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COMPETITION AND PRODUCTIVITY IN JAPANESE MANUFACTURING INDUSTRIES

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ABSTRACT

This paper examines the determinants of productivity in Japanese manufacturing industries, looking particularly at the impact of product market competition on productivity. Using a newly available panel data on around ten thousand firms in Japanese manufacturing for the years 1994-2000, I show that competition, as measured by lower level of industrial price-cost margin, enhances productivity growth, controlling for a broad range of industrial and firm-specific characteristics. Moreover, I suggest that market power, as measured by either individual firm's price-cost margin or market share, has negative impact on productivity level of R&D performing firms.

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1. Introduction

Does competition improve productivity? There is some theoretical basis that competition enhances productivity, but the empirical basis is not strong enough, especially in Japan[1]. There is nevertheless the growing prevalence of opinions emphasizing the importance of competition in the policy arena such as deregulation, re-regulation, and antitrust. This paper examines the determinants of productivity in Japanese manufacturing industries, looking particularly at the impact of product market competition on productivity.

Using a newly available panel data on around ten thousand firms in Japanese manufacturing for the years 1994-2000, I provide some additional support for the view that competition, as measured by lower level of industrial mark-ups, enhances productivity growth, controlling for a broad range of industrial and firm-specific characteristics. Moreover, I suggest that market power, as measured by either individual price-cost margin or market share, has negative impact on productivity level of R&D performing firms.

This paper regards price-cost margin as the main competition indicator. There are several prior studies which treat price-cost margin as a competition index. Boone (2000) provides a convincing argument that any parameter increase that would result in raising 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. Furthermore, Nishimura et al. (1999) shows that there is a negative correlation between international competitiveness and mark-up. Its sensitivity is uniform within an industry though skewness may be problematic in estimation. Overall there is a sound theoretical and empirical support for using price cost margin or other forms of rent as the measure of product market competition.

Traditional competition measures such as Herfindahl index and market share are misleading in certain business fields, because these measures are crucially dependent on the definition of the relevant market and tend to neglect potential as well as international competition. Therefore, price-cost margin would be, arguably, a more desirable measure to gauge the extent of competition, especially in certain manufacturing industries which are confronted with intense international competition.

At first glance, it seems to be obvious that price-cost margin decreases with

[1] There are several prior studies confirming 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. Regrettably there are quite few solid empirical studies concerning Japanese industries.

competitive pressure. However, price-cost margin is apparently affected by not only competition but also by other various economic conditions, such as demand fluctuation, R&D appropriation, and technological opportunity. Accordingly, there are serious endogeneity issues on the relationship between price-cost margin and productivity.

To alleviate endogeneity biases, I utilize 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). By using this estimation method, I treat several key explanatory variables as endogenous. 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).

I will basically follow the empirical strategy by Nickel (1996). I utilize his econometric framework as a basic model in a slightly different specification. Furthermore, I expand the basic model with a broad range of industrial and firm specific characteristics. As will be discussed in detail in the following sections, I will try to incorporate various market conditions as much as possible into empirical formulation to control simultaneity, such as demand fluctuation, R&D activity, diversification, financial constraint, and technological opportunity. Furthermore, I will examine whether R&D performing and non-performing firms may adopt distinct managerial strategies which would result in different productivity dynamics, reflecting the Schumpeterian dynamics.

This paper uses 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 is one of the "specified" statistics, which means that all relevant respondents have legal obligations to respond to them, as is the case in the National Census. The BSBSA has been conducted annually by METI since the second survey 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 and 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 such as Census of Manufacturers are also available in many countries, but price setting, investment, diversification and R&D activities, to name a few, are rarely determined by the unit of establishment as

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

managerial decisions. In this respect, the BSBSA provides valuable information to accomplish empirical studies on firms' competitive behaviors.

The available dataset consists of an unbalanced panel with a large number of cross-section units of manufacturing (more than 13000 firms which are 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, thereby calls for the estimation method that does not require the time dimension to become large in order to obtain consistent parameter estimates.

The rest of the paper is structured as follows. Section 2 gives a theoretical background concerning the relationship between competition and productivity. Section 3 lays out empirical formulation. Section 4 explains variable construction and measurement issues. Section 5 presents empirical findings. Section 6 discusses some implications and reservations of the estimation results. Section 7 concludes the paper.

2. Theoretical Background

There is a broad range of theoretical as well as empirical literatures on the relationship between competition and productivity. It is almost impossible to negate that a lot of important manufacturing sectors are subject to imperfect competition (Hall, 1988; Bresnahan, 1989). In the following, I will review various types of theoretical research which would clarify the relationship between competition and productivity[3].

First, there have been a lot of studies in line with a *neoclassical model of firms*. If firms have market power, their optimum size may differ from minimum cost position, and if economies of scale and/or scope exist, such differences may be more noticeable. Furthermore, 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 market structure (Sutton 1991, 1998). Investment, advertising and R&D are typical examples of such strategic behaviors that would raise sunk cost, and thereby enhance competitive advantage under certain circumstances.

Second, *contract theory of firms* provides various theoretical predictions. The relationship between competition and efficiency incentive can be described by using models of moral hazard with multiple agents. Holmstrom (1982), Hart (1983), Nalebuff and Stiglitz (1983),

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[3] The literature survey hereafter is greatly indebted to Cohen and Levin (1989), Schmalensee (1989), Scherer and Ross (1990), Cohen (1995), Nickel (1996), Geroski (1995, 1999), Meyer and Vickers (1997), Aghion and Howitt (1998), Bartelsman and Doms (2000), Klette and Griliches (2000), Aghion et al. (2001, 2002), and Nishimura et al. (1999, 2003). Obviously the literature review here is not complete and I neglected many important applications to a variety of other related topics, such as macroeconomic dynamics.

Mookherjee (1984), and Meyer and Mookherjee (1987) present models that demonstrate how comparative performance information yielded by competition may enhance efficiency incentives. On the other hand, Scharfstein (1988) and Martin (1993) provide models in which competition in the product market may raise the sensitivity of profits to manager's decision. They find that increased competition tends to be negatively associated with managerial effort. Furthermore, Meyer and Vickers (1997) show that overall welfare effect of comparative performance information can either reinforce or weaken efficiency incentives in dynamic settings depending on underling information structure.

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).

Joint consideration of the impact of R&D and competition needs additional care about the Schumpeterian dynamics in market structure, since R&D incentive depends not only on post-R&D competition, but also on the differences between post- and pre-R&D competition (Arrow, 1962). A standard industrial organization theory predicts that R&D should decline with competition, as more competition reduces the monopoly rents that reward successful innovators (Dasgupta and Stiglitz, 1980). However, a lot of empirical studies 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). Competition may increase the incremental profit from R&D because it may reduce a firm's pre-R&D rents by more than it reduces its post-R&D rents. Competition thereby encourages R&D investments which may lead to higher productivity growth[4].

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; Ericson and Pakes, 1995; Klepper, 1996). Several case studies using relatively long time-series data provide appealing empirical findings which are consistent with predictions of the theoretical

[4] 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.

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, Nelson 1981, 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. Obviously R&D is not the only method to build up organizational capability. There are a lot of other aspects of a firm's organizational capability, such as managerial skill, product market strategies, experiences (learning by doing or *practiced routines*), and IT investment. Bresnahan et al. (2002) present another line of research in a related vein.

The gist which emerged from these growing literatures is that the relationship between competition and productivity has a complex dynamics, and that these models of industry evolution are mainly driven by differences in productivity within and between firms. Different theoretical predictions may be attributable to various assumptions in terms of the source of productivity change. Obviously competition is one of the important driving forces, although the implication for productivity dynamics varies according to different assumptions on market structure and firms' behavior.

3. Empirical Formulation

In an excellent study, Nickel (1996) presents evidence that competition, as measured by lower levels of rents, is associated with a significantly higher rate of total factor productivity (TFP) in UK manufacturing. I utilize his econometric framework as a basic model in a slightly different specification. Furthermore, I expand the basic model with an additive term of R&D stock using the conventional specification of the literature (Griliches 1979, 1986). Both product market competition and R&D investment possibly enhances productivity in an intertwined fashion. Therefore I treat both of them simultaneously in single empirical specification. That is, 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 of real output, l_{it} is log of employment, c_{it} is log of capital stock, k_{it} is log of 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.

This specification assumes that the production function exhibits 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. Note that the present formulation does not make any explicit assumption of global profit maximization, reflecting various predictions of firms' behavior in the literature. Put differently, the model allows for the possibility that intangible 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 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. That is, the endogenous variables are treated symmetrically with the dependent variable y_{it} [5]. 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} and s_{it} beyond $t-1$ are valid instruments[6].

To alleviate endogeneity issues between competition and productivity, I utilize the Arellano-Bond dynamic panel data model (Arellano and Bond, 1991)[7]. This estimator optimally exploits all the linear moment restrictions that follow from the assumption of no serial correlation in the error terms. That is, I estimate the model using orthogonality assumptions between $\Delta\varepsilon_{it}$ and the set of instruments Z_{is}:

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

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[5] 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*.

[6] As is pointed out by Griliches (1986, p.152), "It is possible to use simultaneous equation techniques to estimate such models, but then the argument shifts to the validity of the exogeneity assumption for the particular instruments. In the context of my specific data set, it is hard to think of any valid instruments except for possibly lagged values of the same variables."

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

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

GMM optimally combines the set of orthgonality conditions[8]. 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, 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, this 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

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

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

I will mainly report one-step GMM estimators' results since the standard errors associated with the two-step estimators tend to be seriously downward biased, as shown 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

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[8] I am greatly indebted to Arellano and Bond (1991), Arellano and Honoré (2001) and Bond (2002) as to the following econometric description.

the two-step estimators (Arellano and Bond, 1991).

Generally, estimators which eliminate unobserved fixed effects by first-differencing, and use lagged values of endogenous variables as instruments, tend to perform poorly in situations where the series are close to being random walks. Furthermore, firms' growth rate might be subject to Gibrat's Law (Sutton, 1997; Goddard et al., 2002). Identification would be weak where the series is near unit root process. Blundell and Bond (1998) shows that dynamic panel data models obtained after first differencing have large finite sample bias where the autoregressive parameters is moderately large and the number of time series observations is moderately small. Thus the A-B test statistics and the autoregressive parameters are crucial to examine whether estimates are spurious statistical artifacts or not.

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 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. Accordingly, 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.

4. Variable Construction and Measurement Issues

Variable definitions are summarized in Table 1. Complete definitions are available in the Appendix. I discuss some variable definitions and their measurement issues here because they have important implications for the interpretation of the estimation results.

4.1. Real Output, Real Input of Labor and Capital

As is suggested by Nickel (1996, p738), freely estimated on the parameters of labor and capital, 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[9].

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[9] 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 the 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. Klette 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.

The present specification attempts to alleviate the simultaneity bias in the determination of employment, capital and output by using lagged variables as instruments. 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.

4.2. Product Market Competition

The main indicator of product market competition is constructed by using price-cost margin. I utilize individual price-cost margin as a proxy for market power[10]. At the same time, 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[11]. These competitive measures may contain several misspecification biases. The most important appears to be: (i) estimates of the competition index would suffer from endogeneity bias; and (ii) mark-ups would fluctuate either pro-cyclically or counter-cyclically.

Concerning the fist issue which is the primary concern of the present study, I treat individual firm's price-cost margin as endogenous, and utilize the firm specific competition variable (Δpcm_{it}) 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 as will be explained below.

The second point has been examined extensively in the industrial organization literature[12]. To control market demand fluctuation, I include growth rates of both industrial sales

[10] Concerning the calculation of price-cost margin, see Appendix for more detail.

[11] The conventionally used measures are concentration ratio and the Herfindahl index. In exploratory works, however, I had no statistically significant impact of these traditional competition measures on productivity in various specifications.

[12] Green and Porter (1984) show 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 by specifying that demand is subject to i.i.d. shocks. Haltiwanger and Harrington (1991) and Kandori (1991) further show theoretically that counter-cyclicality is robust with serially correlated demand shocks for a range of values for the discount factor. These 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 and US.

($industrial\_sales_{jt}$) and import penetration ($import\_penetration_{jt}$) in regressions. These variables as well as year dummies are expected to control the cyclical components of productivity dynamics.

4.3. 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) enumerates the caveats of market share as follows: (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; and (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 market share is used as a *time-series* measure, the problems above may be less serious. Nickel (1996, pp.733-4) explains the reason as follows. There are two types of possible causality: (i) competition to firm growth and productivity growth; and (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), the true relationship would be much stronger.

I use market share ($\Delta share_{it}$) and individual price-cost margin (Δpcm_{it}) alternatively in regressions for the sole purpose of robustness check. 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.

To calculate the weighted average market share and the diversity 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. Thus the weighted market share and diversity index ($diversity_{it}$) likely reflect the extent of vertical (as well as horizontal) diversification[13].

4.4. 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-world business activities into a single empirical formulation, I attempt to trace not only R&D activity but also some other related aspects of industrial and firm characteristics as much as possible.

[13] Concerning the variable constructions, see Appendix for more detail.

First, as is specified in the empirical formulation, the effect of R&D stock is measured by γ that is allowed to vary across firms. Estimation of γ may require data on the growth of R&D stock. But if investment in R&D does not depreciate, then data on R&D intensity ($rd\_intensity_{it}$) can be used to capture the R&D effect[14]. 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). Thus the coefficient of R&D intensity can be regarded as the rate of return to R&D[15].

Second, in order to control a firm specific appropriability condition which may affect individual firm's productivity, I contain a technology trade variable ($tech\_trade_{it}$) in regressions. This is defined by technology transaction turnovers (revenue + expenditure) divided by sales. 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 that would induce more R&D expenditures, thus such a firm would be more productive.

Third, in order to control remaining possible appropriation effect, I define the Herfindahl index of R&D expenditures (rd_herf_{jt}). I include this variable in regressions, since I noticed highly distinct distributions of R&D doers as well as the amount of expenditures across industries. Larger industries 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 evenly spread R&D expenditure among firms whereas some other industries concentrate R&D on a few large firms. These differences are likely associated with the R&D appropriation effect across industries[16].

Finally, I contain debt-asset ratio ($debt\_asset_{it}$) in regressions as a financial constraint variable. The Japanese economy in the latter half of 1990s was suffered from severe debt-deflationary pressure. Although this financial predicament would damage the firms with

[14] If R&D investments depreciate, as they likely do, the estimated coefficient may contain some downward bias. Griliches and Lichenberg (1984) find that point estimates rise with the assumed rate of depreciation but that the specification's fit is best with zero rate of depreciation. On the other hand, Hall and Mairesse (1995) suggest that this sort of method is still problematic because of (i) several measurement issues concerning net R&D expenditures, and (ii) possible gestation lag between R&D and productivity, and suggest that the relevant coefficients should be interpreted as an 'excess' rate of return to R&D.

[15] The potential measurement bias on the above-mentioned procedure would be quite serious. Nevertheless, it is very likely that there is some R&D effect on productivity. The main purpose of incorporating the R&D related variables at the present formulation is controlling the very probable source of productivity gain and elucidating the impact of competition on productivity all the more.

[16] This index is accompanied by the similar caveats to the traditional competition measures. 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. Therefore the coefficients of this variable should be interpreted with the utmost caution.

stricter financial constraint, 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, 2002)[17].

Note that diversity index, technology trade, and debt-asset ratio are all included in levels in regressions. Hence these variables are expected to control the cross-sectional correlates of productivity *growth*. In addition I treat these variables as endogenous variables.

5. Results

5.1. Data Issues

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 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%. The industry classification in manufacturing as well as the corresponding number of firms in both full sample and estimation sample is shown in Table 2.

The summary statistics are presented in Tables 3 and 4. Number of observations and basic statistics of R&D performers and non-performers are shown in Table 3. 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. This indicates that R&D performing and non-performing firms adopt distinct managerial strategies which may result in different productivity dynamics.

5.2. Basic Specification

The estimation results of the basic specification are presented in Table 5. The dependent variable is log of 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 is not necessarily identical with each other. Constant returns to scale in labor and capital are imposed in all regressions. All equations are estimated in first differences and include both year

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

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*[18]. This suggests that there may be some very weak tendency to *mean reversion* which has been pointed out by the literature on Gibrat's Law, although it may result from measurement errors.

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 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 the industrial competitive measures ($comp_{jt}$) are strongly significant and positive. This reveals a significant cross-sectional impact of competition on productivity *growth*, controlling for various firm and industry specific characteristics. On the other hand, 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 would be well

[18] Blundell and Bond (1998) show that if lagged dependent variable has a relatively large coefficient, a first differenced estimator such as the Arellano and Bond model may contain significant (mostly upward) bias. In this case, they recommend using the system GMM estimator which utilizes additional moment restriction of the cross-sectional instruments. Fortunately, this bias is not so serious for the present specification, because the autoregressive coefficients are very small.

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. Finally the coefficients of R&D concentration index (rd_herf_{jt}) are negative and significant. This suggests that spreading R&D expenditures among firms has positive impact on productivity growth. Although whether the R&D concentration index can be regarded as a proxy for R&D competition or knowledge spillovers remains to be questionable, it is an interesting finding from the viewpoint of Schumpeterian dynamics[19].

5.3. R&D and Productivity

Next, in order to see whether or not R&D affects productivity growth, I expand the basic specification by including R&D intensity variable. Table 6 shows that the impact of R&D intensity ($rd\_intensity_{it}$) on productivity growth is positive and highly significant. If R&D intensity can be regarded as the rate of return to R&D, 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 Odagiri and Iwata (1986) and Goto and Suzuki (1989).

As for the remaining explanatory variables, I obtain virtually similar results to the basic model. 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 has positive coefficients and both variables are statistically significant.

5.4. R&D Performers and Non-performers

In Table 7, 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 ($\Delta share_{it}$ or Δpcm_{it}) has negative signs and is statistically significant in R&D performers, whereas they are not statistically significant in 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.

On the other hand, industrial competitive effects are virtually preserved in Table 7. Thus it is likely that industrial competitive effects have a robust cross-sectional impact on productivity growth.

[19] Aghion et al. (2002) found that the equilibrium degree of technological 'neck-and-neckness' among firms should decrease with product market competition.

Columns (3) and (4) in Table 7 show that R&D intensity has still positive and marginally 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 an omitted variable bias due to the negligence of knowledge spillovers which are more likely to exist among R&D performers. Spillovers possibly make the estimated coefficients downward biased[20]. R&D performers may have better absorptive capacity and could obtain external knowledge more effectively than non-R&D-performers, as is suggested by Cohen and Levinthahl (1989).

Other salient features of the estimated results in Table 7 are 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. The financial predicament in the 1990s would thereby damage more the non-R&D performers than the R&D-performers. I will discuss some related issues in the next section.

Second, concerning the technology trade variable, Table 6 produced positive and significant result at the 5% significance level. In Table 7, however, this variable is not statistically significant in R&D performers, whereas it is slightly significant in non-R&D performers (at 5 to 10% significance level). The possible reasons for this difference 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.

6. Discussion

6.1. Cross-sectional Competition Effect across Industries

In the previous section, I provided some evidence that product market competition enhanced productivity. Now then, it is worth measuring the quantitative size of the competition effect. Although our competition measures are defined by the basis of both industrial level ($comp_j$) and firm level ($share_{it}$ or pcm_{it}), I will hereafter try to depict the cross-sectional competition effect on the industrial basis following Nickel (1996).

The impact of competition on productivity *growth* is represented by the cross-sectional correlation between industrial competition index ($comp_j$) and productivity growth. In Table 8,

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[20] The fact that the social returns to R&D exceed its private returns due to knowledge spillovers among firms has a sound empirical basis. For example, see Jaffe (1986), Griliches (1992) and Jones and Williams (1998).

by using the competition coefficient of column (3) in Table 5 (2.097), I present the ceteris paribus industry TFP growth differentials generated by the differences in the average value of the competition index across industries. Industry names are placed in the order of productivity differentials.

These differentials are substantial in magnitude, and are broadly consistent with other evidence on the extent of competition in Japanese manufacturing. Less productive industries with negative differentials are newspaper, drug & medicines, publishing, toilet preparations & others, beverage & tobacco, medical instruments, miscellaneous food products, oil products & detergents, industrial inorganic chemicals, and measuring & analytical instruments. On the other hand, highly productive industries with positive differentials consist of petroleum refining, reeling plants & spinning mills, blast furnace & basic steel, sawmills & millwork, dyed & finished textiles, motor vehicles & parts, non-ferrous metals, miscellaneous transport equipment, woven & knitted fabrics, and watches, clocks & related parts.

This simple calculation suggests that the productivity dispersion across industries is extremely large. The lowest group contains many highly regulated industries such as newspapers, drug & medicines, and medical instruments, whereas the highest group consists of industries confronted with fierce domestic as well as international competition, such as reeling plants & spinning mills, blast furnace & basic steel, and motor vehicles & parts.

7.2. Time-series Competition Effect

As was indicated in the previous section, the time-series competition effect presents positive impact on productivity only in R&D performers. Under the present formulation, the impact of market power (either $\Delta share_{it}$ or Δpcm_{it}) is represented by the negative correlation with productivity growth. Price-cost margins and market shares are fluctuated within our observation periods, and these changes partially explain the time-series variation of the productivity level. Hereafter I will measure the long-run competition effect on aggregate basis.

The estimates of proportional change of market share ($\Delta share_{it}$) on productivity growth are -0.048 in column (1) and -0.046 in column (3) in Table 7. This means that around 21 percent increase in market share leads to a 1 percent fall in TFP of R&D performers in the long run. Surprisingly, this magnitude is quite similar to the result of Nickel (1996, p.741). According to Nickel, 25 percent increase in market share leads to a 1 percent fall in TFP in UK manufacturing. It should be noted, however, that the present paper constructed the weighted market share reflecting vertical as well as horizontal diversification to some extent. Therefore it may not be appropriate to compare these two figures straightforwardly. On the other hand, the impact of proportional change of price-cost margin (Δpcm_{it}) on productivity growth is -0.138 in column (2) and -0.146 in column (4) in Table 7. These results suggest that about 7 percent increase in price-cost margin leads to a 1 percent fall in TFP in the long run.

7.3. Selectivity Bias

Sample selectivity 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. For example, 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. Moreover, sample selection bias due to zero-R&D reporting or less-R&D reporting is hardly avoidable[21].

The comparison between the full sample and the estimation sample in Table 3 suggests that firm size measured by permanent employee or real sales in the estimation sample is slightly larger than that in full sample, whereas sales growth rate in estimation sample is relatively lower than that 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 biases.

It is difficult to eliminate these selectivity biases completely under the current empirical specification[22]. By using price-cost margin as an alternative competition measure, however, I expect that the above mentioned sampling bias would be, at least partially, alleviated. There are no significant differences in price-cost margin between full sample and estimation sample as is shown in Table 3[23]. Thus it is arguable that price-cost margin would reflect some potential as well as international competition.

7.4. Competition and the Japanese Economy in the 1990s

Finally I make somewhat speculative comments from the viewpoint of policy implications for the Japanese economy in the 1990s. There was a lively debate on the causes for the productivity decline in the Japanese economy (Motonishi and Yoshikawa, 1999; Hayashi and Prescott, 2002; Nishimura et al., 2003; Fukao et al., 2003; Fukao and Kwon, 2004; Caballero et al., 2004; Jorgenson and Nomura 2005, among others). Regulatory environment, international competition, technological change, malfunction of financial market, IT investment, and evolution of industrial mix would be possible factors that altered the nature and direction of productivity

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[21] Griliches (1994) emphasized this point.

[22] Market turbulence (i.e., entry, exit, and merger) possibly affects productivity dynamics as depicted by Baily et al. (1992), Hopenhayn (1993), Olley and Pakes (1996), Foster et al. (1997), Haltiwanger (1997), Disney et al. (2003), Nishimura et al. (2003), Fukao et al. (2003), and Fukao and Kwon (2004).

[23] The BSBSA data is truncated by the threshold of 50 employees and 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. This inter-industry artifactual move would cause possible another sampling bias.

dynamics.

For instance, Motonishi and Yoshikawa (1999) indicate that corporate investment is the most important factor to explain the long stagnation of Japan during the 1990s. Motonishi and Yoshikawa suggest that for large firms, financial constraints are not significant whereas the converse is true for small firms. On the other hand, Hayashi and Prescott (2002) show that the problem is *not* a breakdown of the financial system, and suggest that lower productivity growth in Japan be ascribable to inefficient supply-side factors, such as aging population and diminishing labor input[24].

The possible reason for the productivity decline in accordance with the findings from the present study appear to be: (i) *less* competitive pressure in certain business fields is one of the possible clues to elucidate the causes for inefficient supply-side sectors; and (ii) the financial predicament in the 1990s might damage more the non-R&D performers rather than small firms.

The first issue is the main concern of the present study. There are several prior studies confirming that less competitive pressure is one of the possible causes for the productivity decline in the 1990s. In a careful study, Nishimura et al. (2003) show that there is no evidence to demonstrate natural selection mechanism of economic Darwinism works even in severe recession periods in the 1990s. They explore a firm's entry, survival, and exit and its relationship with TFP. Their empirical results show that efficient firms in terms of TFP quit while inefficient ones survived in the banking-crisis period of 1996-1997. Fukao and Kwon (2004) also provide the similar finding to Nishimura et al. (2003). That is, a large portion of aggregate productivity growth was attributable to resource reallocation effect, and such *metabolism* did not work well in the latter half of 1990s. Barriers to new competition would be one of the possible clues to clarify the economic slowdown in the 1990s.

In a related vein, Caballero et al. (2004) explains the Japanese productivity decline by the so-called *zombie* effect. That is, failing companies losing cash-flow were kept alive by Japanese banks' bad loans. This is related to the second point I raised above. 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. But it should be noted that the zombie firms were not necessarily small firms.

The present study showed that debt-asset ratio had a negative impact on productivity growth of non-R&D performing firms. This financial predicament would thereby damage more the non-R&D performers than the R&D-performers[25]. R&D-related activities, perhaps, made

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[24] Hayashi and Prescott (2002, p.227) emphasize that although the so-called "credit crunch" hypothesis may be applicable only for the brief period of late 1997 through early 1998, it cannot account for the decade-long stagnation in Japan.

[25] The similar results are also obtained by Fukao and Kwon (2004). They show that TFP gap between 75 and 25 percentile is widening in many industries where R&D intensity is high and internationalization is

firms somewhat resilient to productivity shocks even in the severe recession period. The significance of debt-asset ratio is relatively robust with respect to separate samples of large and small firms. The estimation results by using separated samples by large and small firms are shown in Table 9. The specification fit is rather weak due to serial correlation or invalid over-identification, but the coefficients of debt-asset ratio are significant in both samples. Firm size may be a red herring because non-R&D performers are not necessarily small firms. This finding may be corroborated by Hayashi and Prescott (2002, pp.222-7) showing that despite the collapse of bank loans, small firms found ways to finance investment during the recession period for 1996-1998.

Jorgenson and Nomura (2005) raised another interesting issue concerning productivity decline in Japan. According to Jorgenson and Nomura, there was a significant productivity gap between IT-*producing* and IT-*using* sectors, especially in the latter half of 1990s; Japanese IT-using sectors were in miserable situation in the 1990s except for telecommunications industry; but IT-producing sectors were exceptionally active, especially in the latter half of the1990s. This suggests that IT-using sectors cannot exploit the full potential of IT innovations yet. Policy environments surrounding the IT-using sectors in Japan may not be favorable enough to innovative *use* of IT. Generally, IT-using sectors are less competitive because many those sectors are tightly regulated. Furthermore, collusive behaviors and bid-riggings are ubiquitous in certain business fields in IT-using sectors[26].

7. Concluding Remarks

Our findings suggest that product market competition enhance productivity growth (cross-section effect). Market power has some negative impact upon productivity level in R&D performing firms (time-series effect). 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.

Hayashi and Prescott (2002, p.228) emphasize that “research effort should be focused on determining what policy reform will allow productivity to again grow rapidly”. I agree to this remark. It is quite natural to think that well-designed economic policy is a prerequisite for productivity growth. Above all things, competition policy would be one of the clues to revive the Japanese economy in the 21st century. I hope that the present study may shed some

more advanced.

[26] Japanese antitrust enforcement has slowly but steadily strengthened since the beginning of 1990 with the assist of hard pressure from the US government. At the same time there was (and has been) a considerable opposition from the Japanese business community against stricter antitrust enforcement. The increased movement of strict antitrust enforcement and pro-competitive industrial policy would be an important background to understand the Japanese economy since the 1990s.

additional light on the current productivity debate in Japan.

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, the cause and effect of productivity change in non-manufacturing sectors is an important issue to be explored in future research. The lack of attention to non-manufacturing sectors is mainly due to data constraint, but it must be undoubtedly important to enhance productivity in non-manufacturing sectors in Japan. Non-manufacturing sectors seem to be less competitive than manufacturing sectors due to regulations and enclosed domestic markets. It is therefore very likely that there is still a large growth opportunities left in the non-manufacturing sectors.

Third, Griliches (1998) shows that there are substantial heterogeneity and instability in the coefficients of the estimated Cobb-Douglas production function. This indicates that a more flexible specification of technology would be desirable, as 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. Further, dynamic panel data models are in a developing research area and in many cases GMM for panel data perform poorly in finite samples. I used a large panel dataset and luckily obtained meaningful estimates, although the GMM on first differences may still produce imprecise estimates. A new semi-parametric approach dealing with both selectivity and simultaneity in an intertwined fashion by Olley and Pakes (1996) would be a promising method in future research.

Fourth, I construct the R&D related variables by using the firm level data. But firm level data may not be adequate enough for the purpose of investigating R&D related activities, since some portion of manufacturing firms in Japan are integrated into interlocking groups[27]. Economies of scope and spillovers in R&D may have also caused another possible estimation biases. Furthermore, R&D outsourcing and joint R&D cooperation are more noticeable in the late 1990s in Japan. Ownership structure and R&D cooperation, especially in high-tech sectors, would be very important issues to be explored in future research. Patent data would be a beneficial source of information on these issues (Jaffe and Trajtenberg 2002).

Finally, I must admit that this research adds quite a modest size of knowledge to the understanding of competition effect in the Japanese economy. Evidence from the present study may not be representative enough because the observation period is just for the years 1994-2000.

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

The Japanese economy was in turmoil during the period and many Japanese manufacturing firms were in the process of fundamental adjustment of over-capitalization and excess employment 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.

Appendix: Variable Construction

Real Output, Real Input of Labor and Capital 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 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. Therefore capital stock is represented by the book value of tangible fixed asset deflated by real price of capital goods.

Product Market Competition 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, and p_K is a investment goods deflator (SNA private non-residential investment deflator, Cabinet Office). I simply define d as

$$\delta / (\delta + \rho + \pi_K^e)$$

following Auerbach (1979).

Market Share and Diversity Index 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 $diversity_i = 1$.

Other Control Variables First, in order to control market demand fluctuation, I include growth rates of both industrial sales and import penetration in regressions. Second, 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. Finally, I include the number of R&D doers measured by the Herfindahl index of R&D expenditures (rd_herf_{jt}). I define the measure 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.

References

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

Aghion, P., Dewatripont, M., Rey, P., 1999. Competition, Financial Discipline and Growth. Rev. Econ. Stud. 66, 825-852.

Aghion, P., Harris, C., Howitt, P., Vickers, J., 2001. Competition, Imitation and Growth with Step-by-Step Innovation. Rev. Econ. Stud. 68(3), 467-492.

Aghion, P., Howitt, P., 1992. A Model of Growth through Creative Destruction. Econometrica 60, 323-357.

Aghion, P., Howitt, P., 1998. Endogenous Growth Theory. MIT Press, Cambridge.

Arellano, M., 2003. Panel Data Econometrics. Oxford Univ. Press, Oxford.

Arellano, M., Bond, S., 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. Rev. Econ. Stud. 58, 277-297.

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

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

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

Baily, M. N., Hulten, C., Campbell, D., 1992. Productivity Dynamics in Manufacturing Plants. Brookings Papers on Economic Activity: Microeconomics 2, 187-249.

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

Bartelsman, E. J., Doms, M. 2000. Understanding Productivity: Lessons from Longitudinal Microdata. J. Econ. Lit. 38, 569-594.

Blundell, R., Bond, S. 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. J. Econometrics 87, 115-143.

Blundell, R., Griffith, R., Van Reenen, J. 1995. Dynamic Count Data Models of Technological Innovation. Econ. J. 105, 333-344.

Blundell, R., Griffith, R., Van Reenen, J. 1999. Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms. Rev. Econ. Stud. 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 J. Econ. 31, 549-569.

Bresnahan, T., 1989. Empirical Studies of Industries with Market Power. In Schmalensee, R., Willig, R. D. (eds.), Handbook of Industrial Organization Vol.2, North-Holland, Amsterdam, pp. 1011-1057.

Bresnahan, T., Brynjolfsson, E., Hitt, L., 2002. Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-level Evidence. Quart. J. Econ. 117, 339-376.

Caballero, R. J., Hoshi, T., Kashyap, A. K., 2004. Zombie Lending and Depressed Restructuring in Japan. Mimeograph. Hitotsubashi University Macro-Money Workshop, 18 June.

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

Caves, R. E., 1992. Industrial Efficiency in Six Nations. MIT Press, Cambridge MA.

Chirinko, R., Fazzari, S., 1994. Economic Fluctuations, Market Power and Returns to Scale: Evidence from Firm-level Data. J. Appl. Econometrics 9, 47-69.

Clark, K. B., Fujimoto, T., 1991. Product Development Performance. Harvard Business School Press, Boston.

Cohen, W., 1995. Empirical Studies of Innovative Activity. In Stoneman, P. (ed.), Handbook of the Economics of Innovation and Technological Change. Blackwell, Oxford, pp. 182-264.

Cohen, W. M., Levinthal, D. A., 1989. Innovation and Learning: The Two Faces of R&D. Econ. J. 99, 569-596.

Cohen, W. M., Levin, R. C., 1989. Empirical Studies of Innovation and Market Structure. In Schumalensee, R., Willig, R. D. (eds.), Handbook of Industrial Organization Vol.2, North-Holland, Amsterdam, pp. 1059-1107.

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

Dasgupta, P., Stiglitz, J., 1980. Industrial Structure and the Nature of Innovative Activity. Econ. J. 90, 266-293.

Disney, R., Haskel, J., Heden, Y., 2003. Entry, Exit and Establishment Survival in UK Manufacturing. J. Ind. Econ. 51, 91-112.

Domowitz, I., Hubbard, G., Petersen, B., 1986. Business Cycles and the Relationship between Concentration and Price-Cost Margins. RAND J. Econ. 17, 1-17.

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

Ericson, R., Pakes, A., 1995. Markov-Perfect Industry Dynamics: A Framework for Empirical Work. Rev. Econ. Stud. 62, 53-82.

Foster, L., Haltiwanger, J., Krizan, C. J., 1997. Aggregate Employment Dynamics: Building from Microeconomic Evidence. Amer. Econ. Rev. 87, 115-137.

Fukao, K., Kwon, H. U., 2004. Why Did Japan's TFP Growth Slowdown in the Lost Decade?-An Empirical Analysis Based on Firm-Level Data of Manufacturing Firms. High-Stat Discussion Paper No.50, Institute of Economic Research, Hitotsubashi University.

Fukao, K., Inui, T., Kawai, H., Miyagawa, T., 2003. Sectoral Productivity and Economic Growth in Japan, 1970-1998: An Empirical Analysis Based on the JIP Database. In Ito, T., Rose, A. K. (eds.), Growth and Productivity in East Asia, National Bureau of Economic Research East Asia Seminar on Economics Vol.13. The Univ. of Chicago Press, Chicago.

Geroski, P. A., 1990. Innovation, Technological Opportunity, and Market Structure. Oxford Econ. Pap. 42, 586-602.

Geroski, P. A., 1995. Market Structure, Corporate Performance and Innovative Activity. Oxford Univ. Press, Oxford.

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

Geroski, P. A., Machin, S., Van Reenen, J., 1993. The Profitability of Innovative Firms. RAND J. Econ. 24, 198-211.

Geroski, P. A., Machin, S. J., Walters, C. F., 1997. Corporate Growth and Profitability. J. Ind. Econ. 45, 171-189.

Ghosal, V., 2000. Product Market Competition and the Industry Price-Cost Markup fluctuations: Role of Energy Price and Monetary Change. Int. J. Ind. Organ. 18, 415-444.

Goddard, J., Wilson, J., Blandon, P., 2002. Panel Tests of Gibrat's Law for Japanese Manufacturing. Int. J. Ind. Organ. 20, 415-433.

Goto, A., Suzuki, K., 1989. R&D Capital, Rate of Return on R&D Investment and Spillover of R&D in Japanese Manufacturing Industry. Rev. Econ. Statist. 71, 555-564.

Green E., Porter, R., 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 J. Econ. 10, 92-116.

Griliches, Z., 1986. Productivity, R&D, and Basic Research at the Firm Level in the 1970s. Amer. Econ. Rev. 76, 141-154.

Griliches, Z., 1992. The Search for R&D Spillovers. Scand. J. Econ. 94, S29-S47.

Griliches, Z., 1994. Productivity, R&D, and the Data Constraint. Amer. Econ. Rev. 84, 1-23.

Griliches, Z., 1998. R&D and Productivity. The Univ. of Chicago Press, Chicago.

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

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

Hall, R., 1988. The Relation between Price and Marginal Cost in U.S. Industry. J. Polit. Economy 96, 921-947.

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

Haltiwanger, J., 1997. Measuring and Analyzing Aggregate Fluctuations: The Importance of Building from Microeconomic Evidence. Fed. Reserve Bank St. Louis Rev. 79, 55-77.

Haltiwanger, J., Harrington, Jr., J. E., 1991. The Impact of Cyclical Demand Shock Movements on Collusive Behavior. RAND J. Econ. 22, 89-106.

Hart, O. D., 1983. The Market Mechanism as an Incentive Scheme. Bell J. Econ. 14, 366-382.

Hayashi, F., Prescott, E. C., 2002. The 1990s in Japan: A Lost Decade. Rev. Econ. Dynam. 5, 206-235.

Holmstrom, B., 1982. Moral Hazard in Teams. Bell J. Econ. 13, 324-340.

Hopenhayn, H., 1993. Entry, Exit, and Firm Dynamics in Long Run Equilibrium. Econometrica 60, 649-670.

Jaffe, A. B., 1986. Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits and Market Value. Amer. Econ. Rev. 76, 984-1001.

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

Jensen, M. C., 1986. Agency Costs of Free Cash Flow, Corporate Finance and Takeovers. Amer. Econ. Rev. 76, 323-329.

Jensen, M. C., 2000. A Theory of the Firm, Governance, Residual Claims, and Organizational Forms. Harvard Univ. Press, Cambridge MA.

Jones, C. I., 1995. R&D-Based Models of Economic Growth. J. Polit. Economy 103, 759-784.

Jones, C. I. Williams, J. C., 1998. Measuring the Social Return to R&D. Quart. J. Econ. 113, 1119-1135.

Jorgenson, D. W., Nomura, K., 2005. Information Technology and the Japanese Growth Recovery. J. Japan. Int. Econ. This issue.

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

Jovanovic, B., MacDonald, G., 1994. The Life Cycle of a Competitive Industry. J. Polit. Economy 102, 322-347.

Kandori, M., 1991. Correlated Demand Shocks and Price Wars During Booms. Rev. Econ. Stud. 58, 171-180.

Klepper, S., 1996. Entry, Exit, Growth and Innovation over the Product Life Cycle. Amer. Econ. Rev. 86, 562-83.

Klepper, S., Simon, K. L., 2000. The Making of an Oligopoly: Firm Survival and Technological Change in the Evolution of the U.S. Tire Industry. J. Polit. Economy 108, 728-760.

Klette, T. J., 1996. R&D, Scope Economies, and Plant Performance. RAND J. Econ. 27, 502-522.

Klette, T. J., 1999. Market Power, Scale Economies and Productivity: Estimates from a Panel of Establishment Data. J. Ind. Econ. 47, 451-476.

Klette, T. J., Griliches, Z., 2000. Empirical Patterns of Firm Growth and R&D Investment: A Quality Ladder Model Interpretation. Econ. J. 110, 363-387.

Levin, R., Cohen, W, Mowery, D., 1985. R&D Appropriability, Opportunity, and Market Structure: New Evidence on Some Schumpeterian Hypotheses. Amer. Econ. Rev. 75, 20-24.

Levin, R. C., Klevorick, A., Nelson, R., Winter, S., 1987. Appropriating the Returns from Industrial Research and Development. Brookings Pap. Econ. Act. Microeconomics, 783-820.

Machin, S. Van Reenen, J., 1993. Profit Margins and the Business Cycle: Evidence from UK Manufacturing Firms. J. Ind. Econ. 42, 29-50.

Martin, S., 1993. Endogenous Firm Efficiency in a Cournot Principal-Agent Model. J. Econ. Theory 59, 445-450.

Meyer, M. A., Mookherjee, D., 1987. Incentives, Compensation, and Social Welfare. Rev. Econ. Stud. 54, 209-226.

Meyer, M. A., Vickers, J., 1997. Performance Comparisons and Dynamic Incentives. J. Polit. Economy 105, 547-581.

Mookherjee, D., 1984. Optimal Incentive Scheme with Many Agents. Rev. Econ. Stud. 51, 433-446.

Motonishi, T., Yoshikawa, H. 1999. Causes of the Long Stagnation of Japan during the 1990s. J. Japan. Int. Econ. 12, 181-200.

Nakajima, T., Nakamura, M., Yoshioka, K., 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 Econ. Rev. 49, 310-334.

Nalebuff, B. J., Stiglitz, J. E., 1983. Prizes and Incentives: Toward a General Theory of Compensation and Competition. Bell J. Econ. 14, 21-43.

Nelson, R. R., 1981. Research on Productivity Growth and Productivity Differences: Dead Ends and New Departures. J. Econ. Lit. 19, 1029-1064.

Nickel, S. J., Wadhwani, S., Wall, M., 1992. Productivity Growth in U.K. Companies, 1975-1986. Europ. Econ. Rev. 36, 1055-1091.

Nickel, S. J., 1996. Competition and Corporate Performance. J. Polit. Economy 104, 724-746.

Nickel, S. J., Nicolitsas, D., Dryden, N., 1997. What makes Firms Perform Well? Europ. Econ. Rev. 41, 783-796.

Nishimura, G. K., Nakajima, T., Kiyota, K., 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., Ohkusa, Y., Ariga, K., 1999. Estimating the Mark-up over Marginal Cost: a Panel Analysis of Japanese Firms 1971-1994. Int. J. Ind. Organ. 17, 1077-1111.

Odagiri, H., Iwata, H., 1986. The Impact of R&D on Productivity Increase in Japanese Manufacturing Companies. Res. Pol. 15, 13-19.

Odagiri, H., Yamashita, T., 1987. Price Mark-ups, Market Structure, and Business Fluctuation in Japanese Manufacturing Industries. J. Ind. Econ. 35, 317-331.

Olley, S., Pakes, A., 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica 64, 1263-1297.

Pakes, A., Ericson, R., 1998. Empirical Implications of Alternative Models of Firm Dynamics. J. Econ. Theory 79, 1-45.

Penrose, E., 1959. The Theory of the Growth of the Firms. Basil Blackwell, Oxford.

Rotemberg, J., Saloner, G., 1986. A Supergame-Theoretic Model of Price Wars during Booms. Amer. Econ. Rev. 70, 390-407.

Scharfstein, D. S., 1988. Product Market Competition and Managerial Slack. RAND J. Econ. 19, 147-155.

Scherer, F. M., 1967. Market Structure and the Employment of Scientists and Engineers. Amer.

Econ. Rev. 57, 524-531.

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

Schmalensee, R., 1989. Inter-industry Studies of Structure and Performance. In Schmalensee, R., Willig, R. D. (eds.), Handbook of Industrial Organization Vol.2, North-Holland, Amsterdam, 951-1009.

Slater, M., 1980. The Managerial Limitation to the Growth of Firms. Econ. J. 90, 520-528.

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

Sutton, J., 1997. Gibrat's Legacy. J. Econ. Lit. 35, 40-59.

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

Teece, D., Pisano, G., Shuen, A., 1997. Dynamic Capabilities and Strategic Management. Strategic Management Journal 18, 509-533.

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

Vives, X., 2004. Innovation and Competitive Pressure. CEPR Discussion Paper 4369.

Wooldridge, J. M., 2001. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge MA.

Table 1 Summary of variables

Variables	Definition
output	Real sales (1995 yen; deflated by domestic corporate goods price index by industry, Cabinet Office, 2003)
emp	Number of permanent employees
capital	Gross fixed asset deflated by capital goods deflator (1995yen using SNA private non-residential investment deflator, Cabinet Office, 2003)
industrial_sales	Industrial sales in manufacturing industry (using the whole sample of the BSBSA, METI, 1995-2001) deflated by the domestic corporate goods price deflator by industry.
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.
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.
share	Weighted average market share (see text)
pcm	Price-cost margin (see text)
comp	1 - "Industry-averaged price cost margin" (see text)
rd_herf	Herfindahl index of R&D expenditures in manufacturing industry (see text)
diversity	Diversification index defined using Herfindahl concentration index of firm sales in all sectors (see text)
debt_asset	Total debt to total asset ratio
tech_trade	Technology trade turnovers (revenue + expenditure) divided by sales
size	Number of permanent employees

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

Table 2 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 in full sample (left column) and in estimation sample (right column) for every year. The BSBSA covers all the firms with no less than 50 employees and greater than 30 million yen capitalization.

Table 3 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 4 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:

Regressions are employed 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 5

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 of real sales. The number of consecutive periods for which data are held is at least five years. Some observations for market share (shareit) and price-cost margin (pcmit) are missing differently, therefore the number of observations using shareit as an independent variable is not identical with that using pcmit. Constant returns constraint is imposed in all equations. All equations are estimated in first differences and include both year dummies and industry dummies, although compjt, rd_herfjt, diversityit, debt_assetit, tech_tradeit, and sizeit 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. m1 and m2 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 $\chi 2$. 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. However, the two-step Sargan test may be better fro inference on model specification. The two-step Sargan statistics is $\chi 2(98)=80.51(p=0.901)$.

Table 6

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

Dependent variable: $\Delta output_{it}$

	(1)	(2)	(3)
* $\Delta output_{it-1}$	-0.044 (0.006, p= 0.000)	-0.034 (0.007, p= 0.000)	-0.041 (0.006, p= 0.000)
* Δemp_{it}	0.349 (0.053, p= 0.000)	0.459 (0.062, p= 0.000)	0.375 (0.055, p= 0.000)
* $\Delta capital_{it}$	0.695	0.575	0.666
$\Delta industrial\_sales_{jt}$	0.058 (0.016, p= 0.000)	0.052 (0.016, p= 0.001)	0.059 (0.016, p= 0.000)
$\Delta import\_penetration_{jt}$	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)
* $\Delta share_{it}$		-0.010 (0.014, p= 0.447)	
* Δpcm_{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 5. The GMM estimates reproted are one-step results in all equations.

2) * Variables are treated as endogenous.

Table 7

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

Dependent variable: $\triangle output_{it}$

	R&D performers				non-R&D performers	
	(1)	(2)	(3)	(4)	(5)	(6)
* $\triangle output_{it-1}$	-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)
* $\triangle emp_{it}$	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)
* $\triangle capital_{it}$	0.704	0.645	0.634	0.560	0.392	0.612
$\triangle industrial\_sales_{jt}$	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)
$\triangle import\_penetration_{jt}$	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)		
* $\triangle share_{it}$	-0.048 (0.020, p= 0.015)		-0.046 (0.019, p= 0.015)		-0.009 (0.018, p= 0.618)	
* $\triangle pcm_{it}$		-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 footnotes of Table 5. 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 8 TFP Growth Rate Differentials Generated by Differences in Competition

News paper industries	-52.8%	Furniture & fixtures	2.7%
Drugs & medicines	-46.8%	Electric equipment & computers	3.0%
Publishing industries	-44.5%	Wooden containers & wood	3.3%
Toilet preparations & others	-25.3%	Plastic products	3.5%
Beverages & tobacco	-23.5%	Flour & grain mill products	3.9%
Medical instruments	-21.6%	Rubber & plastic footwear	4.0%
Miscellaneous food products	-15.4%	Pulp & paper mills	4.2%
Oil products & detergents	-13.1%	Electrical industrial machinery	5.6%
Industrial inorganic chemicals	-12.2%	Textile outer garments	5.8%
Measuring & analytical instruments	-9.2%	Household electric appliances	7.6%
Tires & inner tubes	-8.9%	Communication equipment	8.1%
Printing	-6.3%	Prepared feed & fertilizers	8.4%
Clay, pottery & stone products	-4.6%	Fabricated structural metal	8.6%
Petroleum & coal products	-3.6%	Electronic parts & devices	8.6%
Seafood products	-1.7%	Optical instruments & lenses	8.8%
Industrial organic chemicals	-1.2%	Non-ferrous rolling & casting	9.7%
Cement & cement products	-0.5%	Iron & steel	11.9%
Miscellaneous metal work	0.2%	Ordnance & accessories	12.1%
Paper products	0.4%	Leather products & fur skins	12.1%
Chemical fibers	0.9%	Watches, clocks & related parts	12.2%
Miscellaneous electric equipment	1.1%	Woven & knitted fabrics	12.6%
Office & household machines	1.3%	Miscellaneous transport equipment	12.7%
Apparel	1.4%	Non-ferrous metals	12.9%
Livestock products	1.5%	Motor vehicles & parts	12.9%
Glass & glass products	1.6%	Dyed &finished textiles	13.1%
General industrial machinery	1.8%	Sawmills & millwork	13.5%
Special industry machinery	1.8%	Blast furnace & basic steel	16.6%
Other textile mill products	2.1%	Reeling plants & spinning mills	23.1%
Metal working machinery	2.2%	Petroleum refining	23.3%

Note: These differentials are calculated from the unweighted mean.

Table 9

Production function: GMM estimates (large and small firms)

Dependent variable: $\Delta output_{it}$

	Large firms (emp>300)		Small firms	
	(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 5. GMM estimates reproted are one-step results in all equations. Small 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).