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Survival of new software houses :A first report

by

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Abstract

This paper investigates the survival of software houses as the post-entry behavior of new firms. Using logit models and a proportional hazards model, we estimate the determinants of exits among software houses founded in Japan during 1986–1995. We provide estimates for three categories of exit, namely *failure*, *non-failure*, and *merger*. It is found that larger software houses are more likely to survive. Whereas vertical integration, president's education level, and local agglomeration affect a risk of failure, the probability of exit without failure and merger increases with president's age.

Keywords: New firm; Software house; Survival

JEL Classification: G33; L11; L86

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I. INTRODUCTION

The computer industry has been growing rapidly for the last few decades. In the early years, the rapid development of hardware products had been attracting our attention in the computer industry. Now the development of software products is also required for the further growth of the computer industry. The commercial fortunes of new hardware products, it is argued, depend on the availability of complementary software.

Whereas huge electrical firms, such as Fujitsu, NEC, Toshiba, and Hitachi, have been manufacturing main hardware products in Japan, small firms account for a large part of domestic software houses. The future growth of the computer software industry makes entrepreneurs expect new business chances. In fact, many small software houses have been founded in Japan, in particular, before the collapse of the so-called bubble economy. Since a large amount of initial investments is not comparatively required in the software industry, entrepreneurs may be able to found new software houses with ease. However, new idea and knowledge are always required for business success in the software industry, and they have to catch up with the kaleidoscopic changes in new technologies. As a result, it is difficult for the new software houses that lack sufficient capability of surviving changeable environment, and they will be forced to exit.

It is often argued that role of new firms is required for future economic development, since entry of new firms stimulates growth and competition in industries. The software industry is expected as a growing industry, and new firms will play an important role of the further growth. In addition, the growth of the software industry will contribute the demand growth in other industries. In spite of the future growth and economic importance of software products, a few studies have examined software industries, and virtually no analysis of the behavior of new software houses is available.[1] On the other hand, more recent studies have focused on examining the post-entry behavior of new firms. For instance, Audretsch and Mahmood (1994, 1995), Mata et al. (1995), and Honjo (1997) have examined the survival of new firms in manufacturing industries.[2] These studies have not only examined the effect of firm's characteristics on survival but also the differences among industries. On the contrary, they have dealt with different industries regardless of the industry life cycle. That is, these studies have included many declining industries in which there are few new firms, and the role of new firms in such industries would not be so important.

This paper purports to investigate the survival of software houses as the post-entry behavior of new firms. Using logit models and a proportional hazards model, we estimate the determinants of exits (non-survivals) among new software houses. Although exit includes cases such as bankruptcy and merger, the previous studies have not directed their attention to the behavior patterns for exit.[3] In this paper, therefore, we estimate the determinants of each type of exits, using the multinomial logit model.[4] Furthermore, in case of exit due to business failure, we can exactly obtain the date when the software house

[1]Mowery (1996) surveyed the situations of the software industry in the United States, Japan, and European countries.

[2]As another example, Santarelli (1998) examined the survival of new firms in the Italian tourist industry and estimated the relationship between survival and start-up size by regions, using the binary logit model.

[3]Kleijweg and Lever (1996) found the difference between general exit and exit by bankruptcy, although they examined it in the industry-level estimation.

[4]Holtz-Eakin et al. (1994a) examined whether or not self-employed individuals who received inheritances choose other alternatives, such as wage earning or retirement, using the multinomial logit model.

exited. We thus estimate the determinants of failures, using the proportional hazards model with time-dependent covariates.

The paper is organized as follows. In the second section, we explain the data. In the third section, we describe the binary logit model, the multinomial logit model, and the proportional hazards model with time-dependent covariates. In the forth section, we discuss the determinants of exits. In the fifth section, we show the estimated results. Finally, we summarize our findings.

II. DATA

The data on new software houses come from the *TSR Data Bank* (Tokyo Shoko Research; TSR). This data source provides only the latest data on firms (e.g., foundation date, address, paid-up capital, the number of employees, and so on) and presidents (e.g., name, gender, date of birth, finally enrolled school, and so on). In this data source, firms are classified into surviving firms and exiting firms, and the exiting firms are classified into various types, such as business failure (including bankruptcy), shutdown, dissolution, and merger. Using the information on the type, in this paper we classify the cause of exit into three categories: *failure*, *non-failure*, and *merger*. Following the definition by TSR, *failure* is defined as a situation in which firms cannot meet their liabilities and hence cannot conduct economic activities any more; that is, it includes not only those legally claimed as bankrupt but also those regarded as impotent by a dishonored bill. *Non-failure* is defined as a situation in which firms exit without failure and merger. Finally, *merger* is defined as a situation in which firms are extinct by means of merger. While *failure* represents exit without solvency, *non-failure* and *merger* represent exit with solvency.

Moreover, *failure* indicates involuntary exit, but *non-failure* and *merger* may include voluntary exit as well as involuntary one.

We can obtain the information whether or not software houses still exist during a certain period, but cannot necessarily obtain the date when each firm exited. Only for the exit due to failure with debt more than one million of yen, we can exactly obtain the date when the software house exited.

The software houses produce custom or packaged software which corresponds to Code 821 by the three-digit Standard Industrial Classification (SIC). Our sample data consist of 2032 software houses founded in Japan during 1986–1995.[5] Of the total, 253 software houses have exited by the end of 1997. Among the 253 software houses, 135, 91, and 27 software houses are classified into *failure*, *non-failure*, and *merger*, respectively. On the other hand, the date of failure is obtainable for 129 software houses.[6] Among our sample data, 96 software houses have exited by the end of 1995 due to failure.

III. METHODOLOGY

When new firms start business, internal factors which represent the capability of firms including ability of managers affect the survival of firms. In addition to the internal factors, external factors, such as boom and depression, will also affect it.

First, we use the binary logit model to estimate the determinants of exits. The sample size is N. Let z_i denote a vector of covariates for firm i. Using the

[5]We obtained the data from the *TSR Data Bank* in January 1998. Since the time lag between the inspection and the publication of data was available, we obtained the data on software houses which had been founded by the end of 1995.

[6]The dates when the other six software houses exited due to failure were not obtainable, since their debt were less than one million of yen.

binary dependent variable, we capture the survival of new firms. We define D_i as an indicator function which represents whether or not firm i has exited during the observed period.[7] Let X_i and U_i denote a potential failure time and a censored time of firm i, respectively.[8] That is, $D_i = I(X_i \le U_i)$ where $I(\cdot)$ is an indicator function. According to the binary logit model, the probability that firm i has exited during the observed period is defined as follows:

$$P_i = \frac{\exp(z_i'\alpha)}{1+\exp(z_i'\alpha)}, \tag{1}$$

where α is a vector of regression parameters. We obtain the following likelihood function:

$$L^l = \prod_{D_i=1} P_i \prod_{D_i=0} (1-P_i), \tag{2}$$

In order to examine if the distinction is made among the categories of exits, we use the multinomial logit model to estimate the determinants of exits. Let J denote the number of the categories, and $J+1$ choices including survival are available. The probability that firm i chooses type $j(=0,\ldots,J)$ is defined as follows:

$$P_{ij} = \frac{\exp(z_i'\alpha_j)}{\sum_{k=0}^{J}\exp(z_i'\alpha_k)}, \tag{3}$$

where α_k is a vector of regression parameters. We obtain the following likelihood function:

$$L^m = \prod_{i=1}^{N}\prod_{k=0}^{J} P_{ij}, \tag{4}$$

In the logit models, we do not utilize the information on how long the firm survives in the market. Instead of the binary logit model, we also use the proportional hazards model with time-dependent covariates. The proportional

[7]In other words, D_i is an indicator function for censoring which represents whether the time when firm i exited is observed or not.

[8]The censored time indicates the time when we stop observing the exit of firm i.

hazards model was originally proposed by Cox (1972), and the model was extended to allow time-dependent covariates. In order to utilize the information on the duration of survival, the proportional hazards model is more suitable econometric model than the binary logit model.

We explain the proportional hazards model with time-dependent covariates.[9] Time t is defined as firm's age. Let z_{it} denote a vector of covariates for firm i, and the proportional hazards model with time-dependent covariates is defined as follows:

$$\lambda_i(t) = \lambda_0(t)\exp(z'_{it}\beta), \tag{5}$$

where β is a vector of regression parameters, and $\lambda_0(t)$ is an unknown baseline hazard function based on firm's age. Let $Y_i(t)$ denote an indicator function for risk, and $Y_i(t)$ is defined as follows:

$$Y_i(t) = I\left(t \leq \min\{X_i, U_i\}\right). \tag{6}$$

That is, $Y_i(t) = 1$ if firm i is still at risk at time t, and $Y_i(t) = 0$ otherwise.

It is assumed that firm i exits at time t_i. We obtain the partial likelihood function for the N firms as follows:[10]

$$\begin{aligned} L^h &= \prod_{i=1}^{N}\left[\frac{\lambda_0(t_i)\exp(z'_{it_i}\beta)}{\sum_{j=1}^{N} Y_j(t_i)\lambda_0(t_i)\exp(z'_{jt_i}\beta)}\right]^{D_i} \\ &= \prod_{i=1}^{N}\left[\frac{\exp(z'_{it_i}\beta)}{\sum_{j=1}^{N} Y_j(t_i)\exp(z'_{jt_i}\beta)}\right]^{D_i}. \end{aligned} \tag{7}$$

[9] Our description in this paper is based on the multiplicative hazards model that is known as a superset of the Cox's proportional hazards model. For the multiplicative hazards model, see Andersen and Gill (1982).

[10] This likelihood function ignores exits at the same time, but the approximated formulations to calculate this likelihood function are established by several previous studies. In this paper, we use the Breslow's (1974) approximation.

IV. DETERMINANTS OF EXITS

By using the information in the data source, the variables that represents the differences in capabilities of the software houses are measured by firm's characteristics and manager's attributes. Some previous studies have discussed the relationships between survival and size of new firms. For instance, Evans (1987), and Audretsch and Mahmood (1995) found that the probability of survival increased with firm size. Firm size is here measured as the number of employees of the software house.[11] In addition to the number of establishments, paid-up capital of the software house is also included in the regression model. The variable for paid-up capital represents not only firm's size but also firm's financial strength.

Many software houses do not only produce their software products but also supply other software products as a wholesaler or a retailer; that is, the strategy is regarded as vertical integration. As another firm's characteristic, we capture integration strategies. In addition, the variable for integration into information services is also included in the regression model. The software houses gain more benefits by means of integration, but the strategy may simultaneously increase a risk of failure.

More experienced managers may have higher managing ability and be able to avoid failure. Several previous studies have discussed the relationships between survival of firms and manager's attributes. Bates (1990) found that the probability of survival increased with owner's age and education level, using a data source of non-minority male self-employed individuals. However, as

[11] The variable for firm size is not measured as the logarithm of the number of employees, since several firms have no employees.

Holtz-Eakin et al. (1994a) also showed, older managers may be less likely to survive, since the probability of retirement increases with age. In addition, as mentioned before, new idea and knowledge are required for business success in the software industry, and they have to catch up with the kaleidoscopic changes in new technologies. Therefore, younger managers may have more advantage to success in business and to survive.[12] On the other hand, more educated managers may have higher managing ability and be able to avoid failure. As manager's attributes, we use president's age and education level. Moreover, the variable for president's gender is included in the regression model.

In addition to firm's characteristics and manager's attributes, external factors affect the survival of new software houses. As an external factor, we capture local agglomeration to examine whether or not agglomeration affects the survival of new software houses as local competition. Local agglomeration is measured as the number of establishments in each prefecture. The data on the number of establishments are obtained from the *Results of the Survey of Information Service* (Ministry of International Trade and Industry; MITI).

Furthermore, when the proportional hazards model with time-dependent covariates is used in the estimation, we examine the effect of overall macroeconomic situations over time. Overall macroeconomic situations are measured as the growth rate of real gross domestic product (GDP) in each year. The data on the growth rate of real GDP are obtained from the *Annual Report on National Accounts* (Economic Planning Agency).

Table 1 shows the definitions of the variables. Since only the latest data are

[12] According to the *Basic Survey on Wage Structure* (Policy Planning and Research Department, Minister's Secretariat, Ministry of Labor), the average age of programmers is 27.5 for male and 26.8 for female in 1994. The average age of programmers is lowest among the data.

obtainable from the *TSR Data Bank*, $SIZE$ and CAP are the latest ones.

V. EMPIRICAL RESULTS

In Table 2, we estimate the determinants of exits, using the binary logit model. If firm i has exited during 1986–1997, $D_i = 1$; otherwise, $D_i = 0$. Since there is multicolinearity between CAP and $SIZE$, we omit each variable in Equations (ii) and (iii), respectively. In Table 3, we estimate the determinants of exits, using the multinomial logit model. The alternatives are three categories: *failure*, *non-failure*, and *merger*.[13]

In Tables 2, $SIZE$ and CAP have a negative effect on exit. It is found that new software houses with large size are more likely to survive, and the result is consistent with those by the previous studies. Holtz-Eakin et al. (1994a, 1994b) found that the survival of self-employed individuals were positively related to an amount of inheritances and liquid assets which were regarded as liquidity constraints. Although paid-up capital is only obtainable as a measure of financial situations, the result may also suggest that new software houses with sufficient paid-up capital are more likely to survive. However, since the variables represents current size rather than initial size, the result may suggest the reverse causality. In Table 3, while CAP has a significantly negative effect on *failure* and *non-failure*, it has a significantly positive effect on *merger*. Software houses with more capital tend to be merged as rationalization to avoid

[13]In the multinomial logit model, the ratio of the probabilities of choosing any two alternatives is independent of the attributes of any other alternative in the choice set, and this property is termed the independence of irrelevant alternatives. Hauseman and McFadden (1984) suggested that if a subset of the choice set truly was irrelevant, omitting it from the model altogether would not change parameter estimates systematically. Using this specification test, we tested the independence of irrelevant alternatives. As a result, we could not reject a hypothesis that each alternative was independent of the others.

a risk of failure during this period, and firms with a large amount of capital may attract investors as a target for merger and acquisition.

With respect to integration strategies, the vertical integration may affect the survival of new software houses. In particular, $DVIS$ has a significantly positive effect on *failure*, although it is not found that $DVIS$ has the effect on *non-failure* and *merger*. Whereas the vertical integration into wholesale and retail trades increase more benefits, excess resources, such as operational funds and stocks, may be more required for new firms. Thus, the vertical integration may increase a risk of failure.

With respect to manager's attributes, in Table 2, $MAGE$ has a significantly positive effect on exit.[14] The result is not consistent with that by Bates (1990) who found that the probability of survival as self-employed increased with owner's age. It may suggest that new idea and knowledge are required in the software industry and younger presidents have more capability of operating software houses. In Table 3, while the coefficients on $MAGE$ are not significant for *failure* and *merger*, they are significant for *non-failure*. It is found that manager's age significantly affects only exit without failure and merger. Older presidents are more likely to dissolve their firms because, for instance, they cannot find their successors. Unfortunately, from the data source we cannot determine whether or not the current president is an founder, and it may be possible to replace a president during this period. The result may also suggest that older presidents are sent to declining firms in order for dissolution without failure.

On the other hand, $DEDC$ has a negative effect on exit of new software

[14]Following some previous studies, the level and its quadratic terms for age were included in the regression model, but the coefficients on the quadratic term were not significant.

houses, although its coefficients are not always significant. In Table 3, $DEDC$ has a significantly negative effect on *failure*, implying that firms whose presidents have high education level are more likely to survive without failure. Moreover, $DGND$ does not have a significantly effect on exit, and it is not found that president's gender is related to exit of new software houses.

With respect to local agglomeration, $AGGL$ has a significantly positive effect on exit, in particular, on *failure*. New software houses tend to enter into the geographically concentrated area. In fact, about one-third of our sample data has been founded in Tokyo.[15] On the contrary, the result suggests that local agglomeration negatively affects the survival of new software houses. Thus, whereas new firms tend to concentrate in a certain region, agglomeration may lead to local competition and increases a risk of failure of new software houses.

In Tables 2 and 3, the vertical integration, president's education level, and local agglomeration significantly affect only on *failure*. While *Non-failure* and *merger* include voluntary strategic exits, *failure* may exclude it. The cause of *failure* is more likely to be restricted among the types of exits. As already explained, we estimate the determinants of failures among new software houses during 1986-1995, using the proportional hazards model with time-dependent covariates.[16]

Table 4 shows the estimated results. In Table 4, $MAGE$, $AGGL$, and $GRGDP$ are the time-dependent covariates that vary in each year. The results

[15] We also used the dummy variable for the software houses located in Tokyo, and its coefficients were significantly positive. This result may also support that local agglomeration positively affect exit of new software houses.

[16] With respect to the exits whose dates of closure were not obtainable, the finally revised dates were obtainable. It was assumed that the firms had been surviving by the dates; that is, U_i is the finally revised date and $D_i = 0$ for them. Then, these firms were excluded from our sample data. We estimated the determinants of failures, using these two regression models. As a result, we obtained the similar results, and here we reported the former one.

are almost consistent with those of *failure* in Table 3. In addition, *GRGDP* has a significantly negative effect on failure of new software houses.[17] During this period, new firms have confronted the bubble economy and the post-bubble depression. The result suggests that boom and depression significantly affect failure of new software houses.

VI. CONCLUSION

In this paper, we estimated the determinants of exits among software houses founded in Japan during 1986–1995, using two logit models and the proportional hazards model with the time-dependent covariates. It was found that new software houses with sufficient size or paid-up capital were more likely to survive. With respect to manager's attributes, president's age and education level affected the survival of new software houses, and the effect was different among the types of exits. It was also found that vertical integration and local agglomeration increased the probability of failure of new software houses, and macroeconomic situation were significantly related it.

The empirical evidence presented in this paper confirms the importance of new firm's characteristics as determinants of the post-entry behavior. Moreover, the results in this paper have suggested that the behavior of new firms is different among the types of exits. Several previous studies have found an evidence that the firm's behavior of entry and exit depends on its type in the industry-level estimation (Mata, 1993; Kleijweq and Lever, 1996), and we have shown the evidence in the firm-level estimation.

[17] We also used the data on investments for information processing and related equipment by private firms as the variable for macroeconomic situations, but could not obtain a more significant result.

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Table 1. Definitions of Variables

Variable	Model	Definition
SIZE	L, PH	Number of employees.
CAP	L, PH	Logarithm of paid-up capital.
DVIS	L, PH	Dummy variable for the vertical integration into wholesale and retail trades (SIC 5231, 5232, 5395, 5841, 5842, and 5952).
DHIS	L, PH	Dummy variable for the integration into other information services (SIC 8221, 8222, and 8229).
MAGE	L	Logarithm of president's age when the firm was founded.
	PH	Logarithm of president's age.
DGND	L, PH	Dummy variable for the male president.
DEDC	L, PH	Dummy variable for the president who have finally enrolled in technical college, junior college, university, or abroad school.
AGGL	L	Number of establishments in the prefecture when the firm was founded.
	PH	Number of establishments in the prefecture in each year.
GRGDP	PH	Growth rate of real GDP in each year.

Note : L and PH indicate the logit models and the proportional hazards model, respectively.

Table 2. Determinants of exits (logit model)

	(i)	(ii)	(iii)
$SIZE \times 10^{-3}(i)$	-0.002	-2.949^{*}	
	(0.002)	(0.002)	
$CAP(i)$	-0.151^{**}		-0.189^{***}
	(0.076)		(0.068)
$DVIS(i)$	0.237	0.250	0.241
	(0.157)	(0.157)	(0.157)
$DHIS(i)$	-0.170	-0.192	-0.203
	(0.367)	(0.367)	(0.367)
$MAGE(i)$	1.375^{***}	1.245^{***}	1.343^{***}
	(0.328)	(0.321)	(0.327)
$DEDC(i)$	-0.210	-0.266	-0.213
	(0.161)	(0.159)	(0.161)
$DGND(i)$	-0.096	-0.146	-0.106
	(0.517)	(0.518)	(0.512)
$AGGL \times 10^{-3}(p)$	1.296^{**}	1.086^{**}	1.302^{**}
	(0.540)	(0.528)	(0.540)
$L.L.$	-728	-730	-729
N	2032	2032	2032

Note : i and p indicate the variable changed by software houses and prefectures (regions), respectively. Standard errors in parentheses. ***, **, and * indicate significant at the 1%, 5%, and 10% level, respectively. All equations include constant term and time dummy variables which represent the foundation year of each firm.

Table 3. Determinants of exits (multinomial logit model)

	i			ii			iii		
Cause of exit	Failure	Non-failure	Merger	Failure	Non-failure	Merger	Failure	Non-failure	Merger
$SIZE \times 10^{-3}(i)$	−6.843*	−5.562	−0.217	−9.894***	−8.869**	0.199			
	(3.907)	(3.716)	(0.472)	(3.812)	(3.749)	(0.341)			
$CAP(i)$	−0.181*	−0.245*	0.509***				−0.289***	−0.345***	0.480***
	(0.109)	(0.112)	(0.151)				(0.096)	(0.112)	(0.142)
$DVIS(i)$	0.572***	−0.267	−0.058	0.579***	−0.237	−0.109	0.589***	−0.255	−0.059
	(0.200)	(0.271)	(0.518)	(0.199)	(0.269)	(0.519)	(0.200)	(0.271)	(0.518)
$DHIS(i)$	0.380	−1.482	0.045	0.360	−1.490	0.222	0.322	−1.560	−0.054
	(0.448)	(1.020)	(0.782)	(0.447)	(1.020)	(0.779)	(0.446)	(1.019)	(0.790)
$MAGE(i)$	0.632	2.993***	−0.346	0.522	2.800***	0.653	0.536	2.914***	−0.326
	(0.427)	(0.533)	(0.936)	(0.420)	(0.522)	(0.890)	(0.425)	(0.533)	(0.938)
$DEDC(i)$	−0.467**	0.131	0.446	−0.499**	0.067	0.657	−0.472**	0.121	0.455
	(0.200)	(0.272)	(0.630)	(0.199)	(0.270)	(0.622)	(0.200)	(0.272)	(0.630)
$DGND(i)$	−0.316	1.156	−1.255	−0.369	1.159	−0.904	−0.336	0.921	−1.223
	(0.630)	(0.954)	(1.068)	(0.630)	(0.995)	(1.057)	(0.625)	(0.863)	(1.067)
$AGGL \times 10^{-3}(p)$	2.241***	0.115	0.943	1.998***	−0.204	1.869	2.255***	0.119	0.950
	(0.727)	(0.864)	(1.568)	(0.710)	(0.846)	(1.536)	(0.727)	(0.864)	(1.570)
$L.L.$		−930			−938			−934	
N		2032			2032			2032	

Note : i and p indicate the variable changed by software houses and prefectures (regions), respectively. Standard errors in parentheses. ***, **, and * indicate significant at the 1%, 5%, and 10% level, respectively. All equations include constant term and time dummy variables which represent the foundation year of each firm.

Table 4. Determinants of failures (proportional hazards model)

	(i)	(ii)	(iii)
$SIZE(i)$	-0.006	-0.011^{**}	
	(0.005)	(0.005)	
$CAP(i)$	-0.346^{**}		-0.450^{***}
	(0.140)		(0.122)
$DVIS(i)$	0.521^{**}	0.538^{**}	0.547^{**}
	(0.224)	(0.223)	(0.224)
$DHIS(i)$	0.506	0.468	0.473
	(0.469)	(0.468)	(0.470)
$MAGE(it)$	0.998^{*}	0.783	0.901
	(0.555)	(0.548)	(0.551)
$DEDC(i)$	-0.238	-0.307	-0.240
	(0.232)	(0.230)	(0.232)
$DGND(i)$	0.371	0.302	0.330
	(0.969)	(0.981)	(0.928)
$AGGL \times 10^{-3}(pt)$	0.458^{***}	0.384^{**}	0.466^{***}
	(0.166)	(0.163)	(0.166)
$GRGDP(t)$	-0.156^{*}	-0.162^{**}	-0.157^{*}
	(0.081)	(0.081)	(0.081)
$L.L.$	-652	-655	-653
N	2032	2032	2032

Note : i, p, and t indicate the variable changed by software houses, prefectures (regions), and time, respectively. Standard errors in parentheses. ***, **, and * indicate significant at the 1%, 5%, and 10% level, respectively.