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The Shadow of Death: Pre-exit Performance of Firms in Japan

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The Shadow of Death:

Pre-exit Performance of Firms in Japan[§]

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Abstract

This paper examines the pre-exit productivity performance and asks how productivity affects future survival, using firm-level data in Japan for 1995–2002. We found that firms did not face "sudden death" but there was a "shadow of death." Future exiting firms had lower performance four years before their exit. Besides, within a hair's breadth of death, the unobserved heterogeneity of firm such as management effort played an important role in the firm survival. (73 words)

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1. Introduction

A number of studies have examined the relationship between firm performance and firm survival. Recent empirical studies have found that there was a "shadow of death" in firm performance: firms that will exit in the future have lower performance several years earlier. For instance, Griliches and Regev (1995) focused on total factor productivity (TFP) as a performance measure of Israeli firms and found that those that would exit in the future showed significantly less productivity in the present. This "shadow of death" is also found in France and Germany. Bellone, Musso, Nesta, and Quéré (2005) investigated the differences in profitability, size and TFP between future survivors and future exiting firms in France. By examining the mean differences in the performance indicators between two types of firms by exit year cohort, they confirmed that the future exiting firms had significantly lower performance than future survivors. Almus (2004) focused on employment growth as a firm performance measure and examined the difference in employment growth between survivors and exiting firms in Eastern and Western Germany. Based on the matching method, the study also found that future exiting firms presented lower annual growth rate of employment than survivors five years before exit.

This paper builds upon these studies and empirically examines the effects of pre-exit performances of firms on firm survival, or the "shadow of death," in greater detail. The paper asks how productivity affects the future survival of firms, controlling for their size and unobserved heterogeneity. The data used in this analysis are firm-level panel data in Japan for 1995–2002. Our data consist of firms in manufacturing and wholesale/retail trade industries, and the number of firms exceeds 2,100 annually after sifting the usable data. The goal of this paper is to provide stylized facts on which to base future theoretical and empirical work.

The paper brings together and contributes to three streams of literature. The first stream is comprised of studies of the relationship between firm survival and firm performance, and is found in Mata and Portugal (1994), Audrestch and Mahmood (1995), Disney, Haskel, and Heden (2003), and Görg and Strobl (2003). We extend these studies, controlling for unobserved heterogeneity as well as observed firm characteristics. Recent theoretical and empirical studies have emphasized the importance of (observed) firm/plant heterogeneity (e.g., Bernard, Eaton, Jensen, and Kortum, 2003; Melitz, 2003). Besides, in the estimation of hazard models, estimated coefficients may be biased if unobserved firm heterogeneity exists.[1] However, previous studies based on hazard models did not take into account unobserved firm heterogeneity. The unobserved heterogeneity of firm, such as management efforts, cannot be observed by researchers although it may have significant influence on the firm survival. To control for unobserved firm heterogeneity, this paper employs a hazard model developed by Prentice and Gloeckler (1978) and extended by Meyer (1990).

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[1] See, for instance, Heckman and Singer (1984) for the discussion on the relationship between unobserved heterogeneity and associated biases in the hazard models.

The second stream is the theoretical literature on the relationship between productivity and firm dynamics and is found, for example, in Hopenhayn (1992). In this study, Hopenhayn (1992) assumed that a random productivity shock j followed the Markov process that was independent across firms. The distribution of the productivity for each firm was represented by the following distribution function: $f(j_t \mid j_{t-1})$, $f'(j_t) < 0$. A firm exits from the market if its profits fall below a certain threshold level. Since profits are assumed to depend on productivity level, the exit of firms also depends on their productivity levels. Note that the productivity shock is assumed to be strictly decreasing in the last productivity shock. This Markov process implies that the survival probability of a firm in year t will increase if the productivity of firm in year $t-1$ is high and vice versa for less productive firms. Gradual declines in productivity ultimately cause the exit of firms from the market, which implies the existence of the "shadow of death." This paper investigates the empirical implication of Hopenhayn (1992).

The third stream is literature that examined firm survival in Japan. The Japanese economy has been in long-term recession since the burst of the bubble economy in 1990. Accordingly, the rapid increase in bankruptcy of firms has become a serious problem. The number of firm bankruptcies increased from 1991 to 2000 and exceeded 19,000 in 2001, the second highest number since the survey began in 1952 (Figure 1). Several studies have addressed the issue in Japan. Honjo (2000) and Kimura and Fujii (2003) performed survival analyses for 1986–1994 and 1994–1999, respectively. Our study is different from these studies in that we control for the effect of unobserved heterogeneity and examine the longer-term effects of firm performance on firm survival.

=== Figure 1 ===

Section 2 presents the methodology employed in this paper. Section 3 discusses the data and issue of performance measurement. A presentation of econometric results follows in Section 4. We conclude in Section 5 with a summary of the major findings.

2. Methodology

This paper employs a Prentice–Gloeckler–Meyer hazard model. The model was first proposed by Prentice and Gloeckler (1978) and extended by Meyer (1990), which is summarized as follows. Let T_i be the length of firm i 's survival time (or the length of spell) while C_i represents the censoring time. There are two types of firm. One exits from the market during the observed period and the other remains in the market until the end of the observed period, or is (right) censored. The discrete-time hazard function for firm i (i.e., the probability that the firm i exits in interval t and $t+1$, where t indicates time after entry) is defined by:

$$l_i(t+1) = \Pr[k_i \geq t+1 \mid k_i \geq t], \tag{1}$$

where $k_i = \min(T_i, C_i)$. The associated discrete-time survivor function for firm i is:

$$
\begin{aligned}
S_i(t+1) &= \Pr[k_i \geq t+1] \\
&= \Pr[k_i \neq t \mid k_i \geq t] \times \Pr[k_i \neq t-1 \mid k_i \geq t-1] \times \ldots \times \Pr[k_i \neq 0 \mid k_i \geq 0] \qquad (2) \\
&= \prod_{t=0}^{t} \{1 - l_i(t)\}.
\end{aligned}
$$

Note that equation (2) is rewritten as:[2]

$$
l_i(t+1) = 1 - \exp\left\{ -\int_t^{t+1} \tilde{l}_i(t)\,dt \right\}, \qquad (3)
$$

where $\tilde{l}_i(t)$ is a continuous-time hazard function.

Denote $z_i(t)$ as a covariate that summarizes observed performances for firm i in year t. Suppose that unobserved heterogeneity is described as a random variable a_i that is independent of $z_i(t)$; a_i follows the gamma distribution with a mean of one and variance s^2;[3] and the continuous-time hazard rate for firm i in time t takes the following proportional hazards form:

$$
\tilde{l}_i(t) = a_i\, l_0(t) \exp\{z_i(t)' b\} = l_0(t) \exp\{z_i(t)' b + \ln a_i\} \qquad (4)
$$

where $l_0(t)$ is the (unknown) baseline hazard and b is a vector of parameters to be estimated. Following Meyer (1990), we assume that $z_i(t)$ is constant in the interval between t and $t+1$. The discrete-time hazard function is thus:

$$
l_i(t+1) = 1 - \exp\left[-\exp\{g(t) + z_i(t)' b + \ln a_i\} \right], \qquad (5)
$$

where $g(t) = \ln \int_t^{t+1} l_0(t)\,dt$.[4] The associate discrete-time survivor function is:

[2] For the derivation of equation (3), see Technical Appendix 1.
[3] Abbring and Van den Berg (2005) found that the distribution of heterogeneity converged to a gamma distribution in a large class of hazard models with proportional unobserved heterogeneity
[4] For the derivation of equation (5), see Technical Appendix 1.

$$S_i(t+1 \mid z_i(t)) = \prod_{t=0}^{t}\{1 - l_i(t)\} = \prod_{t=0}^{t}\exp\left[-\exp\left\{g(t) + z_i(t)'b + \ln a_i\right\}\right]. \tag{6}$$

Let d_i be an indicator variable that takes the value of one for a firm that exits from the market (i.e., $T_i \leq C_i$) and zero otherwise. Log-likelihood is obtained by conditioning on the unobserved a_i and then integrating over its distribution (Meyer, 1990).

$$\log L = \begin{cases} \displaystyle\sum_{i=1}^{N}\log\left\{\left[1 + s^2\sum_{t=0}^{k_i-1}\exp\{g(t) + z_i(t)'b\}\right]^{-s^{-2}} \right. \\ \qquad\displaystyle \left. -d_i\left[1 + s^2\sum_{t=0}^{k_i}\exp\{g(t) + z_i(t)'b\}\right]^{-s^{-2}}\right\} \quad \text{if} \quad k_i > 1; \\ \displaystyle\sum_{i=1}^{N}\log\left\{1 - d_i\left[1 + s^2\sum_{t=0}^{k_i}\exp\{g(t) + z_i(t)'b\}\right]^{-s^{-2}}\right\} \quad \text{if} \quad k_i = 1. \end{cases} \tag{7}$$

The log-likelihood of a hazard rate without unobserved heterogeneity ($\tilde{l}_i(t) = l_0(t)\exp\{z_i(t)'b\}$) corresponds to $\lim_{s^2 \to 0}\log L$.

The parameters to be estimated are s^2 and b. The importance of unobserved heterogeneity is confirmed from the log-likelihood ratio test of $s^2 = 0$. The hazard rate directly captures the probability that a firm will exit in the next time given that it survives until time t. Estimated coefficients have the interpretation of the ratio of the hazards for one-unit change in the corresponding covariate. Thus, if performance contributes to the firm survival, the coefficient b must indicate significantly *negative* signs: $b < 0$. Similarly, the "shadow of death" is examined by $z_i(t - t)'b$, where $t = 0,..., t$. If the "shadow of death" exists, $b < 0$

is expected.

The last issue we should discuss is how to specify the baseline hazard function $g(t)$. There are two popular specifications. One is to specify the baseline hazard as the parametric Weibull specification, which includes a covariate defined as the log of the time-sequence variable. The other is the flexible nonparametric specification that includes a time-specific dummy as a covariate. A recent study by Dolton and van der Klaauw (1995) suggested that the flexible nonparametric specification is much more reliable than the parametric specification in the sense that the parametric specification constrains the general shape of baseline hazard function. We thus employ the nonparametric specification in the baseline model. The baseline model is described as follows:

$$g(t-t)+z_i(t-t)'b = \sum_{s=1}^{t-t} g_s D_s + z_i(t-t)'b, \tag{8}$$

where D_t is a dummy variable that takes value of one in t and zero otherwise.

3. Data and Measurement Issues

3.1. Data

We use the confidential firm-level database METI (various years), which is widely used in entry/exit studies in Japan.[5] This survey was first conducted in 1991, then in 1994, and annually thereafter. The main purpose of the survey is to statistically capture the overall picture

[5] For instance, see Kimura and Fujii (2003), Nishimura, Nakajima, and Kiyota (2005), and Fukao and Kwon (2006).

of Japanese corporate firms in light of their activity diversification, globalization, and strategies for research and development and information technology. The strength of the survey is its sample coverage and reliability of information. The survey is comprised of all firms with 50 or more employees and with capital of more than 30 million yen.

The survey covers mining, manufacturing and service industries, although some service industries such as finance, insurance and software services are not included. The limitation of the survey is that some information on financial and institutional features such as *keiretsu* is not available and small firms with less than 50 workers (or with capital of less than 30 million yen) are excluded.

From these surveys, we constructed a panel data set for the years from 1995 to 2002 (hereafter referred to as the METI database). We drop from our sample firms for which the firm's age (questionnaire-level year minus establishment year), total wages, tangible assets, value-added (sales minus purchases), or the number of workers were not positive or responses incomplete. The firms that disappear and reappear in the database are also dropped from our sample. In this paper, "entry" is defined as when firms appear in the database. Similarly, "death" or "exit" is when they disappear from the database. We focus on manufacturing, wholesale and retail industries since the number of firms in other industries is rather small. Firms that entered the market before 1995 are excluded so that the data are consistent with the model (i.e., to avoid the problem of left censoring).[6]

Table 1 presents the exit patterns of firms, by entry year cohort. The number of firms exceeds 2,023 annually.[7] Although the total number of firms increased from 1995 to 2002, a large number of firms exited. Table 1 indicates that conditional survival rate, which is defined as the number of firms in current year divided by those in previous year, is 76.7–91.6 percent, implying that about 10–25 percent of firms in each cohort exit from the market within one year of entry. Table 1 also shows that more than one-third of firms exit within three years and about more than half of the firms exit within six years.[8]

=== Table 1 ===

It is worth emphasizing the importance of broad industry coverage in the firm level study. In analyzing firm with multiple establishments, it is very important to cover both manufacturing and wholesale/retail trade. The METI database assigns a firm to the single three-digit industry that accounts for the largest proportion of the value of its sales. Indeed, firms that have both production plants and related sales branches often change their product mix between manufacturing (products) and wholesale/retail trade (services).[9]

[6] For more detail about the left censoring problem, see Wooldridge (2002, p.700).
[7] Note thus that our data on exiting firms includes firms that shrunk or diversify out manufacturing or wholesale/retail trade sectors. The number of firms and exits are summarized in Table A1, by sector.
[8] This result is not specific to Japan. For instance, about 70 percent of new firms exit within 10 years in France (Bellone, Musso, Nesta, and Quéré, 2005).
[9] For the importance of diversifying firms in entry/exit, see Dunne, Roberts, and Samuelson (1988) and Dunne, Klimek, and Roberts (2005).

Table 2 presents a transition matrix of industries from 1995 to 2002. Table 2 indicates that 0.9-3.0 percent of firms changed their product mix between manufacturing and wholesale/retail trade during two consecutive years. Accordingly, a firm-level study that utilized manufacturing firms would only regard the changes in product mix between manufacturing and wholesale/retail trade as entry and exit. Such a study would thus overestimate the effects of entry and exit. Since our data cover both manufacturing and wholesale/retail trade, this study captures firm entry and exit behavior more accurately.[10]

=== Table 2 ===

One concern is that the determinants of exit through merger and acquisition (M&A) can be different from those of exit through bankruptcy.[11] The problem is that the METI database cannot identify the difference between these two types of M&A. If a number of firms with good productivity performance experienced exit through M&A, the survival analysis might indicate that the firms with high productivity exited from the market.[12] In order to exclude the effects of M&A on our study, we use the information on M&A from RECOF (2003).[13] After checking

[10] This result also implies that the sectoral analysis may not be appropriate for the firm level analysis because there is a possibility that firms diversify out from the industry as well as exit from the market. Without detailed information on the exit, it is difficult to identify such difference.

[11] For the importance of economic differences between forms of exit, see Schary (1991).

[12] McGuckin and Nguyen (1995) found that the plants exited through ownership change had higher than average productivity in the United States.

[13] RECOF (2003) defined exit date as the date reported in a newspaper. Since the METI database collects the information by each Japanese fiscal year (from April to March in Japan), this may possibly cause the difference of exit year between the METI database and RECOF (2003). For instance, a firm exit in February 2002 is regarded as an exit in 2002 by RECOF (2003) but an exit in 2001 by the METI database. In order to avoid this problem, the firm is also regarded as having

whether each death in the METI database is reported as an exit through M&A, we confirmed that no firms exited through M&A.

3.2. Measurement Issues

3.2.1. Productivity

To make comparisons across firms and time-series, we employ the multilateral index method in computing TFP developed by Caves, Christensen, and Diewert (1982) and extended by Good, Nadiri, Roller, and Sickles (1983). This multilateral index uses a separate hypothetical firm as a reference point for each cross section of observations by industry and chain-links the reference points together over time in the same way as the conventional Theil–Törnqvist index of productivity growth. The index relies on a single reference point that is constructed as a hypothetical firm that has the arithmetic mean values of log output, log input, and input cost shares over firms in each year. Denote TFP for firm $i\,(=1,\ldots,N)$ in year $t\,(=0,\ldots,T)$ in a given sector as q_{it}. Each firm's output and inputs are measured relative to this reference point in each year and then the reference points are chain-linked over time. The TFP index for firm i in year t is defined as:

$$\begin{aligned}\ln q_{it} \approx &\left(\ln y_{it} - \overline{\ln y}_t\right) + \sum_{t=1}^{t}\left(\overline{\ln y}_t - \overline{\ln y}_{t-1}\right) \\ &- \sum_{j=1}^{J}\frac{1}{2}\left(s_{ijt} + \bar{s}_{jt}\right)\left(\ln x_{ijt} - \overline{\ln x}_{jt}\right) - \sum_{t=1}^{t}\sum_{j=1}^{J}\frac{1}{2}\left(\bar{s}_{jt} + \bar{s}_{jt-1}\right)\left(\overline{\ln x}_{jt} - \overline{\ln x}_{jt-1}\right)\end{aligned} \tag{9}$$

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exited by M&A if the difference of exit year between the METI database and RECOF (2003) is just one year.

where $\ln y_{it}$, $\ln x_{ijt}$, and s_{ijt} are the log output, log input of factor j, and the cost share of factor j for firm i, respectively. $\overline{\ln y}_t$, $\overline{\ln x}_{jt}$, and $\bar{s}_{jt}$ are the same variables for the hypothetical reference firm in year t and are equal to the arithmetic mean of the corresponding variable for all firms in a certain industry in the year.

The first term of the first line in the above equation is the deviation of the firm's output from the output of the reference point in the industry in year t, and the second term is the cumulative change in the output reference point between year t and the initial year, $t = 0$. The two terms in the second line perform the same operation for each factor input j and are weighted by the average of the cost shares for firm i and the reference point in year t. Hence, the index measures the TFP of each firm in each year relative to that of the hypothetical firm in the initial year. Output is defined as gross output while inputs are capital, labor, and intermediate inputs. As for other additional data and their manipulation, see Technical Appendix 2.

3.2.2. Control Variable

We use firm size as a control variable. Several empirical studies found that large firms are more likely to survive than small firms.[14] For instance, Dunne, Roberts, and Samuelson

[14] Note that there are some situations that large firms have incentives to exit faster than small firms. Without economies of scale, small firms might be expected to exit first. With scale economies, however, there emerge several situations in which large firms are more likely to exit from the market. This is because the smaller firm will operate at a variable cost disadvantage with respect to the larger firm with economies of scale. For instance, in the duopoly environment with declining demand and a

(1989) examined U.S. manufacturing plants from 1967 to 1977 and found that failure rates declined with size and age. Similar findings have been obtained for Ireland (Görg and Strobl, 2003), Japan (Kimura and Fujii, 2003), Portugal (Mata and Portugal, 1994), and the United Kingdom (Disney, Haskel, and Heden, 2003). In all these studies, firm size was measured by the number of workers. Following these studies, this paper measures firm size as the number of workers.

Another possible performance indicator is profitability. Note, however, that profitability can be a good performance indicator only for listed firms.[15] The reason is as follows. First of all, the availability of financial data in the METI database is quite limited. Second, and more importantly, corporate tax is determined based on profits and is charged only when firms earn profits in Japan. Furthermore, firms must publish their financial report only when they are listed in the Stock Exchange. Firms that are not listed in the Stock Exchange do not have to publish their financial reports.

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single plant, Ghemawat and Nalebuff (1985) theoretically proved the existence of a unique subgame-perfect Cournot–Nash equilibrium where the larger firm exits first. Whinston (1988) further extended Ghemawat and Nalebuff (1985) and showed that the exit pattern became more complex when firms had multiple-plant operations. Thus, he concluded that it was difficult to generalize Ghemawat and Nalebuff's (1985) prediction. Lieberman (1990) empirically examined these two predictions and found that both predictions received some empirical support. Small firms were more likely to exit. Large multi-plant firms had higher rates of exit than single-plant firms once the effects of firm size hold constant.

[15] According to the National Tax Agency, the proportion of the firms in deficit was 72.5 percent in 1999, 72.4 percent in 2000, 72.3 percent in 2001, and 73.8 percent in 2002, respectively. For more detail, see National Tax Agency website <http://www.nta.go.jp/category/toukei/menu/houjin/h15/data/04.xls>.

Listed firms are likely to show their profitability well since their profits directly affect their stock prices. On the other hand, nonlisted firms have a strong incentive to understate their profits since they do not have to publish financial reports and do not have to pay corporate tax when they do not earn profits. For this institutional reason, productivity can be a better performance indicator than profitability.

Note that our definition of t is not necessarily the same as time following establishment, or firm age, because of the threshold of the survey. Several studies have found that young firms are more likely to exit from the market (i.e., Dunne, Roberts, and Samuelson, 1988). Some of these found that firms were especially likely to exit from the market within a few years of entry. For instance, in Japan, about half of new firms exit from the market within five years (Nishimura, Nakajima, and Kiyota, 2005). Similarly, in France, about 70 percent of new firms exit within 10 years (Bellone, Musso, Nesta, and Quéré, 2005). If both young and old firms have the same probability to appear in the survey, the estimated coefficients may be biased without controlling for firm age. We thus include firm age to the baseline model.

In sum, the baseline model is written as follows.

$$g(t-t)+z_i(t-t)'b = \sum_{s=1}^{t-t} g_s D_s + b_1 \ln q_{it-t} + b_2 \ln L_{it-t} + b_3 AGE_{it-t}, \tag{10}$$

where $\ln q_{it-t}$ is the natural log of TFP; $\ln L_{it-t}$ is the natural log of employment scale that is scaled by the industry average in the initial year; AGE_{it-t} is firm age.

4. Results

4.1. Baseline Model

Tables 3 and 4 present the estimation results of the baseline model without and with unobserved heterogeneity, respectively.[16] In the estimation results, the productivity and employment differences among industries are removed when we pool firms of different industries since the hypothetical reference firm varies across industries and employment of firm is normalized by the average employment scale of its industry.

=== Tables 3 and 4 ===

There are three messages in this table. First, unobserved firm heterogeneity has a significant effect on firm survival analysis in a few years before firm exit. In Table 4, the p-value of the log-likelihood ratio test of $s^2 = 0$ indicate significant heterogeneity in $t = 1$ and $t = 2$. This implies that the unobserved heterogeneity such as management effort plays an important role in the firm survival especially within a hair's breadth of death. Besides, the estimated coefficients will be smaller for the estimation results with unobserved heterogeneity than those without. This result suggests that the estimation results without controlling for unobserved heterogeneity underestimate the effects of productivity and firm size on firm survival.

[16] Estimation is performed in Stata 8.2, using the `pgmhaz8` command (Stata module to estimate discrete time (grouped data) proportional hazards models by Stephen P. Jenkins, September 2004).

Second, we can confirm the "shadow of death" effect. The significantly negative coefficients of $\ln q_{it-t}$ are observed from $t = 1$ to $t = 4$. Although the coefficients become small as the lag length increases, the coefficients of productivity are significantly negative four years before exit. The results mean that future exiting firms present significantly lower productivity four years before exit.

Third, firm size is also an important factor for firm survival. Most of the coefficients of firm size indicate negative signs. The results imply that large firms are more likely to survive, which is consistent with the findings for US firms by Dunne, Roberts, and Samuelson (1989). Firm size as well as productivity is a good indicator for the future survival of firms.

We also checked the sensitivity to the truncation level since the threshold level of the survey might have affected the results. Using firms with 51 or more workers, we reestimated the baseline model.[17] We found that our major findings did not change even when we changed the threshold level. These results suggest that our main conclusion is not sensitive to the inclusion of firm age and the changes in the threshold level.

4.2. Discussion

4.2.1. Alternative Specification of Baseline Hazard

One concern is that the results might be sensitive to the specification of baseline hazard.

[17] Results are presented in Table A5.

To examine this, we estimated an alternative model with the parametric Weibull specification in the baseline hazard. The alternative model is described as follows:

$$g(t-t)+z_i(t-t)'b = g\ \ln(t-t)+b_0+b_1\ln q_{it-t}+b_2\ln L_{it-t}\,. \qquad (11)$$

Table 5 indicates the estimation results of the model with the parametric Weibull specification of the baseline hazard. Although the scale of coefficients changes slightly, all the coefficients maintain the same significance level. Note also that Akaike's Information Criteria (AIC) in Table 5 indicate almost the same values as in Table 4. This result implies that the major conclusions do not change even when we change the specification of the baseline hazard.

=== Table 5 ===

4.2.2. Productivity Growth and Firm Survival

Another important question might be the effects of growth on firm survival. If the future exiting firms have different growth paths from future survivors, there is an important implication for modeling the firm dynamics. We thus include the growth of TFP as independent variables to test the effects of growth on firm survival. The regression equation is as follows:

$$g(t-t)+z_i(t-t)'b = \text{Eq.(10)}+b_3\Delta\ln q_{it-t}\,, \qquad (12)$$

where $\Delta\ln q_{it-t}$ is the growth of TFP.

Table 6 presents the results that examine the effects of level and growth at the same time. The results are almost the same as those of Table 4 even after we control for the growth of productivity. The unobserved heterogeneity has a significant effect when $t = 1$. Both TFP and firm size are good indicators in predicting the future firm exits several years before the firm exit. Moreover, TFP growth is also a useful variable for predicting future firm exits. The coefficients of the TFP growth also indicate significantly negative signs two years before the exit of firms. The result suggests that firms with higher productivity growth have different survival probability (and thus different firm dynamics) from firms with lower productivity growth.

=== Table 6 ===

4.2.3. Predicted Survivor Function

One useful way to describe the effects of productivity gaps on firm survival is to estimate a survivor function. From equation (7), the discrete-time survivor function $S_i(t)$ for firm i in year t thus is:

$$\begin{aligned} S_t(l_i(t)) &= \prod_{t=0}^{t}\{1-l_i(t)\} = \exp\left[\sum_{t=0}^{t}\ln\{1-l_i(t)\}\right] \\ &= \exp\left[\sum_{t=0}^{t}-\exp\{g(t)+z_i(t)'b+\ln a_i\}\right]. \end{aligned} \tag{13}$$

For predictions, we used parameters that are obtained from the first column in Table 4 while baseline covariates were set to the hypothetical reference firm in the industry in the initial period of 1995 (i.e., $\ln TFP = \ln(1.00)$, $\ln L = \ln(1.00)$, and $AGE = 24.8$). We considered the case in which $\ln a_i = 0$. To examine the effects of productivity gaps, we also estimated a survivor function where productivity is 10 percent higher than the baseline model.

Figure 2 presents the estimated survivor function. The figure indicates that, after seven years, the probability of survival is five percentage points higher for productive firms ($\ln TFP = \ln(1.10)$) than for average firms ($\ln TFP = \ln(1.00)$). The results suggest that a firm with 10 percent higher productivity than an industry average firm has a four percent higher probability of survival than the average firm.

=== Figure 2 ===

5. Concluding Remarks

This paper empirically examines the pre-exit performances of firms in greater detail. The paper focuses on productivity as firm performance. To examine the "shadow of death," this paper uses firm-level panel data in Japan for 1995–2002. One of the most important contributions in this paper is that, to our knowledge, this is the first attempt to incorporate unobserved firm heterogeneity in firm survival analysis.

The major findings are summarized as follows. First, firms do not face "sudden death" but there is a "shadow of death." Future exiting firms have lower performance four years before their exit. Second, within a hair's breadth of death, the unobserved heterogeneity such as management effort plays an important role in the firm survival. Besides, the estimation results without controlling for unobserved heterogeneity underestimate the effects of productivity and firm size on firm survival. Finally, both productivity and firm size are good indicators for predicting the future survival of firms. The future exiting firms are significantly less productive and significantly smaller than future survivors. Besides, growth of productivity can also be an indicator of future exit.

It is also important to note the limitations of our paper. One of the most important limitations is that the data do not include firms with less than 50 workers. Although the METI database is used in various studies of firm exit, some exits are not necessarily the same as the "death" or the "bankruptcy" of the firms. In order to examine the "death" of a firm more correctly, it has to be emphasized that the quality and the coverage of the firm-level data must be improved and expanded, which is an unspectacular but important subject for the government.

Technical Appendix 1. Derivation of Equations (3) and (5)

The connection between continuous- and discrete-time duration models is derived by Lunde, Timmermann, and Blake (1999), which is summarized as follows. From equation (1), we have:

$$l_i(t+1) = \Pr[k_i \geq t+1 \mid k_i \geq t] = \frac{F_i(t+1) - F_i(t)}{S_i(t)} = \frac{S_i(t) - S_i(t+1)}{S_i(t)} = 1 - \frac{S_i(t+1)}{S_i(t)}, \qquad \text{(A1)}$$

where $F_i(t)(=1-S_i(t))$ is the cumulative distribution function. Define continuous-time cumulative function as: $H_i(t) = \int_0^t \tilde{l}_i(t)dt$, where $\tilde{l}_i(t)$ is a continuous-time hazard function. Note that $S_i(t) = \exp\{-H_i(t)\}$ since:

$$H_i(t) = \int_0^t \tilde{l}_i(t)dt = \int_0^t \frac{f_i(t)}{S_i(t)}dt = -\int_0^t \frac{1}{S_i(t)} \left\{ \frac{dS_i(t)}{dt} \right\} dt = -\ln\{S_i(t)\}.$$

From equation (A1), we thus have equation (3):

$$l_i(t+1) = 1 - \frac{S_i(t+1)}{S_i(t)} = 1 - \frac{\exp\left\{-\int_0^{t+1} \tilde{l}_i(s)ds\right\}}{\exp\left\{-\int_0^{t} \tilde{l}_i(s)ds\right\}} = 1 - \exp\left\{-\int_t^{t+1} \tilde{l}_i(s)ds\right\} \tag{3}$$

From equations (3) and (4),

$$l_i(t+1) = 1 - \exp\left[-\int_t^{t+1} l_0(t)\exp\{z_i(t)'b + \ln a_i\}dt\right].$$

Since $z_i(t)$ is constant in interval t and $t+1$,

$$\begin{aligned} l_i(t+1) &= 1 - \exp\left[-\exp\{z_i(t)'b + \ln a_i\}\int_t^{t+1} l_0(t)dt\right] \\ &= 1 - \exp\left[-\exp\{z_i(t)'b + \ln a_i\}\exp\left\{\ln \int_t^{t+1} l_0(t)dt\right\}\right] \\ &= 1 - \exp\left[-\exp\{z_i(t)'b + \ln a_i\}\exp\{g(t)\}\right], \end{aligned} \tag{A2}$$

where $g(t) = \ln \int_t^{t+1} l_0(t)dt$. We thus have:

$$l_i(t+1) = 1 - \exp\left[-\exp\{g(t) + z_i(t)'b + \ln a_i\}\right]. \tag{5}$$

Technical Appendix 2. Construction of Multilateral TFP index

Output

There are two ways to define output: gross output and net output, or value-added. It is clear that a production function based on gross output is a less restrictive formulation of inputs. Moreover, studies based on micro-level data favor gross rather than value-added output because the double counting of intermediate *outputs* does not become a severe problem at the micro level where there are few intraindustry transactions.[18] This study thus used gross output.

Gross output is defined as: (sales – operating cost + personnel cost + depreciation cost) / output price index. Output price index was from the System of National Accounts (SNA) output price deflator obtained from the Economic and Social Research Institute (ESRI) website.[19]

Inputs

Inputs consisted of labor, capital, and intermediate input. Labor was defined as man-hours. Working hour data were from the Ministry of Health, Labour and Welfare (2005).[20] Capital stock was estimated from tangible assets, following Nishimura, Nakajima, and Kiyota (2005). Intermediate input was defined as: (operating cost – personnel cost – depreciation cost) / input price index.[21] The input price index was the SNA input price deflator obtained from the ESRI website.[22]

Costs

Labor cost was defined as total wage payments. Capital cost is defined as real capital stock K_{it} times user cost p_{Kit}. Following Kiyota and Okazaki (2005), we defined the user

[18] At the macro level, where the outputs of an industry can be used as inputs by another industry in assembling final goods, value-added measure is preferred because value added nets out the transactions of intermediate *outputs*. For more detail on this issue, see McGuckin and Nguyen (1993).
[19] Gross Domestic Product and Factor Income Classified by Economic Activities (Deflators on Outputs) <http://www.esri.cao.go.jp/en/sna/h17-nenpou/n90fcs2d_en.xls>
[20] Ministry of Health, Labour and Welfare (2005) Table 127 Average monthly working days and actual working hours by industry and size.
[21] Operating cost = cost of sales + selling and general administrative expenses.
[22] Gross Domestic Product and Factor Income Classified by Economic Activities (Deflators on Inputs) <http://www.esri.cao.go.jp/en/sna/h17-nenpou/n90fcs2d_en.xls>

cost as:

$$p_{Kit} = p_{It}\left(\frac{1-t_t f_i}{1-t_t}\right)\left(r_t + d_{it} - \frac{\dot{p}_{It}}{p_{It}}\right),$$

where p_{It} is the investment goods deflator obtained from Toyo Keizai (2005); t_t is the corporate tax rate on business income from the Ministry of Finance website;[23] r_t is the interest rate that is defined as a 10-year bond yield (annual average) obtained from Toyo Keizai (2005); d_{it} is depreciation rate and from the KEO Data Base;[24] f_i is derived so that the following equations are satisfied:

$$f_i = \sum_{t=1}^{T} \frac{(1-d_{it})^{t-1} d_{it}}{(1+r_i)^{t-1}} \quad \text{and} \quad (1-d_{it})^T \approx 0.05.$$

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

References

Abbring, Jaap H. and Gerard J. Van den Berg, 2005, "The Unobserved Heterogeneity Distribution in Duration Analysis," Department of Economics, Free University Amsterdam, manuscript.

Almus, Matthias, 2004, "The Shadow of Death: An Empirical Analysis of the Pre-Exit

[23] <http://www.mof.go.jp/jouhou/syuzei/siryou/houzin/hou03.htm>

[24] The depreciation rate used in this paper is the same as that used in Nishimura, Nakajima, and Kiyota (2005).

Performance of New German Firms," *Small Business Economics*, 23(3): 189-201.

Audrestch, David B. and Talat Mahmood, 1995, "New-firm Survival: New Results using a Hazard Function," *Review of Economics and Statistics*, 77(1): 97-103.

Bellone, Flora, Patrick Musso, Lionel Nesta, and Michel Quéré, 2005, "Recent Trends in Firms Productivity, Entry and Exit Patterns in French Manufacturing Industries," WP-GREDEG-2005-6.

Bernard, Andrew B., Jonathan Eaton, J. Bradford Jensen, and Samuel Kortum, 2003, "Plants and Productivity in International Trade," *American Economic Review*, 93(4): 1268-1290.

Caves, Douglas W., Laurits R. Christensen, and W. Erwin Diewert, 1982, "Output, Input, and Productivity Using Superlative Index Numbers," *Economic Journal*, 92(365): 73-86.

Disney, Richard, Jonathan Haskel, and Ylva Heden, 2003, "Entry, Exit and Establishment Survival in UK Manufacturing," *Journal of Industrial Economics*, 51(1): 91-112.

Dolton, Peter and Wilbert van der Klaauw, 1995, "Leaving Teaching in the UK: A Duration Analysis," *Economic Journal*, 105(429): 431-444.

Dunne, Timothy, Mark J. Roberts, and Larry Samuelson, 1988, "Patterns of Firm Entry and Exit in U.S. Manufacturing Industries," *RAND Journal of Economics*, 19(4): 495-515.

Dunne, Timothy, Mark J. Roberts, and Larry Samuelson, 1989, "The Growth and Failure of U.S. Manufacturing Plants," *Quarterly Journal of Economics*, 19(4): 495-515.

Dunne, Timothy, Shawn D. Klimek, and Mark J. Roberts, 2005, "Exit from Manufacturing Markets: The Role of Entrant Experience," *International Journal of Industrial Organization*, 23(5-6): 399-421.

Fukao, Kyoji and Hyeog Ug Kwon, 2006, "Why Did Japan's TFP Growth Slow Down in the Lost Decade? An Empirical Analysis Based on Firm-level Data of Manufacturing Firms," *Japanese Economic Review*, 57(2): 195-228.

Ghemawat, Pankaj and Barry Nalebuff, 1985, "Exit," *RAND Journal of Economics*, 16(2): 184-194.

Good, David H., M. Ishaq Nadiri, Lars-Hendrik Roller, and Robin C. Sickles, 1983, "Efficiency and Productivity Growth Comparisons of European and U.S. Air Carriers: A First Look at the Data," *Journal of Productivity Analysis*, 4(1-2): 115-125.

Görg, Holger and Eric Strobl, 2003, "Multinational Companies, Technology Spillovers and Plant Survival," *Scandinavian Journal of Economics*, 105(4): 581-595.

Griliches, Zvi and Haim Regev, 1995, "Firm Productivity in Israeli Industry," *Journal of Econometrics*, 65(1): 175-203.

Heckman, James and Burton Singer, 1984, "A Method for Minimizing the Distributional Assumptions in Econometric Models for Duration Data," *Econometrica*, 52(2): 271-320.

Honjo, Yuji, 2000, "Business Failure of New Firms: An Empirical Analysis Using A

Multiplicative Hazards Model," *International Journal of Industrial Organization*, 18(4): 557-574.

Hopenhayn, Hugo A., 1992, "Entry, Exit, and Firm Dynamics in Long Run Equilibrium," *Econometrica*, 60(5): 1127-1150.

Kimura, Fukunari and Takamune Fujii, 2003, "Globalizing Activities and Rate of Survival: Panel Data Analysis on Japanese Firms," *Journal of the Japanese and International Economies*, 17(4): 538-560.

Kiyota, Kozo and Tetsuji Okazaki, 2005, "Foreign Technology Acquisition Policy and Firm Performance in Japan, 1957-1970: Micro-Aspect of Industrial Policy," *International Journal of Industrial Organization*, 23(7-8): 563-586.

Lieberman, Marvin B., 1990, "Exit from Declining Industries: "Shakeout" or "Stakeout"?" *RAND Journal of Economics*, 21(4): 538-554.

Lunde, Asger, Allan Timmermann, and David Blake, 1999, "The Hazards of Mutual Fund Underperformance: A Cox Regression Analysis," *Journal of Empirical Finance*, 6(1): 121-152.

Mata, José and Pedro Portugal, 1994, "Life Duration of New Firms," *Journal of Industrial Economics*, 42(3): 227-245.

McGuckin, Robert H. and Sang V. Nguyen, 1993, "Post-reform Industrial Productivity

Performance of China: New Evidence from the 1985 Industrial Census Data," *Economic Inquiry*, 31(3): 323-341.

McGuckin, Robert H. and Sang V. Nguyen, 1995, "On Productivity and Plant Ownership Change: New Evidence from the Longitudinal Research Database," *RAND Journal of Economics*, 26(2): 257-276.

Melitz, Marc J., 2003, "The Impact of Trade on Aggregate Industry Productivity and Intra-Industry Reallocations," *Econometrica*, 71(6): 1695-1725.

Meyer, Bruce D., 1990, "Unemployment Insurance and Unemployment Spells," *Econometrica*, 58(4): 757-782.

Ministry of Economy, Trade and Industry (METI), various years, *Kigyou Katsudou Kihon Chousa Houkokusho* [*the Results of the Basic Survey of Japanese Business Structure and Activities*], Tokyo: Shadanhoujin Tsuusan Toukei Kyoukai. [In Japanese]

Ministry of Health, Labour and Welfare, 2005, *Roudou Toukei Nenpou 2005* [*Yearbook of Labour Statistics 2005*], Tokyo: Statistics and Information Department, Minister's Secretariat, Ministry of Health, Labour and Welfare. [In Japanese]

Nishimura, Kiyohiko G., Takanobu Nakajima, and Kozo Kiyota, 2005, "Does Natural Selection Mechanism Still Work in Severe Recessions? Examination of the Japanese Economy in the 1990s," *Journal of Economic Behavior and Organization*, 58(1): 53-78.

Prentice, Ross and L. Gloeckler, 1978, "Regression Analysis of Grouped Survival Data with Application to Breast Cancer Data," *Biometrics*, 34(1): 57-67.

RECOF Corporation, 2003, *Nihon Kigyo no M&A Databook 1988-2002* [*M&A Databook of Japanese Companies 1988 to 2002*]. [In Japanese]

Schary, Martha A., 1991, "The Probability of Exit," *RAND Journal of Economics*, 22(3): 339-353.

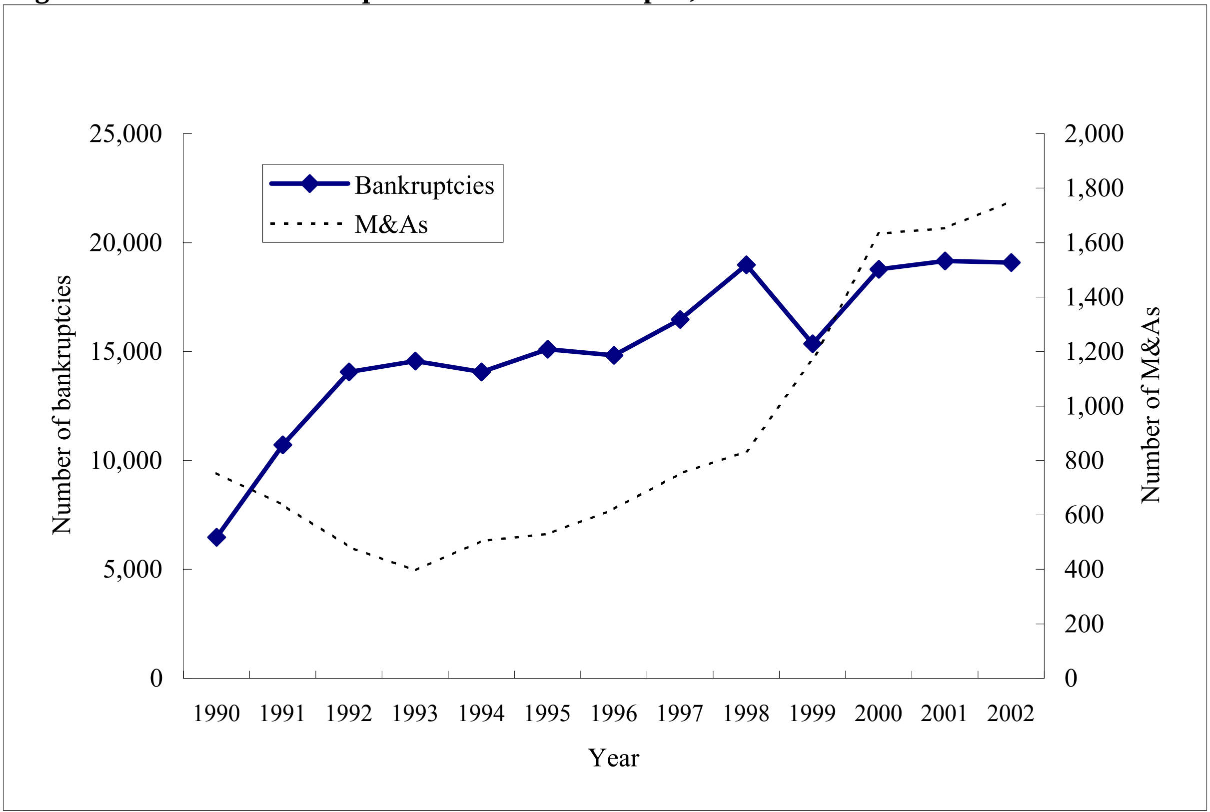
Tokyo Shoko Research (TSR), various years, *Zenkoku Kigyo Tosan Hakusho* [*Bankruptcy White Paper*], Tokyo: Tokyo Shoko Reserch. [In Japanese]

Toyo Keizai Inc., 2005, *Keizai Toukei Nenkan* [*Yearbook of Economic Statistics*], Tokyo: Toyo Keizai. [In Japanese]

Whinston, Michael D., 1988, "Exit with Multiplant Firms," *RAND Journal of Economics*, 19(4): 568-588.

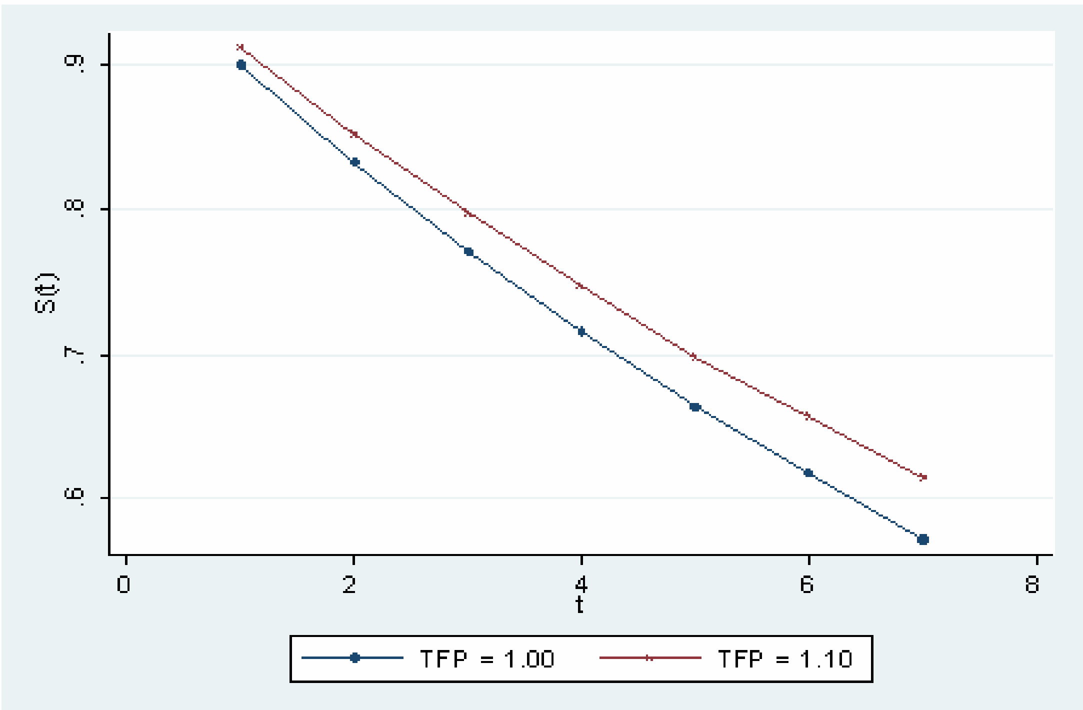
Wooldridge, Jeffrey M., 2002, *Econometric Analysis of Cross Section and Panel Data*, Cambridge, MA: MIT Press.

Figure 1. Number of Bankruptcies and M&As in Japan, 1990-2002



Sources: 1) TSR (various years).
2) RECOF(2003).

Figure 2. Predicted Survivor Functions: Difference of Productivity



Predicted survival rate at t .	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$	$t = 7$
TFP = 1.00	0.90	0.83	0.77	0.72	0.66	0.62	0.57
TFP = 1.10	0.91	0.85	0.80	0.75	0.70	0.66	0.61

Table 1. Exit of "New" Firms, by Entry Year Cohort

	Entry year								
	1995	1996	1997	1998	1999	2000	2001	2002	Total
1995	2,023								2,023
1996	1,718	956							2,674
1997	1,550	790	971						3,311
1998	1,406	684	797	876					3,763
1999	1,288	614	684	731	759				4,076
2000	1,173	552	592	645	587	893			4,442
2001	1,072	489	513	553	501	700	973		4,801
2002	972	439	446	475	423	584	746	792	4,877
Conditional survival rate (previous year = 100)									
	1995	1996	1997	1998	1999	2000	2001	2002	Total
1995									
1996	84.9								
1997	90.2	82.6							
1998	90.7	86.6	82.1						
1999	91.6	89.8	85.8	83.4					
2000	91.1	89.9	86.5	88.2	77.3				
2001	91.4	88.6	86.7	85.7	85.3	78.4			
2002	90.7	89.8	86.9	85.9	84.4	83.4	76.7		
Unconditional survival rate (entry year = 100)									
	1995	1996	1997	1998	1999	2000	2001	2002	Total
1995	100.0								
1996	84.9	100.0							
1997	76.6	82.6	100.0						
1998	69.5	71.5	82.1	100.0					
1999	63.7	64.2	70.4	83.4	100.0				
2000	58.0	57.7	61.0	73.6	77.3	100.0			
2001	53.0	51.2	52.8	63.1	66.0	78.4	100.0		
2002	48.0	45.9	45.9	54.2	55.7	65.4	76.7	100.0	

Source: The METI database.

Table 2. Transition Matrix between Manufacturing and Wholesale/retail Trade

		year *t-1* (number of firms)		year *t-1* (%)	
	year *t*	Manufacturing	Wholesale /retail trade	Manufacturing	Wholesale /retail trade
1995-96	Manufacturing	913	22	97.0	2.6
	Wholesale/retail trade	28	819	3.0	97.4
	Total	941	841	100.0	100.0
1996-97	Manufacturing	1,219	27	97.3	2.5
	Wholesale/retail trade	34	1,060	2.7	97.5
	Total	1,253	1,087	100.0	100.0
1997-98	Manufacturing	1,504	27	98.2	2.0
	Wholesale/retail trade	27	1,329	1.8	98.0
	Total	1,531	1,356	100.0	100.0
1998-99	Manufacturing	1,751	21	97.9	1.4
	Wholesale/retail trade	37	1,508	2.1	98.6
	Total	1,788	1,529	100.0	100.0
1999-00	Manufacturing	1,821	49	97.9	2.9
	Wholesale/retail trade	40	1,639	2.1	97.1
	Total	1,861	1,688	100.0	100.0
2000-01	Manufacturing	2,017	40	99.1	2.2
	Wholesale/retail trade	18	1,753	0.9	97.8
	Total	2,035	1,793	100.0	100.0
2001-02	Manufacturing	2,171	23	98.5	1.2
	Wholesale/retail trade	33	1,858	1.5	98.8
	Total	2,204	1,881	100.0	100.0
1995-02	Manufacturing	11,396	209	98.1	2.1
	Wholesale/retail trade	217	9,966	1.9	97.9
	Total	11,613	10,175	100.0	100.0

Source: The METI database.

Table 3. "Shadow of Death" Effects without Unobserved Heterogeneity

		τ=1	*τ=2*	*τ=3*	*τ=4*	*τ=5*	*τ=6*
ln $TFP_{t-\tau}$		-1.135***	-1.037***	-0.643***	-0.669**	-0.722**	-0.581
		[0.104]	[0.145]	[0.225]	[0.279]	[0.364]	[0.584]
ln $L_{t-\tau}$		-0.377***	-0.354***	-0.303***	-0.271***	-0.264***	-0.216**
		[0.025]	[0.032]	[0.039]	[0.048]	[0.062]	[0.086]
$AGE_{t-\tau}$		-0.002**	-0.005***	-0.005***	-0.006**	-0.003	-0.004
		[0.001]	[0.001]	[0.002]	[0.002]	[0.003]	[0.004]
Hazard rate							
	TFP	0.321	0.355	0.526	0.512	0.486	0.559
	L	0.686	0.702	0.739	0.762	0.768	0.806
	AGE	0.998	0.995	0.995	0.994	0.997	0.996
N		25,090	17,639	12,316	8,252	5,087	2,734
No. of obsevations		-9,606.8	-6,106.3	-4,126.4	-2,675.3	-1,612.7	-834.0
AIC		0.767	0.693	0.671	0.650	0.636	0.614

Notes: 1) ***, **, and * indicate level of significance at 1%, 5%, and 10%, respectively. Figures in brackets indicate standard errors.
2) AIC: Akaike's Information Criteria.

Source: The METI database.

Table 4. "Shadow of Death" Effects with Unobserved Heterogeneity

		τ=1	*τ=2*	*τ=3*	*τ=4*	*τ=5*	*τ=6*
ln $TFP_{t-\tau}$		-1.442***	-1.472***	-0.695**	-0.730**	-0.857	-0.704
		[0.179]	[0.266]	[0.274]	[0.349]	[0.522]	[0.821]
ln $L_{t-\tau}$		-0.412***	-0.427***	-0.337***	-0.301***	-0.317***	-0.282
		[0.033]	[0.051]	[0.067]	[0.079]	[0.117]	[0.197]
$AGE_{t-\tau}$		-0.002**	-0.007***	-0.006***	-0.007**	-0.003	-0.005
		[0.001]	[0.002]	[0.002]	[0.003]	[0.003]	[0.006]
LR Test of $\sigma^2 = 0$		0.010***	0.007***	0.249	0.304	0.280	0.334
Hazard rate							
	TFP	0.236	0.229	0.499	0.482	0.424	0.495
	L	0.662	0.652	0.714	0.740	0.728	0.754
	AGE	0.998	0.993	0.994	0.993	0.997	0.995
No. of obsevations		25,090	17,639	12,316	8,252	5,087	2,734
Log-likelihood		-9,604.1	-6,103.3	-4,126.2	-2,675.2	-1,612.5	-833.9
AIC		0.766	0.693	0.672	0.650	0.637	0.614

Notes: 1) σ^2 is obtained from the estimated coefficient of ln σ^2: exp(ln σ^2).
2) For other notes and source, see Table 3.

Table 5. "Shadow of Death" Effects: Alternative Duration Dependence

	τ=1	*τ=2*	*τ=3*	*τ=4*	*τ=5*	*τ=6*
ln $TFP_{t-\tau}$	-1.342***	-1.445***	-0.685**	-0.739**	-0.846*	-0.704
	[0.181]	[0.261]	[0.269]	[0.354]	[0.509]	[0.821]
ln $L_{t-\tau}$	-0.395***	-0.420***	-0.333***	-0.305***	-0.309***	-0.282
	[0.030]	[0.049]	[0.064]	[0.079]	[0.115]	[0.197]
$AGE_{t-\tau}$	-0.002*	-0.006***	-0.006***	-0.007**	-0.003	-0.005
	[0.001]	[0.002]	[0.002]	[0.003]	[0.003]	[0.006]
LR Test of $\sigma^2 = 0$	0.073*	0.008***	0.264	0.283	0.311	0.334
Hazard rate						
TFP	0.261	0.236	0.504	0.478	0.429	0.495
L	0.674	0.657	0.717	0.737	0.734	0.754
AGE	0.998	0.994	0.994	0.993	0.997	0.995
No. of obsevations	25,090	17,639	12,316	8,252	5,087	2,734
Log-likelihood	-9,611.3	-6,103.8	-4,126.7	-2,675.5	-1,612.9	-833.9
AIC	0.767	0.693	0.671	0.650	0.636	0.614

For notes and source, see Table 3.

Table 6. "Shadow of Death" Effects: Level and Growth

	τ=1	*τ=2*	*τ=3*	*τ=4*	*τ=5*
ln $TFP_{t-\tau}$	-1.816***	-1.129***	-0.951**	-0.860*	-0.863
	[0.309]	[0.385]	[0.436]	[0.521]	[1.184]
ln $L_{t-\tau}$	-0.546***	-0.369***	-0.324***	-0.328***	-0.428*
	[0.056]	[0.058]	[0.074]	[0.106]	[0.240]
$AGE_{t-\tau}$	-0.008***	-0.007***	-0.007**	-0.003	-0.006
	[0.002]	[0.002]	[0.003]	[0.003]	[0.006]
TFP growth $_{t-\tau,\, t-\tau-1}$	0.907***	-0.822*	-0.056	0.609	0.753
	[0.330]	[0.435]	[0.542]	[0.649]	[1.228]
LR Test of $\sigma^2 = 0$	0.000***	0.206	0.295	0.351	0.182
Hazard rate					
TFP	0.163	0.323	0.386	0.423	0.422
L	0.579	0.691	0.723	0.720	0.652
AGE	0.992	0.993	0.993	0.997	0.994
TFP growth	2.477	0.440	0.946	1.839	2.123
No. of obsevations	17,639	12,316	8,252	5,087	2,734
Log-likelihood	-6,069.5	-4,109.4	-2,671.0	-1,610.1	-831.9
AIC	0.689	0.669	0.650	0.636	0.614

For notes and source, see Table 3.

Table A1. Number of Firms and Exits, by Industry

	Number of firms								Number of exits						
	1995	1996	1997	1998	1999	2000	2001	2002	1995-1996	1996-1997	1997-1998	1998-1999	1999-2000	2000-2001	2001-2002
Food products	146	186	241	269	304	315	347	350	17	22	26	15	28	29	38
Textile products	20	22	27	29	29	25	27	27	6	3	7	5	7	2	5
Wearing-apparel and other ready-made textile products	44	51	61	52	53	56	54	53	11	10	18	10	11	9	7
Timber and wooden products	16	20	31	32	34	36	37	32	5	1	7	4	2	5	8
Furniture and fixtures	18	22	29	31	29	34	30	27	3	3	6	3	4	6	10
Pulp and paper	33	43	47	62	71	83	71	71	6	6	3	2	7	14	12
Publishing and printing	69	83	109	150	154	170	188	194	7	7	6	21	21	21	21
Leather tanning and leather products	5	5	3	7	3	6	5	5	0	2	0	4	1	2	1
Rubber products	12	17	21	19	19	22	26	28	0	0	1	2	2	1	3
Chemical products	48	69	74	94	109	117	134	142	4	9	4	5	14	7	15
Petroleum and coal products	62	86	112	114	123	135	143	153	7	8	15	12	12	23	16
Ceramic, stone and clay products	47	68	73	89	84	90	101	88	7	11	8	13	11	12	19
Iron and steel	24	27	41	48	44	51	63	67	4	2	5	8	6	5	2
Non-ferrous metals	18	29	26	32	37	44	52	44	0	2	2	3	4	5	9
Fabricated metal products	75	108	125	152	161	174	182	184	7	12	19	15	23	27	26
General machinery	104	139	197	219	249	268	295	301	17	14	23	24	34	37	35
Electrical machinery	162	215	276	312	337	395	430	458	27	20	27	24	40	57	56
Transportation machinery	96	123	143	159	169	171	194	220	17	8	16	19	22	13	23
Precision machinery	33	44	49	57	63	73	78	100	4	3	3	4	6	9	5
Other manufacturing	34	47	49	57	52	64	66	66	9	8	7	3	8	10	8
Wholesale trade	605	796	997	1,094	1,208	1,268	1,314	1,310	94	109	149	138	163	213	223
Retail trade	352	474	580	685	744	845	964	957	53	74	72	112	101	107	174
Total	2,023	2,674	3,311	3,763	4,076	4,442	4,801	4,877	305	334	424	446	527	614	716

Source: The METI database.

Table A2. Summary Statistics

	Level				Growth	
		Mean				Mean
	N	ln TFP	ln L	AGE	N	TFP
1995	2,023	-0.050	4.707	27.0		
1996	2,674	-0.039	4.734	26.5	1,718	0.011
1997	3,311	-0.039	4.761	27.1	2,340	0.002
1998	3,763	-0.057	4.764	27.3	2,887	-0.018
1999	4,076	-0.040	4.787	27.6	3,317	0.015
2000	4,442	-0.018	4.815	27.4	3,549	0.018
2001	4,801	-0.032	4.833	27.5	3,828	-0.014
		Standard error				Standard error
		ln TFP	ln L	AGE		TFP
1995		0.108	0.753	15.737		
1996		0.114	0.752	15.854		0.080
1997		0.107	0.762	16.005		0.081
1998		0.116	0.758	16.120		0.071
1999		0.114	0.763	16.350		0.070
2000		0.113	0.775	16.622		0.074
2001		0.117	0.788	16.795		0.080

Source: The METI database.

Table A3. Correlation Matrix

N=25,090	ln TFP	ln L	AGE	D_1	D_2	D_3	D_4	D_5	D_6	D_6
ln TFP	1.000									
ln L	-0.019	1.000								
AGE	-0.058	0.012	1.000							
D_1	-0.051	-0.060	-0.100	1.000						
D_2	0.001	-0.020	-0.045	-0.337	1.000					
D_3	0.017	0.004	0.003	-0.286	-0.228	1.000				
D_4	-0.006	0.024	0.032	-0.247	-0.197	-0.167	1.000			
D_5	0.015	0.035	0.061	-0.209	-0.167	-0.141	-0.122	1.000		
D_6	0.045	0.038	0.071	-0.173	-0.138	-0.117	-0.101	-0.086	1.000	
D_7	0.016	0.032	0.084	-0.137	-0.110	-0.093	-0.080	-0.068	-0.056	1.000

N = 17,639	ln TFP	ln L	AGE	TFP Growth
ln TFP	1.000			
ln L	-0.024	1.000		
AGE	-0.070	0.015	1.000	
TFP Growth	0.335	-0.024	-0.017	1.000

Source: The METI database.

Table A4. "Shadow of Death" Effects: Alternative Threshold Level

	τ=1	*τ=2*	*τ=3*	*τ=4*	*τ=5*	*τ=6*
ln $TFP_{t-\tau}$	-1.537***	-1.499***	-0.713**	-0.719*	-0.711	-0.867
	[0.189]	[0.277]	[0.290]	[0.375]	[0.461]	[0.869]
ln $L_{t-\tau}$	-0.386***	-0.383***	-0.276***	-0.251***	-0.219**	-0.222
	[0.037]	[0.054]	[0.067]	[0.083]	[0.109]	[0.175]
$AGE_{t-\tau}$	-0.003**	-0.008***	-0.006***	-0.007**	-0.003	-0.007
	[0.001]	[0.002]	[0.002]	[0.003]	[0.003]	[0.006]
LR Test of $\sigma^2 = 0$	0.000***	0.003***	0.281	0.301	0.466	0.368
Hazard rate						
TFP	0.215	0.223	0.490	0.487	0.491	0.420
L	0.680	0.682	0.759	0.778	0.803	0.801
AGE	0.997	0.992	0.994	0.993	0.997	0.993
No. of obsevations	24,541	17,295	12,076	8,095	4,994	2,688
Log-likelihood	-9,177.8	-5,827.0	-3,927.0	-2,550.4	-1,535.9	-804.5
AIC	0.749	0.675	0.652	0.632	0.618	0.603

For notes and source, see Table 3.