan. Evidence from this paper may not be representative because the observation period is just for the years 1994-2000, which would be in some sense a distinctive period, in that many Japanese firms have been in the process of fundamental adjustment of over-capitalization under serious debt-deflationary pressure. Furthermore, detailed investigation of the individual industry and its comparison with industry aggregates is required before any strong conclusion could be drawn about the relationship between competition and productivity.

References

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2002) "Competition and Innovation: An Inverted U Relationship," NBER Working Paper, No.9269.

Aghion, P., M. Dewatripont and P. Rey (1999) "Competition, Financial Discipline and Growth," *Review of Economic Studies* 66, 825-852.

Aghion, P., C. Harris, P. Howitt and J. Vickers (2001) "Competition, Imitation and Growth with Step-by-Step Innovation," *Review of Economic Studies* 68(3), 467-492.

Aghion, P. and P. Howitt (1992) "A Model of Growth through Creative Destruction," *Econometrica* 60, 323-357.

Aghion, P. and P. Howitt (1998) *Endogenous Growth Theory*, Cambridge: MIT Press.

Arellano, M. (2003) *Panel Data Econometrics,* Oxford: Oxford University Press.

Arellano, M. and S. Bond (1991) "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies* 58, 277-297.

Arellano, M. and B. Honoré (2001) "Panel Data Models: Some Recent Developments," in J. J. Heckman and E. Leamer eds., *Handbook of Econometrics* vol.5, Amsterdam: North-Holland (Elsevier), 3229-3296.

Arrow, K. (1962) "Economic Welfare and the Allocation of Resources for Invention," in R.R. Nelson, ed., *The Rate and Direction of Inventive Activity*, Princeton University Press.

Auerbach, A. J. (1979) "Inflation and the Choice of Asset Life," *Journal of Political Economy* 87(3), 621-638.

Bain, J. S. (1951) "Relation to Profit Rate to Industry Concentration: American Manufacturing," *Quarterly Journal of Economics* 65, 293-324.

Bain, J. S. (1956) *Barriers to New Competition*, Cambridge: Harvard University Press.

Baltagi, B. H. (2001) *Econometric Analysis of Panel Data*, 2nd ed., New York: John Wiley and Sons.

Blundell, R. and S. Bond (1998) “Initial Conditions and Moment Restrictions in Dynamic Panel Data Models,” *Journal of Econometrics* 87, 115-143.

Blundell, R., R. Griffith, and J. Van Reenen (1995) “Dynamic Count Data Models of Technological Innovation,” *Economic Journal* 105, 333-344.

Blundell, R., R. Griffith, and J. Van Reenen (1999) “Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms,” *Review of Economic Studies* 66, 529-554.

Bond, S. (2002) “Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice,” Cemmap working Paper CWP09/02, The Institute for Fiscal Studies, Department of Economics, UCL.

Boone, J. (2000) “Competitive Pressure: The Effects on Investments in Product and Process Innovation,” *Rand Journal of Economics* 31(3), 549-569.

Bresnahan T. (1989) “Empirical Studies of Industries with Market Power,” in R. Schmalensee and R. D. Willig eds., *Handbook of Industrial Organization* vol.2, Amsterdam: North-Holland, 1011-1057.

Caballero, R. J. and A. Jaffe (1993) “How High are the Giants Shoulders: an Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth.” in O. J. Blanchard and S. Fischer, eds., *NBER Macroeconomics Annual* vol.8, Cambridge MA: MIT Press.

Caves, R. E. (1992) *Industrial Efficiency in Six Nations*, Cambridge MA: MIT Press.

Chirinko, R. and S. Fazzari (1994) “Economic Fluctuations, Market Power and Returns to Scale: Evidence from Firm-level Data,” *Journal of Applied Econometrics* 9, 47-69.

Clark, K. B. and T. Fujimoto (1991) *Product Development Performance*, Boston: Harvard Business School Press.

Cohen, W. (1995) “Empirical Studies of Innovative Activity,” in P. Stoneman ed. *Handbook of the Economics of Innovation and Technological Change*, Blackwell, 182-264.

Cohen, W. M. and D. A. Levinthal (1989) “Innovation and Learning: The Two Faces of R&D,” *Economic Journal* 99, 569-596.

Cohen, W. M. and S. Klepper (1996) “A Reprise of Size and R&D,” *Economic Journal* 106, 925-951.

Cohen, W. M. and R. C. Levin (1989) “Empirical Studies of Innovation and Market Structure,” in R. Schumalensee and R. D. Willig eds., *Handbook of Industrial Organization* vol.2, Amsterdam: North-Holland, 1059-1107.

Crépon, B., E. Duguet, and J. Mairesse (1998) “Research, Innovation, and Productivity: An Econometric Analysis at the Firm Level,” NBER Working Paper, No.6696.

Disney, R., J. Haskel and Y. Heden (2003) “Entry, Exit and Establishment Survival in UK Manufacturing,” *Journal of Industrial Economics* 51, 91-112.

Domowitz, I., G. Hubbard, and B. Petersen (1986) “Business Cycles and the Relationship between Concentration and Price-Cost Margins,” *Rand Journal of Economics* 17, 1-17.

Dosi, G., R. Nelson and S. Winter (2000) *The Nature and Dynamics of Organizational Capabilities*, New York: Oxford University Press.

Ericson, R. and Pakes (1995) “Markov-Perfect Industry Dynamics: A Framework for Empirical Work,” *Review of Economic Studies* 62 (1), 53-82.

Geroski, P. A. (1990) “Innovation, Technological Opportunity, and Market Structure,” *Oxford Economic Papers* 42, 586-602.

Geroski, P. A. (1995) *Market Structure, Corporate Performance and Innovative Activity*, Oxford: Oxford University Press.

Geroski, P. A. (1998) “An Applied Econometrician’s View of Large Company Performance,” *Review of Industrial Organization* 13, 271-93.

Geroski, P. A. (1999) “The Growth of Firms in Theory and Practice,” CEPR Discussion Paper, No.2092.

Geroski, P. A., S. Machin, J. Van Reenen (1993) “The Profitability of Innovative Firms,” *Rand Journal of Economics* 24(2), 198-211.

Geroski, P. and R. Pomroy (1990) “Innovation and the Evolution of Market Structure,” *Journal of Industrial Economics* 38(3), 299-314.

Geroski, P. A., S. J. Machin, and C. F. Walters (1997) “Corporate Growth and Profitability,” *Journal of Industrial Economics* 45(2), 171-189.

Ghosal, V. (2000) “Product Market Competition and the Industry Price-Cost Markup fluctuations: Role of Energy Price and Monetary Change,” *International Journal of Industrial Organization* 18, 415-444.

Goddard, J., J. Wilson and P. Blandon (2002) “Panel Tests of Gibrat’s Law for Japanese Manufacturing,” *International Journal of Industrial Organization* 20, 415-433.

Goto, A. and K. Suzuki (1989) “R&D Capital, Rate of Return on R&D Investment and Spillover of R&D in Japanese Manufacturing Industry,” *Review of Economics and Statistics* 71(4), 555-564.

Green E. and R. Porter (1984) “Noncooperative Collusion under Imperfect Information,” *Econometrica* 52, 87-100.

Griliches, Z. (1979) “Issues in Assessing the Contribution of Research and Development to Productivity Growth,” *Bell Journal of Economics* 10(1), 92-116.

Griliches, Z. (1986) “Productivity, R&D, and Basic Research at the Firm Level in the 1970s,” *American Economic Review* 76(1), 141-154.

Griliches, Z. (1992) “The Search for R&D Spillovers,” *Scandinavian Journal of Economics* 94, S29-S47.

Griliches, Z. (1994) "Productivity, R&D, and the Data Constraint," *American Economic Review* 84, 1-23.

Griliches, Z. (1998) *R&D and Productivity*, Chicago: the University of Chicago Press.

Griliches, Z. and F. Lichtenberg (1984) "R&D and Productivity Growth at the Industry Level: Is There Still a Relationship?" in Z. Griliches ed., *R&D, Patents, and Productivity*, Chicago: the University of Chicago Press, 465-496.

Griliches, Z. and J. Mairesse (1983) "Comparing Productivity Growth: An Exploration of French and U.S. Industrial and Firm Data," *European Economic Review* 21, 89-119.

Griliches, Z. and J. Mairesse (1984) "Productivity and R&D at the Firm level," in Z. Griliches ed., *R&D, Patents, and Productivity*, Chicago: the University of Chicago Press, 339-374.

Griliches, Z. and J. Mairesse (1990) "R&D and Productivity Growth: Comparing Japanese and U.S. Manufacturing Firms," in C. R. Hulton ed., *Productivity Growth in Japan and the United States*, Chicago: University of Chicago Press, 317-340.

Grossman, G. M. and E. Helpman (1991) *Innovation and Growth in the Global Economy,* Cambridge MA: MIT Press.

Hall, B. H. (1999) "Innovation and Market Value," NBER Working Paper, No.6984.

Hall, R. (1988) "The Relation between Price and Marginal Cost in U.S. Industry," *Journal of Political Economy* 96(5), 921-947.

Hall, B. H. and J. Mairesse (1995) "Exploring the Relationship between R&D and Productivity in French Manufacturing Firms," *Journal of Econometrics* 65, 263-294.

Hart, O. D. (1983) "The Market Mechanism as an Incentive Scheme," *Bell Journal of Economics* 14, 366-382.

Holmstrom, B. (1982) "Moral Hazard in Teams," *Bell Journal of Economics* 13, 324-340.

Hopenhayn, H. (1993) "Entry, Exit, and Firm Dynamics in Long Run Equilibrium," *Econometrica* 60(3), 649-670.

Jaffe, A. B. and M. Trajtenberg (2002) *Patents, Citations & Innovations: A Window on the Knowledge Economy*, Cambridge MA: MIT Press.

Jensen, M. C. (1986) "Agency Costs of Free Cash Flow, Corporate Finance and Takeovers," *American Economic Review Paper and Proceedings* 76, 323-329.

Jensen, M. C. (2000) *A Theory of The Firm, Governance, Residual Claims, and Organizational Forms*, Cambridge MA: Harvard University Press.

Jones, C. I. (1995) "R&D-Based Models of Economic Growth", *Journal of Political Economy* 103, 759-784.

Jones, C. I. and J. C. Williams (1998) "Measuring the Social Return to R&D," *Quarterly Journal of Economics* 113, 1119-1135.

Jovanovic, B. (1982) "Selection and the Evolution of Industry," *Econometrica* 50, 649-670.

Jovanovic, B. and G. MacDonald (1994) "The Life Cycle of a Competitive Industry," *Journal of Political Economy* 102(2), 322-347.

Klepper, S. (1996) "Entry, Exit, Growth and Innovation over the Product Life Cycle," *American Economic Review* 86, 562-83.

Klepper, S. and K. L. Simon (2000), "The Making of an Oligopoly: Firm Survival and Technological Change in the Evolution of the U.S. Tire Industry," *Journal of Political Economy* 108(4), 728-760.

Klette, T. J. (1996) "R&D, Scope Economies, and Plant Performance," *Rand Journal of Economics* 27(3), 502-522.

Klette, T. J. (1999) "Market Power, Scale Economies and Productivity: Estimates from a Panel of Establishment Data," *Journal of Industrial Economics* 47(4), 451-476.

Klette, T. J. and Z. Griliches (2000) "Empirical Patterns of Firm Growth and R&D Investment:

A Quality Ladder Model Interpretation," *Economic Journal* 110, 363-387.

Levin, R., W. Cohen, D. Mowery (1985) "R&D Appropriability, Opportunity, and Market Structure: New Evidence on Some Schumpeterian Hypotheses," *American Economic Review Papers and Proceedings* 75, 20-24.

Levin, R. C., A. Klevorick, R. Nelson and S. Winter (1987) "Appropriating the Returns from Industrial Research and Development," *Brookings Papers on Economic Activity: Microeconomics*, 783-820.

Machin, S. and J. van Reenen (1993) "Profit Margins and the Business Cycle: Evidence from UK Manufacturing Firms," *Journal of Industrial Economics* 42, 29-50.

Martin, S. (1993), "Endogenous Firm Efficiency in a Cournot Principal-Agent Model," *Journal of Economic Theory* 59, 445-450.

Meyer, M. A. and J. Vickers (1997) "Performance Comparisons and Dynamic Incentives," *Journal of Political Economy* 105(3), 547-581.

Nakajima, T., M. Nakamura, and K. Yoshioka (1998), "An Index Number Method for Estimating Scale Economies and Technical Progress Using Time-series or Cross-sectional Data: Sources of Total Factor Productivity Growth for Japanese Manufacturing, 1964-1988," *Japanese Economic Review* 49, 310-334.

Nickel, S. J., S. Wadhwani and M. Wall (1992) "Productivity Growth in U.K. Companies, 1975-1986," *European Economic Review* 36, 1055-1091.

Nickel, S. J. (1996) "Competition and Corporate Performance," *Journal of Political Economy* 104(4), 724-746.

Nickel, S. J., D. Nicolitsas and N. Dryden (1997) "What makes Firms Perform Well?" *European Economic Review* 41, 783-796.

Nishimura, G. K., T. Nakajima, and K. Kiyota (2003) "Does Natural Selection Mechanism Still Work in Severe Recessions? –Examination of the Japanese Economy in the 1990s–," CIRJE Discussion Papers, F-222, University of Tokyo.

Nishimura, K. G., Y. Ohkusa, and K. Ariga (1999) "Estimating the Mark-up over Marginal Cost: a Panel Analysis of Japanese Firms 1971-1994," *International Journal of Industrial Organization* 17, 1077-1111.

Odagiri, H. and H. Iwata (1986), "The Impact of R&D on Productivity Increase in Japanese Manufacturing Companies," *Research Policy* 15, 13-19.

Odagiri, H. and T. Yamashita (1987) "Price Mark-ups, Market Structure, and Business Fluctuation in Japanese Manufacturing Industries," *Journal of Industrial Economics* 35(3), 317-331.

Olley, S. and A. Pakes (1996) "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica* 64(6), 1263-1297.

Pakes, A. and R. Ericson (1998) "Empirical Implications of Alternative Models of Firm Dynamics," *Journal of Economic Theory* 79, 1-45.

Penrose, E. (1959), *The Theory of the Growth of the Firms*, Oxford: Basil Blackwell.

Rotemberg, J. and G. Saloner (1986) "A Supergame-Theoretic Model of Price Wars during Booms," *American Economic Review* 70, 390-407.

Scherer, F. M. (1967) "Market Structure and the Employment of Scientists and Engineers," *American Economic Review* 57(3), 524-531.

Scherer, F. M. and D. Ross (1990) *Industrial Market Structure and Economic Performance* 3rd Edition, Boston MA: Houton Mifllin Company.

Schmalensee, R. (1989) "Inter-industry Studies of Structure and Performance," in R. Schmalensee and R. D. Willig eds., *Handbook of Industrial Organization* vol.2, Amsterdam: North-Holland, 951-1009.

Slater, M. (1980) "The Managerial Limitation to the Growth of Firms," *Economic Journal* 90, 520-528.

Spence, M. A. (1984) “Cost Reduction, Competition, and Industry Performance,” *Econometrica* 52, 101-121.

Sutton, J. (1991) *Sunk Costs and Market Structure: Price Competition, Advertising, and the Evolution on Concentration*, Cambridge MA: MIT Press.

Sutton, J. (1997) “Gibrat’s Legacy,” *Journal of Economic Literature* 35, 40-59.

Sutton, J. (1998) *Technology and Market Structure: Theory and History*, Cambridge MA: MIT Press.

Teece, D., G. Pisano and A. Shuen (1997) “Dynamic Capabilities and Strategic Management,” *Strategic Management Journal* 18, 509-533.

Torii, A. (2001) *Efficiency in Japanese Industries*, Tokyo: NTT Publishing (in Japanese).

Vives, X. (2004) “Innovation and Competitive Pressure,” mimeo.

Wooldrdge, J. M. (2001), *Econometric Analysis of Cross Section and Panel Data*, Cambridge MA: MIT Press.

Table 1 Summary of variables

Variables	Definition	Unit of observations
output	Real sales (1995 yen; deflated by domestic corporate goods price index by industry, Cabinet Office, 2003)	Firm - year
emp	Number of permanent employees	Firm - year
capital	gross fixed asset deflated by capital goods deflator (1995yen using SNA private non-residential investment deflator, Cabinet Office, 2003)	Firm - year
industrial_sales	Industrial sales in manufacturing industry (using the whole sample of the Basic Survey of Japanese Business Structure and Activities, METI, 1995-2001) deflated by the domestic corporate goods price deflator by industry.	Industry - year
import_penetration	Imports divided by home demand in manufacturing industry (the JIP database constructed using the Input-Output Table, the Economic and Social Research Institute, Cabinet Office, 2003). We imputed the 1998 data for the missing 1999 and 2000 data.	Industry - year
rd_intensity	R&D expenditure divided by value added. We use R&D deflators (JIP database, Cabinet Office) and wholesale price index (Cabinet Office) as the respective deflators.	Firm - year
share	Weighted average market share (see text)	Firm - year
pcm	Price-cost margin (see text)	Firm - year
comp	1 - "Industry-averaged price cost margin" (see text)	Industry - year
rd_herf	Herfindahl index of R&D expenditures in manufacturing industry (see text)	Industry - year
diversity	Diversification index defined using Herfindahl concentration index of firm sales in all sectors (see text)	Firm - year
debt_asset	Total debt to total asset ratio	Firm - year
tech_trade	Technology trade turnovers (revenue + expenditure) divided by sales	Firm - year
size	Number of permanent employees	Firm - year

Data sources: *The Basic Survey of Japanese Business Structure and Activities* (METI, 1995-2001) except some deflators and the import penetration index as explained above.

Table 2 R&D performers and non-performers（manufacturing industries, 1994～2000）

		All		R&D performers		Non-performers	
		Full sample	Estimation sample	Full sample	Estimation sample	Full sample	Estimation sample
Number of observations (total)		92941	67477	43116	33451	49825	34026
Number of firms (every year)	1994	13038	8717	6320	4564	6718	4153
	1995	13654	9609	6453	4894	7201	4715
	1996	13527	10238	6229	4991	7298	5247
	1997	13392	10238	6112	5000	7280	5238
	1998	13363	10238	6076	4961	7287	5277
	1999	13162	9569	6091	4702	7071	4867
	2000	12805	8868	5835	4339	6970	4529

Full sample (annual average, standard deviations are in parentheses)

	All	R&D performers	Non-performers	Student's t-value	p-value
Real sales（1995 million yen）	19233.3 (133540.3)	34355.4 (192322.3)	6147.3 (29810.9)	-32.29	0.000
Permanent employees	415.3 (1790.0)	677.3 (2555.9)	188.5 (461.6)	-41.90	0.000
Sales growth rate	0.52% (16.1%) (69867 firms)	0.89% (14.7%) (33512 firms)	0.18% (17.2%) (36355 firms)	-5.89	0.000
Employment adjustment rate（%）	-1.33% (12.6%) (69867 firms)	-1.28% (11.8%) (33163 firms)	-1.38% (13.4%) (36704 firms)	-1.07	0.287
Price-cost margin	0.19 (0.13)	0.21 (0.13)	0.17 (0.13)	-47.49	0.000
Debt-asset ratio	0.73 (0.35)	0.69 (0.25)	0.76 (0.42)	33.18	0.000
Real value added per employee (1995 million yen)	6.85 (4.27)	7.74 (4.58)	6.08 (3.81)	-60.38	0.000
Firm age (since establishment year through 1994-2000)	37.75 (14.91)	40.49 (15.07)	35.38 (14.36)	-52.87	0.000

Estimation sample (annual average, standard deviations are in parentheses)

	All	R&D performers	Non-performers	Student's t-value	p-value
Real sales（1995 million yen）	23151.5 (155255.6)	39834.9 (216517.1)	6750.0 (34233.3)	-27.84	0.000
Permanent employees	480.5 (2061.6)	762.9 (2853.1)	202.9 (520.5)	-35.61	0.000
Sales growth rate	0.43% (15.2%) (56849 firms)	0.76% (28403 firms)	0.10% (16.3%) (28446 firms)	-5.20	0.000
Employment adjustment rate（%）	-1.31% (12.0%) (56849 firms)	-1.32% (11.2%) (28115 firms)	-1.3% (12.7%) (28734 firms)	0.18	0.857
Price-cost margin	0.19 (0.13)	0.21 (0.13)	0.16 (0.13)	-44.36	0.000
Debt-asset ratio	0.71 (0.26)	0.67 (0.24)	0.74 (0.27)	33.85	0.000
Real value added per employee (1995 million yen)	7.07 (4.26)	7.90 (4.59)	6.24 (3.72)	-51.66	0.000
Firm age (since establishment year through 1994-2000)	38.96 (14.59)	41.57 (14.69)	36.39 (14.01)	-46.94	0.000

Table 3 Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
output	67477	23151.46	155255.60	84.31	9104792
annual growth rate (%)	56849	0.43	15.24	-169.23	174.65
emp	67477	480.48	2061.62	50	77185
annual change (%)	56849	-1.31	11.96	-267.22	296.37
capital	67477	7208.69	42868.88	0	1423501
annual change (%)	56813	2.20	28.13	-616.12	830.90
industrial_sales	420	4434326.43	6325494.38	33284	43112537
annual change (%)	420	-0.42	13.56	-125.28	76.44
import_penetration	420	0.0847	0.0837	0.0015	0.6085
annual change (%)	420	4.49	39.57	-380.14	450.15
rd_intensity	67477	0.0390	0.1436	-26.16	5.56
share	64783	0.0032	0.0119	0	0.4179
annual change (%)	53821	0.28	45.86	-752.55	787.78
pcm	67477	0.1856	0.1287	-0.3632	0.9942
annual change (%)	55012	0.91	42.35	-775.61	734.67
comp	420	0.8140	0.0607	0.5473	0.9577
rd_herf	420	0.1549	0.1065	0.0213	0.9942
diversity	67477	1.4218	0.6435	1	11.3792
debt_asset	67477	0.7072	0.2593	0	10.0485
tech_trade	67477	0.0008	0.0062	0	0.3435

Notes:

We employed regressions in first differences in terms of output, emp, capital, industrial_sales, import_penetraion, share, and pcm. The annual growth rate of these variables are also shown in the table. On the other hand, the remaining variables (rd_intensity, comp, rd_herf, diversity, debt_asset, tech_trade, and emp) are entered in levels.

Table 4

Production function: GMM estimates (basic model)

Dependent variable: $\Delta output_{it}$

	(1)	(2)	(3)
* $\Delta output_{it-1}$	-0.046 (0.006, p= 0.000)	-0.035 (0.007, p= 0.000)	-0.043 (0.006, p= 0.000)
* Δemp_{it}	0.327 (0.053, p= 0.000)	0.443 (0.062, p= 0.000)	0.347 (0.056, p= 0.000)
* $\Delta capital_{it}$	0.719	0.592	0.696
$\Delta industrial\_sales_{jt}$	0.057 (0.016, p= 0.000)	0.052 (0.016, p= 0.001)	0.059 (0.016, p= 0.000)
$\Delta import\_penetration_{jt}$	0.008 (0.004, p= 0.060)	0.009 (0.004, p= 0.028)	0.008 (0.004, p= 0.063)
* $\Delta share_{it}$		-0.013 (0.014, p= 0.352)	
* Δpcm_{it}			-0.016 (0.015, p= 0.305)
$comp_{jt}$	2.450 (0.305, p= 0.000)	2.357 (0.292, p= 0.000)	2.156 (0.307, p= 0.000)
rd_herf_{jt}	-0.310 (0.049, p= 0.000)	-0.311 (0.048, p= 0.000)	-0.289 (0.049, p= 0.000)
* $diversity_{it}$	0.050 (0.023, p= 0.028)	0.037 (0.022, p= 0.099)	0.029 (0.022, p= 0.198)
* $debt\_asset_{it}$	-1.063 (0.270, p= 0.000)	-1.193 (0.249, p= 0.000)	-1.046 (0.248, p= 0.000)
* $tech\_trade_{it}$	2.385 (1.513, p= 0.115)	2.540 (1.400, p= 0.070)	2.422 (1.446, p= 0.094)
* $size_{it}$	-1.20e-05 (1.52e-05, p=0.420)	-1.40e-05 (1.41e-05, p=0.322)	-1.65e-05 (1.47e-05, p=0.264)
m_1	-30.99 (p = 0.000)	-29.29 (p = 0.000)	-27.79 (p = 0.000)
m_2	-0.00 (p = 0.996)	-0.89 (p = 0.376)	-0.74 (p = 0.462)
Sargan	$\chi^2(98) = 79.31$ (p = 0.625)	$\chi^2(98) = 117.70$ † (p = 0.085)	$\chi^2(98) = 103.6$ (p = 0.331)
Observation	26121 (10231 firms)	24671 (9683 firms)	25118 (9963 firms)

Notes:

1) The dependent variable is log (real sales). The number of consecutive periods for which data are held is at least five years. Some observations for market share ($share_{it}$) and price-cost margin (pcm_{it}) are missing differently, therefore the number of observations using *share* as an independent variable is not identical with that using price cost margin (pcm_{it}). Constant returns constraint is imposed in all equations. All equations are estimated in first differences and include both year dummies and industry dummies, although $comp_{jt}$, rd_herf_{jt}, $diversity_{it}$, $debt\_asset_{it}$, $tech\_trade_{it}$, and $size_{it}$ are all entered in level as control variables. Firm size is measured by permanent employees.

2) The equations are estimated using the dynamic panel data model based on Arellano and Bond (1991). The GMM estimates reproted are one-step results. Asymptotic standard errors and p-values are reported in parentheses. m_1 and m_2 are Arellano-Bond tests that average autocovariance in residuals of order 1 and 2 are zero, i.e., they are tests for the null on no first-order and second-order serial correlations, asymptotically N(0,1). Sargan statistics are used for testing of over-identifying restrictions for the GMM estimators, asymptotically χ^2. P-values are also reported. All computations are done using STATA.

3) * Variables are treated as endogenous.

4) † indicates that Sargan test from the one-step homoskedastic estimator in column (2) marginally rejects the null that the over-identifying restrictions are valid. This could be due to heteroskedasticity.

Table 5

Production function: GMM estimates (R&D and productivity)

Dependent variable: $\triangle output_{it}$

	(1)	(2)	(3)
* $\triangle output_{it-1}$	-0.044 (0.006, p= 0.000)	-0.034 (0.007, p= 0.000)	-0.041 (0.006, p= 0.000)
* $\triangle emp_{it}$	0.349 (0.053, p= 0.000)	0.459 (0.062, p= 0.000)	0.375 (0.055, p= 0.000)
* $\triangle capital_{it}$	0.695	0.575	0.666
$\triangle industrial\_sales_{jt}$	0.058 (0.016, p= 0.000)	0.052 (0.016, p= 0.001)	0.059 (0.016, p= 0.000)
$\triangle import\_penetration_{jt}$	0.006 (0.004, p= 0.172)	0.007 (0.004, p= 0.090)	0.005 (0.004, p= 0.195)
* $rd\_intensity_{it}$	0.576 (0.169, p= 0.001)	0.482 (0.144, p= 0.001)	0.608 (0.170, p= 0.000)
* $\triangle share_{it}$		-0.010 (0.014, p= 0.447)	
* $\triangle pcm_{it}$			-0.014 (0.015, p= 0.354)
$comp_{jt}$	2.387 (0.302, p= 0.000)	2.295 (0.290, p= 0.000)	2.097 (0.302, p= 0.000)
rd_herf_{jt}	-0.306 (0.049, p= 0.000)	-0.309 (0.048, p= 0.000)	-0.286 (0.048, p= 0.000)
* $diversity_{it}$	0.048 (0.023, p= 0.034)	0.033 (0.022, p= 0.134)	0.027 (0.022, p= 0.216)
* $debt\_asset_{it}$	-1.035 (0.261, p= 0.000)	-1.164 (0.244, p= 0.000)	-1.008 (0.239, p= 0.000)
* $tech\_trade_{it}$	3.141 (1.482, p= 0.034)	3.214 (1.378, p= 0.020)	2.847 (1.411, p= 0.044)
* $size_{it}$	-5.68e-06 (1.51e-05, p=0.708)	-8.57e-06 (1.41e-05, p=0.544)	-9.56e-06 (1.46e-05, p=0.509)
m_1	-32.18 (p = 0.000)	-30.57 (p = 0.000)	-29.34 (p = 0.000)
m_2	0.06 (p = 0.954)	-0.77 (p = 0.440)	-0.83 (p = 0.407)
Sargan	$\chi^2(98) = 82.20$ (p = 0.874)	$\chi^2(112) = 125.67$ (p = 0.178)	$\chi^2(112) = 109.07$ (p = 0.561)
Observation	26121 (10231 firms)	24671 (9683 firms)	25118 (9963 firms)

Notes:

1) See footnotes of Table 4. The GMM estimates reproted are one-step results in all equations.

2) * variables are treated as endogenous.

Table 6

Production function: GMM estimates (R&D performers and non-performers)

Dependent variable: $\Delta output_{it}$

	R&D performers				non-R&D performers	
	(1)	(2)	(3)	(4)	(5)	(6)
* $\Delta output_{it-1}$	-0.024 (0.008, p= 0.003)	-0.022 (0.008, p= 0.004)	-0.022 (0.008, p= 0.003)	-0.019 (0.007, p= 0.009)	-0.033 (0.009, p= 0.000)	-0.052 (0.008, p= 0.000)
* Δemp_{it}	0.320 (0.098, p= 0.001)	0.377 (0.099, p= 0.000)	0.388 (0.090, p= 0.000)	0.459 (0.092, p= 0.000)	0.641 (0.063, p= 0.000)	0.440 (0.055, p= 0.000)
* $\Delta capital_{it}$	0.704	0.645	0.634	0.560	0.392	0.612
$\Delta industrial\_sales_{jt}$	0.056 (0.021, p= 0.007)	0.053 (0.020, p= 0.007)	0.059 (0.020, p= 0.004)	0.057 (0.019, p= 0.003)	0.054 (0.024, p= 0.021)	0.073 (0.024, p= 0.003)
$\Delta import\_penetration_{jt}$	0.011 (0.007, p= 0.107)	0.007 (0.007, p= 0.270)	0.008 (0.007, p= 0.241)	0.004 (0.006, p= 0.495)	0.008 (0.005, p= 0.138)	0.008 (0.005, p= 0.139)
* $rd\_intensity_{it}$			0.242 (0.115, p= 0.036)	0.232 (0.120, p= 0.053)		
* $\Delta share_{it}$	-0.048 (0.020, p= 0.015)		-0.046 (0.019, p= 0.015)		-0.009 (0.018, p= 0.618)	
* Δpcm_{it}		-0.138 (0.028, p= 0.000)		-0.146 (0.026, p= 0.000)		0.013 (0.018, p= 0.445)
$comp_{jt}$	2.264 (0.405, p= 0.000)	1.742 (0.403, p= 0.000)	2.294 (0.387, p= 0.000)	1.771 (0.387, p= 0.000)	2.356 (0.413, p= 0.000)	2.410 (0.448, p= 0.000)
rd_herf_{jt}	-0.396 (0.075, p= 0.000)	-0.345 (0.074, p= 0.000)	-0.392 (0.072, p= 0.000)	-0.336 (0.071, p= 0.000)	-0.231 (0.062, p= 0.000)	-0.227 (0.064, p= 0.000)
* $diversity_{it}$	-0.001 (0.031, p= 0.987)	-0.016 (0.031, p= 0.614)	-0.012 (0.030, p= 0.691)	-0.025 (0.030, p= 0.396)	0.065 (0.030, p= 0.032)	0.048 (0.031, p= 0.114)
* $debt\_asset_{it}$	-0.357 (0.208, p= 0.086)	-0.210 (0.207, p= 0.311)	-0.359 (0.199, p= 0.072)	-0.222 (0.197, p= 0.261)	-1.483 (0.405, p= 0.000)	-1.250 (0.324, p= 0.000)
* $tech\_trade_{it}$	3.294 (2.115, p= 0.119)	2.518 (2.092, p= 0.229)	3.315 (2.042, p= 0.104)	2.558 (2.022, p= 0.206)	2.501 (1.172, p= 0.033)	2.237 (1.253, p= 0.074)
* $size_{it}$	-4.09e-06 (1.36e-05, p=0.764)	0.63e-06 (1.36e-05, p=0.963)	-1.78e-06 (1.31e-05, p=0.892)	3.11e-06 (1.30e-05, p=0.811)	6.02e-04 (3.92e-04, p=0.124)	4.86e-04 (4.32e-04, p=0.261)
m_1	-17.19 (p = 0.000)	-18.39 (p = 0.000)	-19.50 (p = 0.000)	-20.96 (p = 0.000)	-30.56 (p = 0.000)	-24.84 (p = 0.000)
m_2	-0.56 (p = 0.573)	-1.75 (p = 0.080)	-0.61 (p = 0.543)	-2.06 (p = 0.039)	-0.26 (p = 0.794)	0.57 (p = 0.570)
Sargan	$\chi^2(98)$ = 87.24 (p = 0.774)	$\chi^2(98)$ = 77.55 (p = 0.937)	$\chi^2(112)$ = 106.87 (p = 0.619)	$\chi^2(112)$ = 91.08 (p = 0.927)	$\chi^2(98)$ = 74.57 (p = 0.963)	$\chi^2(98)$ = 87.20 (p = 0.774)
Observation	12868 (5453 firms)	12868 (5489 firms)	12868 (5453 firms)	12868 (5489 firms)	11803 (5377 firms)	12250 (5615 firms)

Notes:

1) See footnote of Table 4. The GMM estimates reproted are one-step results in all equations. R&D performers are defined as firms reporting non-zero R&D expenditures and non-performers reporting no R&D expenditures within observation periods.

2) * variables are treated as endogenous.

Table A1 Industry classification in BSBSA and number of firms (manufacturing industries)

#	Industry name	Number of firms													
		1994		1995		1996		1997		1998		1999		2000	
1	Livestock products	195	124	223	139	204	150	220	154	222	156	232	148	216	135
2	Seafood products	194	114	211	139	205	147	197	144	200	142	202	132	202	126
3	Flour & grain mill products	42	26	47	26	42	26	41	26	45	26	37	24	34	23
4	Miscellaneous food products	791	506	847	571	854	630	858	632	885	632	887	599	858	553
5	Beverages & tobacco	173	126	178	135	177	143	160	136	167	141	169	128	155	117
6	Prepared feed & fertilizers	41	24	43	24	39	28	40	31	39	28	40	27	46	28
7	Reeling plants & spinning mills	61	26	47	26	43	27	48	29	36	28	38	23	32	22
8	Woven & knitted fabrics	142	84	134	83	122	85	122	85	105	84	96	77	78	61
9	Dyed &finished textiles	127	86	120	85	116	92	116	93	111	93	112	90	90	72
10	Other textile mill products	123	73	121	80	118	87	117	88	118	88	105	79	102	76
11	Textile outer garments	399	200	381	205	370	225	340	215	322	218	297	190	253	157
12	Apparel	122	55	144	73	131	70	132	81	108	80	91	70	84	62
13	Sawmills & millwork	146	91	167	105	150	107	161	110	153	105	151	98	139	89
14	Wooden containers & wood	22	10	21	12	21	14	19	12	21	12	15	11	19	13
15	Furniture & fixtures	198	104	193	113	188	123	184	127	184	126	177	114	171	101
16	Pulp & paper mills	151	103	152	113	142	105	133	103	121	103	111	90	116	87
17	Paper products	291	207	299	219	297	248	311	251	317	244	326	237	312	214
18	News paper industries	81	56	80	60	82	64	80	63	92	65	86	63	88	60
19	Publishing industries	99	67	107	69	103	72	107	73	109	72	125	68	125	65
20	Printing	505	369	554	418	553	439	570	450	598	449	588	427	569	393
21	Industrial inorganic chemicals	103	86	117	95	108	96	113	100	113	99	107	91	104	85
22	Industrial organic chemicals	190	147	193	157	203	166	186	158	183	159	194	154	185	138
23	Chemical fibers	22	18	21	18	20	18	18	16	20	16	18	13	17	11
24	Oil products & detergents	145	113	145	114	145	115	138	119	139	116	142	110	139	105
25	Drugs & medicines	201	144	203	156	201	164	193	167	192	167	203	166	197	154
26	Toilet preparations & others	241	176	253	194	265	212	259	209	259	213	271	204	255	186
27	Petroleum refining	31	26	27	23	28	24	26	24	27	24	26	22	22	18
28	Petroleum & coal products	26	14	25	17	25	20	25	19	26	21	26	18	28	20
29	Plastic products	624	442	657	477	660	513	664	517	662	517	685	510	665	471
30	Tires & inner tubes	14	9	12	10	11	10	13	11	11	10	10	10	13	10
31	Rubber & plastic footwear	134	86	134	101	135	103	139	105	133	105	127	95	124	88
32	Leather products & fur skins	50	26	45	22	40	26	38	27	42	27	35	21	38	21
33	Glass & glass products	97	69	99	72	95	73	104	74	96	71	102	67	100	62
34	Cement & cement products	256	154	269	169	252	172	236	175	239	178	228	156	232	141
35	Clay, pottery & stone products	261	153	251	163	258	183	253	179	237	176	217	162	195	142
36	Blast furnace & basic steel	165	127	161	124	176	136	170	138	151	133	165	136	187	140
37	Iron & steel	234	161	264	175	236	181	236	179	236	182	206	157	210	148
38	Non-ferrous metals	51	33	52	40	51	41	51	43	51	42	54	38	54	33
39	Non-ferrous rolling & casting	277	191	290	215	275	218	266	217	280	228	265	206	263	194
40	Fabricated structural metal	347	220	370	237	362	258	357	264	350	268	334	244	313	225
41	Miscellaneous metal work	605	433	650	492	639	522	623	512	661	528	655	501	656	487
42	Metal working machinery	243	158	262	180	256	192	270	194	272	202	235	177	228	161
43	Special industry machinery	361	240	396	282	423	305	392	292	418	301	388	273	419	274
44	Office & household machines	149	106	157	112	157	120	159	122	154	123	157	122	160	117
45	General industrial machinery	717	492	760	561	756	599	798	617	751	590	758	561	744	510
46	Electrical industrial machinery	394	287	421	319	414	332	402	322	381	318	383	294	394	283
47	Household electric appliances	204	123	209	131	195	142	168	123	151	113	146	100	117	81
48	Communication equipment	282	179	286	198	295	218	294	216	287	208	295	196	267	170
49	Electric equipment & computers	185	121	189	119	188	124	186	136	185	130	189	123	191	111
50	Electronic parts & devices	605	416	637	477	666	528	692	533	710	538	702	513	693	465
51	Miscellaneous electric equipment	180	125	213	146	208	152	206	153	207	154	211	145	230	161
52	Motor vehicles & parts	898	659	931	717	927	756	913	750	919	755	913	711	863	670
53	Miscellaneous transport equipment	219	158	213	166	211	170	222	175	237	181	219	163	213	152
54	Medical instruments	70	47	81	57	86	61	84	61	87	62	86	56	84	50
55	Optical instruments & lenses	62	48	56	47	65	55	69	57	70	58	72	54	75	54
56	Watches, clocks & related parts	29	20	33	26	35	26	33	27	31	25	29	18	22	14
57	Measuring & analytical instruments	166	108	178	125	184	131	169	133	163	129	168	126	166	113
58	Ordnance & accessories	9	6	6	4	5	4	4	3	4	4	4	4	6	4
59	Miscellaneous manufacturing	288	145	319	176	314	190	267	168	275	175	252	157	247	145
	Total	13038	8717	13654	9609	13527	10238	13392	10238	13363	10238	13162	9569	12805	8868

Note: The numbers of firms are given inr full sample (left column) and in estimation sample (right column) for each year. The BSBSA covers all the firms with no less than 50 employees or greater than 30 million yen capitalization.

Table A2

Production function: GMM estimates (large and small firms)

Dependent variable: $\Delta output_{it}$

	Large firms (emp>300)		Small firms (emp≦300)	
	(1)	(2)	(3)	(4)
* $\Delta output_{it-1}$	-0.023 (0.011, p= 0.033)	-0.017 (0.010, p= 0.091)	-0.036 (0.010, p= 0.000)	-0.052 (0.008, p= 0.000)
* Δemp_{it}	0.312 (0.106, p= 0.003)	0.270 (0.101, p= 0.007)	0.545 (0.083, p= 0.000)	0.440 (0.055, p= 0.000)
* $\Delta capital_{it}$	0.711	0.747	0.491	0.612
$\Delta industrial\_sales_{jt}$	0.067 (0.029, p= 0.021)	0.071 (0.028, p= 0.011)	0.048 (0.017, p= 0.005)	0.073 (0.024, p= 0.003)
$\Delta import\_penetration_{jt}$	0.002 (0.009, p= 0.805)	0.003 (0.008, p= 0.686)	0.011 (0.004, p= 0.007)	0.008 (0.005, p= 0.139)
* $\Delta share_{it}$	-0.024 (0.023, p= 0.306)		-0.035 (0.018, p= 0.050)	
* Δpcm_{it}		-0.049 (0.030, p= 0.105)		0.013 (0.018, p= 0.445)
$comp_{jt}$	2.291 (0.468, p= 0.000)	2.143 (0.488, p= 0.000)	2.304 (0.355, p= 0.000)	2.410 (0.448, p= 0.000)
rd_herf_{jt}	-0.222 (0.089, p= 0.013)	-0.196 (0.088, p= 0.026)	-0.326 (0.054, p= 0.000)	-0.227 (0.064, p= 0.000)
* $diversity_{it}$	0.090 (0.037, p= 0.015)	0.085 (0.037, p= 0.022)	0.052 (0.026, p= 0.047)	0.048 (0.031, p= 0.114)
* $debt\_asset_{it}$	-0.963 (0.251, p= 0.000)	-0.662 (0.266, p= 0.013)	-0.815 (0.362, p= 0.024)	-1.250 (0.324, p= 0.000)
* $tech\_trade_{it}$	1.319 (2.798, p= 0.637)	-0.603 (2.822, p= 0.831)	2.737 (0.808, p= 0.001)	2.237 (1.253, p= 0.074)
* $size_{it}$	-9.47e-06 (1.27e-05, p=0.455)	-6.55e-06 (1.26e-05, p=0.604)	-9.72e-04 (3.06e-04, p=0.001)	4.86e-04 (4.32e-04, p=0.261)
m_1	-17.98 (p = 0.000)	-17.60 (p = 0.000)	-17.26 (p = 0.000)	-24.84 (p = 0.000)
m_2	-2.20 (p = 0.028) †	-1.54 (p = 0.123)	-1.15 (p = 0.251)	0.57 (p = 0.570)
Sargan	$\chi^2(98) = 77.77$ (p = 0.935)	$\chi^2(98) = 60.73$ (p = 0.999)	$\chi^2(98) = 151.75$ †† (p = 0.0004)	$\chi^2(98) = 87.20$ (p = 0.774)
Observation	6947 (2704 firms)	6929 (2723 firms)	17724 (7222 firms)	12250 (5615 firms)

Notes:

1) See footnote of Table 4. GMM estimates reproted are one-step results in all equations. Small and medium firms are defined by the number of permanent employees which is no more than 300.

2) * variables are treated as endogenous.

3) † indicates that serial correlation test from the one-step homoskedastic estimator in column (1) cannot reject the null of no second-order autocorrelation. This may imply that the estimates are inconsistent.

4) †† indicates that Sargan test rejects the null that the over-identifying restrictions are valid. However, this could be due to heteroskedasticity. Therefore we reported robust estimates and serial correlation tests in column (3).