

Growth and Survival Determinants of Chinese Private Firms:

Fieldwork evidence and econometric estimates

by

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Abstract

This paper reports on one of the first empirical attempts to investigate small firm growth and survival, and their determinants, in the Peoples' Republic of China. The work is based on field work evidence gathered from a sample of 83 Chinese private firms (mainly SMEs) collected initially by face-to-face interviews, and subsequently by follow-up telephone interviews a year later. We extend the models of Gibrat (1931) and Jovanovic (1982), which traditionally focus on size and age alone (e.g. Brock and Evans, 1986), to a 'comprehensive' growth model with two types of additional explanatory variables: firm-specific (e.g. business planning); and environmental (e.g. choice of location). We estimate two econometric models: a 'basic' age-size-growth model; and a 'comprehensive' growth model, using Heckman's two-step regression procedure. Estimation is by log-linear regression on cross-section data, with corrections for sample selection bias and heteroskedasticity. Our results refute a pure Gibrat model (but support a more general variant) and support the learning model, as regards the consequences of size and age for growth; and our extension to a comprehensive model highlights the importance of location choice and customer orientation for the growth of Chinese private firms. In the latter model, growth is explained by variables like planning, R&D orientation, market competition, elasticity of demand etc. as well as by control variables. Our work on small firm growth achieves two things. First, it upholds the validity of 'basic' size-age-growth models, and successfully applies them to the Chinese economy. Second, it extends the compass of such models to a 'comprehensive' growth model incorporating firm-specific and environmental variables.

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1 Introduction

This paper aims to provide one of the first empirical attempts to investigate small firm growth and survival, and their determinants, in the Peoples' Republic of China (hereafter denoted simply 'China'). Our starting point is Gibrat's (1931) law of proportionate effects (see Sutton, 1997) and Jovanovic's (1982) learning theory. We extend these models, which traditionally focus on size and age alone e.g. Brock and Evans (1986), to a 'comprehensive' growth model with two types of additional explanatory variables: firm-specific (denoted FS) (e.g. business planning); and environmental (denoted EN) (e.g. choice of location). Estimation of our model is by log-linear regression on cross-section data, with correction for sample selection bias and heteroskedasticity. Our results refute a pure Gibrat model (but support a more general variant) and confirm the learning model, as regards the consequences of size and age for growth; and our extension to a comprehensive model highlights the importance of locational choice and customer orientation for the growth of Chinese private firms.

The work is based on field work evidence gathered from a sample of 83 Chinese private firms (mainly SMEs) collected initially by face-to-face interviews, and subsequently by follow-up telephone interviews a year later. A binary probit model of firm survival is estimated on these data, and provides good predictions of survival, based on variables like gearing, cash flow problems, and customer orientation, as well as several control variables. This model is then used for sample selectivity correction in two econometric model: a 'basic' age-size-growth model; and

a ‘comprehensive’ growth model. Both are estimated by Heckman’s (1979) two-step regression procedure. In the latter model, growth is explained by variables like planning, R&D orientation, market competition, elasticity of demand etc. as well as by control variables. To summarise, our work on firm growth achieves two things. First, it upholds the validity of ‘basic’ size-age-growth models, and successfully applies them to the Chinese economy. Second, it extends the compass of such models to a ‘comprehensive’ growth model incorporating firm-specific and environmental variables.

Although our sample size is relatively small ($N = 83$), from the standpoint of national datasets, it is large from a field work perspective, given the high costs of this type of data acquisition. The advantage of our new database is that it contains key variables relevant to modern research into small firms (e.g. customer orientation) which are not available generally in most large national datasets. True, the latter may have tens of thousands of sampled firms, but for each of these, often only a handful of variables is involved¹, most of which are gathered for reasons other than economic research (e.g. taxation). Our research is therefore more concerned with detailed prototyping of relatively richly specified models on a small dense dataset, rather than with testing highly stylised simple models on large national datasets.

Studies of high growth small firms have been carried out extensively in the West (e.g. Davidsson, Delmar and Wiklund, 2006). Such high growth firms have been referred to as “gazelles” by David Birch (1979) in the USA, and as ‘ten percenters’ by David Storey (1996) in the UK. Given that such firms make a disproportionate contribution to the growth of an economy, it seems to us to be strategically important for China also to develop this type of research. Amongst

¹ Although we still favour parsimonious models, and a limited number of variables is used in this paper, the key point is that the authors have a wider range of relevant variables to choose from than do most investigators of determinants of small firm growth.

other things, the study of small and medium-sized enterprises (SMEs)² has important potential policy payoff, including the alleviation of social problems (e.g. the large number of laid-off city workers) and the maintaining of China's rapid national economic growth. The first Chinese National SME conference was held in Beijing in 2002. This turned attention for the first time to the importance of SME development for the private sectors³. This initiative led to a formally legalized strategy, as embodied in China's SME Promotion Law of 2003, which rolled out a new policy aimed at supporting SME growth in China⁴. However, it remains doubtful whether the benefits from fostering the SMEs in the West have been as tangible as were first thought possible, and whether (such as they are) they will also transpire for China, a country governed by a very different ideology, with an economic system that has only recently become market mediated again. As research workers, we would argue that in order to understand better this big issue, we must start by enquiring into the very fundamentals of the size-age-growth relationship. Here, we must also ask what other variables, besides the obvious ones of size and age, have significant impact on firm grow, especially in the early stages. Understanding how firms start, we may better understand how they progress. As Lao Tzu⁵ put it, 1500 years ago, 'the journey of a thousand miles commences with a single step'.

The remainder of this paper is organized as follows. In Section 2, a brief literature review is conducted, covering some relevant formalization of growth models of the small firm. Section 3 describes the field work methods we have used,

2 As shown by the statistics from National Statistics Bureau of China, 99% of enterprises in China are SMEs.

3 As proposed by the Chinese Communist Party's 16th representative conference, the majority of state-owned SMEs in China have been privatised since 1997.

4 This involved a tightening up of definitions of firm types. For example, in 2003, the National Bureau of Statistics in China (NBS) introduced a temporary size division of firms for just six industrial categories (viz. manufacturing, building, transportation and logistics, wholesale and retailing, food and accommodation, and postal service). In this setting, new size divisions (of a firm's size, in a statistical sense) were defined as follows: 'small' if it hires less than 600 full time equivalent employees, 'medium' if it hires from 600 to 3,000; and 'large' if it hires more than 3,000.

5 Lao Tzu (BC571-471), the founder of Taoism in China.

explains how our dataset was constructed, and shows how our variables were defined. Sections 4 is devoted to presenting the specification of what we characterise as ‘basic’ and ‘comprehensive’ growth models of the small firm, as well as that of a the survival (selection) model of the small firm. Sections 5 reports on our statistical and econometric estimates, interprets this evidence, and then discusses their implications. Overall conclusions are drawn in the final Section 6. Detailed definitions of variables are given in an Appendix.

2 Brief Literature Review of Firm Growth

Arguably, it is because the observed elongated L-shape of the long run average total cost (LRATC), and empirical estimates the level of minimum efficient scale (MES) have failed fully to explain market concentration, that the relationship between firm size and growth, of the renowned Gibrat’s (1931) ‘Law of Proportionate Effects’, has been so extensively discussed and tested in the West, since the 1950s. Gibrat’s Law says that the proportional change in a firm’s size is independent of size and of preceding growth rates. Support for this Law has been buttressed by the pioneering empirical works of Hart and Prais (1956), Simon and Bonini (1958), Simon and Ijiri, (1964), Pashigian and Hymer (1962), though this early work has focussed especially larger firms, rather than on the small firms or SMEs that are our interest here. However, when Mansfield (1962, p. 1044) incorporated small firms into his empirical analysis, he found that ‘smaller firms have relatively high death rates and those that survive tend to have higher and more variable growth rates than larger firms’. This inverse relationship between firm size and growth subsequently has also been supported by further empirical works⁶, including that of Du Reitz (1975), Evans (1987a, b), Brock and Evans (1986), Reid (1993), Mata (1994), Hart (2000),

⁶ It should be noted that some of these studies – like Farinas and Mareno (2000) - implied this negative relationship between growth and size was subject to certain conditions e.g. size, survival, age.

Rodriguez *et al.* (2003), Yasuda (2005), Aslan (2008). In the face of this evidence, many research workers have adopted an eclectic stance, suggesting that Gibrat's Law is increasingly approached as firm size becomes larger, or that the Law only holds for firms above a certain size. Below this threshold size, the Law would be refuted⁷ (Hall, 1987; Dunne and Hughes, 1994; Hart and Oulton, 1996; Farinas and Moreno, 2000).⁸

With this caveat, the *negative* relationship between firm size and growth was provisionally recognized, although Singh and Whittington (1975, p. 24), working with very large firms, have even proposed a *positive* relationship, albeit a statistically weak one, which they ascribed to 'the persistence of growth rates over time'. This 'time dependent' influence has subsequently been modelled formally by Jovanovic (1982) in his 'learning theory' of firm growth, which argues that a firm can improve its performance by market experience, leading to an unfolding of efficiency improvement, caused by learning over time. Thus, it is the 'efficient' firms (or 'good learners') which survive and grow, whereas the less efficient ones ('poor learners') decline and may even dissolve. Thus, within a given size class, younger firms tend to grow faster than the older firms, (Evans, 1987a, 1987b; Variyam and Kraybill, 1992; Reid, 1993; Audretsch 1995a, 1995b; Rodriguez, et al. 2003; Yasuda, 2005). Some have argued that this learning theory was only applicable to firms below a certain age (Farinas and Moreno, 2000), and others that it was only applicable to firms for whom growth was measured by employment (Heshmati, 2001). Yet others have held that such a relationship may simply fail to hold in a certain sectors and industries⁹ e.g.

⁷ It should be noted here that how you measure growth can make a difference to the empirical findings on growth, for example, in Heshmati (2001), Gibrat's Law holds if the growth variable is defined by employment, yet fails if it is defined by sales.

⁸ In terms of equation (3) below, it would imply that β becomes closer to unity, as size increases. In the limit, when $\beta = 1$, the Gibrat Law holds.

⁹ For instance, in the case of the hardware manufacturing industry in India, Das (1995) and for services in the Netherlands, Audretsch, Klomp and Thurik (2005). See also the case of Portugeses services, Macas Nunes and Serrasqueiro, (2009).

Audretsch et al (2005). To conclude, whilst the effects of size and age on firm growth are not unanimously agreed, it is widely accepted that these two variables, size and age, have become regarded as principal determinants of firm growth.

However, besides size and age, various other determinants of firm growth have been proposed in the Western economic literature. Some important, if not exhaustive, firm-specific determinants which can be incorporated into models of firm growth include: planning (Penrose, 1955); research and development activities (Miller, 1983; Hall, 1987); and business strategy (Porter, 1980, 1985, 1996; Reid, 1993, 2000). Further, so-called 'environmental' (in the sense of business environment, not physical environment) control variables (e.g. customer price sensitivity, market competition, sector and location) also need to be considered as potentially significant determinants of firm growth.

3 Data and Variables

This section considers two matters: data gathering; and the definition and motivation of key variables. First, we consider field work procedures, instrumentation and sample attributes. Second, we discuss how key variables were defined, and how they were inspired.

3.1 Database

The data used in this study were obtained from two stages of fieldworks carried out in ten major cities in the Guangdong Province of China. In the first stage, between the months of September and December of 2004, the owner-managers of 83 privately owned firms were interviewed in Chinese, in fact-to-face meetings, by one of the authors and his co-fieldworkers¹⁰ using an administered questionnaire. The

¹⁰ These were students and faculty, in international business and finance, at the Guangdong University of Foreign Studies. They were trained by one of the co-authors, who also prototyped the instrumentation, and participated in the fieldwork, including bench-testing the instrumentation in pilot interviews.

sampling criteria for the selection of firms were that they should be: (a) privately owned firms, (b) financially independent (i.e. not subsidiaries), and (c) located in the territory of Guangdong Province. The second stage of fieldwork took place approximately one year later (in February 2006), and used telephone interviews: (a) to identify surviving firms (76 out of 83); and (b) to collect data on full-time employment, which enabled the calculation of annual growth rates between 2004 and 2006.

Our approach to the survival and growth of firms is felt to be advantageous in a several ways. First, Chinese official agencies so far have only collected data for 'large scale firms' (with annual sales of more than 5 million Chinese Yuan), which largely overlooks the small firms in the population of all firms. Second, such data as are available are most often highly aggregative, and therefore of little use for the micro-econometric analysis which we wish to undertake. Third, deficiencies of publicly provided data have yet to establish their credibility. Independent commercial data providers in China are emerging, but their standing is uncertain. They usually claim to hold a large dataset of tens of thousands of firms, yet the variables available can be dangerously sparse and statistically inadequate¹¹. Our study aims to avoid the deficiencies of these new commercial data providers. Instead, we have gathered a large number of variables for each of 83 private firms at our first stage interviews, and subsequently have obtained further employment information from the survivors of the same sample in our second stage follow-up interviews. Proceeding in this way, allows us to do two things. First, to examine further growth determinants, and second, to correct for sample selection bias in our estimated growth equations.

¹¹ For example, it may contain only the name of the person legally in charge, the telephone and fax numbers, and the postal address. This does not go beyond what the yellow pages can provide, and is useless for micro-econometric work.

Of necessity, given severe problems of access to the field in China, we have had to adopt a ‘snowball’ sampling method for our study. Thus firms in our sample were obtained by the pursuit of personal referrals from faculty members in International Business, within the School of English. These referrals gave us access to a large student body, composed of nearly 180 students majoring in English combined with International Business or Finance at the Guangdong University of Foreign Studies (GDUFS) in China. Essentially, these students (often from a family business background) acted as “gatekeepers” to our field. Based on briefings from one author, the other author first visited and interviewed 29 firms in person. On the basis of this experience, 30 student teams from GDUFS (with 3 to 5 students per team) were trained in interviewing. These students visited an additional 60 firms at an average cost of approximately of just 100 Chinese Yuan per firm. In undertaking this work, we enjoyed the advantage that Guangdong was one of the earliest Provinces in China to ‘marketize’ its polity, successfully exploiting its locational advantage of close physical proximity to Hong Kong and Macau to create the beginnings of an entrepreneurial culture. This no doubt facilitated field access.

With alternative methods to ours, like ‘cold calling’, one selects firms randomly from a sampling frame (e.g. constructed from the yellow pages), but firms approached in this way are likely to be completely unwilling to cooperate. Most Chinese owner-managers would simply rebuff such ‘cold contacts’ before even contemplating the prospect of undertaking a one and a half hours interview, which delves into the working of their firm. In China, ‘guan xi’ (i.e. network connection) is a vital prerequisite to fieldwork research of the kind we have conducted. Thus, ‘pure’ random sampling could not be used without denying us access to the field entirely. As it turns out, our own sampling procedure was perfectly satisfactory, in terms of being

highly representative (as we shall substantiate below) of the population of firms. We are therefore persuaded by what Scott and Marshall (2005) have argued in a related social science context, that for certain inaccessible groupings of individuals if the only sample that can be obtained at all is by other than probability sampling, then one has to go along with that, and aim to provide the best sample possible in these restrictive conditions. They use the example of inaccessibility of certain religious sects. It would be improper to describe the Chinese business community as akin to a religious group. Yet they can appear equally mysterious and unapproachable without suitable ‘guan xi’ connections.

Fortunately, the representativeness of the sample seems encouragingly satisfactory. We found that the correlation between the sample data and the economic data on the population of firms in major cities of Guangdong Province to be strong and significant. We sampled by the ten largest cities in Guangdong, and the correlations between the sample distribution and the population distribution by cities gives Kendall’s $\tau_b = 0.754$ and Pearson’s $\rho = 0.877$, which are both significant at the 0.01 level, on a two tailed test. Concerning coverage by industrial sector, our sample comprises all the categories of interest at the one-digit level, for China’s National Standard of Industrial Classification (CNSIC). By ownership (e.g. public/private) distribution, and by size (e.g. small, medium, large) distribution, the correlation between sample and population distribution was very high in each case. Despite the unavoidable constraints on our sampling method, our sample itself does seem to represent reasonably the population of private firms in the Guangdong Province of China.

3.2 Variables

Growth is commonly measured in terms of employment, sales or assets, or variants of these (see Appendix). Making the best of our available data, the dependent variable we chose for our growth model was defined in terms of growth in employment¹² (in natural logarithm), where here employment is measured by the number of full-time employees¹³.

Our chosen independent variables include generic variables (e.g. size and age) inspired by previous work, and other ones inspired by current research interests. Size is measured as above, and age (*Age04*) is measured by the number of years from business inception to the time of first-stage interview. Other explanatory variables, we have noted, can be categorized into two groups: firm-specific variables (e.g. planning, research and development, and business strategy), and ‘environmental’¹⁴ variables (e.g. customer price sensitivity, market competition, sector and location). In the first group, planning (*Planning*) is defined by a count of the number of plans undertaken by the firm. Research and development refers to the degree of R&D orientation (*R&DOrient*). Next, of the environmental variables, three are concerned with business strategy, namely, customer orientation (*CustomerOrient*), the price elasticity of demand (i.e. the customers’ sensitivity to price cuts) (*Elasticity*), and the degree of market competition (*Competition*). The environmental variables are completed with sectoral and locational dummy variables (see the detailed definitions of variables in the Appendix).

The mean employment size in the sample was 56.85 ($s = 116.22$) at inception, and 212.05 ($s = 458.195$) at first interview. Thus our firms are not usually micro-firms, but lie squarely in the middle of conventional SME size definitions.

¹² For instance, the employment growth rate is defined as $[\ln(\text{employment}_{2006}) - \ln(\text{employment}_{2004})] \div 1.5$. The time interval between our two interviews was approximated as 1.5 years.

¹³ We did not have sufficiently detailed data to compute full time equivalent workers, or to use hours worked as a measure of labour input or effort.

¹⁴ In the sense of the industrial, commercial and business environment.

From Box-plots of various size measures we found that both the median size and the inter quartile range increased over time. The skewness for these various measures ranged from 2.48 to 6.27, with kurtosis typically greater than zero. This suggests a positively skewed non-normal distribution, and is one reason for adopting a log transformation of size, a procedure fully justified by the theoretical treatment of Sections 4 below.

In Table 1, summary statistics of all the key variables to be used in our growth model are reported. These will be utilized in the econometric modelling of Section 5.

Table 1 Summary Statistics of Key Variables in Growth Models (N=76)

Variables	Mean (μ)	Std. Dev.(σ)	Min	Max
<i>GrowthEmploy1</i>	1.1263	0.374	0.41	3.54
<i>SizeEmploy04</i>	211.050	458.323	5	3000
<i>Age04</i>	6.400	4.802	1	21
<i>Planning</i>	3.820	1.515	1	7
<i>R&Dorient</i>	2.120	0.916	1	3
<i>CustomerOrient</i>	2.315	1.113	1	3
<i>Elasticity</i>	2.407	1.174	1	4
<i>Competition</i>	2.634	0.619	1	3
<i>Sector</i>	0.398	0.492	0	1
<i>Location</i>	0.578	0.497	0	1

According to Table 1, a ‘typical’ or average firm had an annual growth rate of around 1.13 (in natural logarithm), that is about 3% per annum. It had been established for six and a half years and had 200 employees. It was typically in a non-manufacturing industry (*Sector*), and most commonly operated in the capital city Guangzhou (*Location*). In terms of firm specific variables, we can say the following.

The typical firm used planning methods regularly (about four times over a six year period, on average) (*Planning*). It had some, but not strong, R&D orientation (*R&Dorient*). It had moderate customer orientation (*CustomerOrient*). The business ‘environment’ variables include *Elasticity* and *Competition*. They show that the typical firm experiences an inelastic response to price cutting by 5%, other things being equal (*Elasticity*). This suggests that price cutting will not be a common voluntary strategy by these firms – if it occurs at all, it will be in competitive response to rivals’ price cutting. Competition is perceived to be very strong, which suggests, given the finding on elasticity, that non-price competition is intense (*Competition*).

4 The Model

In this section, the groundwork for our ‘comprehensive’ growth model is built up by particular reference to Gibrat’s Law (1931) and to the adaptations of it by the likes of Jovanovic (1982), Evans (1987a, b) and Brock and Evans (1986).

As Gibrat’s Law stated, the probability of a given proportional change in the size of any firm was the same as that for all firms, regardless of the size and preceding growth rates of a firm. It amounts to saying that the sequence of a firm’s size $\{S_t\}$ will grow randomly in each period of time (t, t-1) due to the diverse uncertain factors that impinge upon it, as represented by the sequence $\{\varepsilon_t\}$ of uncorrelated random variables ε_t with mean m and variance σ^2 . The incremental change in size in each time period will be a random proportion ε_t of its initial size at the start of each period, as follows: $\Delta S_t = S_t - S_{t-1} = \varepsilon_t S_{t-1}$ which implies:

$$S_t = (1 + \varepsilon_t) S_{t-1} \quad (1)$$

Thus, by recursive substitution size S_t can be expressed as a function of the initial size S_0 :

$$\begin{aligned}
S_t &= (1 + \varepsilon_t)(1 + \varepsilon_{t-1}) \cdots (1 + \varepsilon_2)(1 + \varepsilon_1) S_0 \\
&= S_0 \prod_{\tau} (1 + \varepsilon_{\tau}) \tag{2}
\end{aligned}$$

As noted by Steindl (1965), taking natural logs of (2) gives:

$$\ln S_t \approx \ln S_0 + \sum_{\tau} \varepsilon_{\tau}$$

Then, under very general conditions, the Central Limit theorem says that, assuming $\ln S_0$ is negligibly small compared to $\ln S_t$ as $t \rightarrow \infty$, then the distribution of $\ln S_t$ approximates to that of a normal variate with mean mt and variance $\sigma^2 t$. Put another way, firm size S_t has an asymptotically lognormal distribution, a distribution with a well recognised positive skew, Aitchison and Brown (1969). This is the archetypical stochastic model of firm growth, and it stands as a challenge to deterministic theories of firm growth.

Unfortunately, this formulation suggests an unstable process in that the mean of log size and its variance are increasing over time. Fortunately, a variant of (1) is available, which overcomes this difficulty. One such variant¹⁵ is:

$$S_t = A S_{t-1}^{\beta} (1 + \varepsilon_t) \quad \text{where} \quad \beta = \sqrt{\rho}$$

where A captures firms' shared (exogenous) market growth, and β captures firms' endogenous growth. Taking natural logs we get¹⁶:

$$s_t = \alpha + \beta s_{t-1} + \mu_t \tag{3}$$

where $s_t = \ln S_t$, $\alpha = \ln A$, $s_{t-1} = \ln S_{t-1}$, and $\mu_t = \ln (1 + \varepsilon_t)$.

Equation (3) has been widely estimated in the literature, and is the basis of the models specified in estimable form in equations (5) and (7) below, and indeed, of the actual estimated models of Tables 3 and 4 below. That the variance is stable over

¹⁵ Inspired by Kalecki (1945) and popularised by Klein (1962)

¹⁶ This equation lends itself to a convenient phase-space representation, with S_t as ordinate and S_{t-1} as abscissa, and $0 < \beta < 1$ being a stable equilibrium condition. The closer is β to unity, the closer is the model to Gibrat's Law, until for $\beta = 1$, Gibrat's Law is satisfied, cf. Reid (2007, Ch.16).

time is easily demonstrated as follows. From (3), by setting $\beta = \sqrt{\rho}$, we get an expression for s_t by successive substitution:

$$s_t = \alpha [1 - (\sqrt{\rho})^t] / (1 - \sqrt{\rho}) + \sum_{\tau} (\sqrt{\rho})^{t-\tau} \mu_{\tau} \quad (4)$$

from which the following variance term is determined:

$$\text{var} (s_t) = \sigma_{\mu}^2 (1 - \rho^t) / (1 - \rho)$$

from which $\text{var} (s_t)$ has the limit

$$\sigma_{\mu}^2 / (1 - \rho) \text{ as } t \rightarrow \infty \text{ for } 0 < \rho < 1.$$

That is, the variance of log size, s_t , does *not* increase with time. Note too that the restriction on ρ to the unit interval also restricts β of equation (3) to the unit interval for the positive root. This implies stability of the stochastic equation (3) above, and thus an equilibrium log of firm size (and therefore of firm size itself) is determined for $0 < \beta < 1$. This may also be demonstrated by making t large in equation (4), from which we get equilibrium log firm size as

$$\alpha / (1 - \sqrt{\rho}) = \alpha / (1 - \beta)$$

which will be achieved in the long run and must be positive.

In later developments, Jovanovic (1982), Evans (1987a, b) and Brock and Evans (1986) have incorporated “age” as a new variable into the growth model, reflecting entrepreneurial learning. This formulation may be expressed as:

$$\ln G_{it+\tau} = \ln f(S_{it}, A_{it}) + u_{it} \quad (5) \quad \text{where}$$

S_{it} and A_{it} are the size and age of firm i at time t and u_{it} is the error term. $G_{it+\tau}$ refers to the growth rate of firm i ($i = 1, 2, \dots, N$) in terms of growth variables which are of research interest (e.g. employment growth) in period $t + \tau$ ($t = 1, 2, \dots, T$) where τ is the time period over which growth is measured. Thus growth is calculated as:

$$G_{it+\tau} = (S_{it+\tau}/S_{it})^{\frac{1}{\tau}} \quad (6)$$

The size-age-growth relationship may be expressed in generalised form by equation (7) below, by substituting (6) into (5) and adding other firm-specific and environmental variables, as well as a sample selection bias correction (IMR) variable¹⁷ to the growth equation:

$$\begin{aligned} (\ln S_{it+\tau} - \ln S_{it})/\tau = & \alpha_0 + \alpha_1 \ln S_{it} + \alpha_2 \ln A_{it} + \\ & \alpha_3 (\ln S_{it})^2 + \alpha_4 (\ln A_{it})^2 + \alpha_5 (\ln S_{it} \times \ln A_{it}) + \boldsymbol{\beta}^T \mathbf{X}_{it} + u_{it} \end{aligned} \quad (7)$$

where the function $f(\cdot)$ of (5) is now expressed explicitly in terms of both the levels of size and age, and of their squares and interactions, all expressed in natural logarithms as in (7), a specification adopted in several previous studies e.g. Brock and Evans (1986). \mathbf{X}_{it} is a vector of variables ($FS_{it}, EN_{it}, IMR_{it}$) and $\boldsymbol{\beta}$ is a conformable vector of estimable coefficients (with T denoting transpose). \mathbf{X}_{it} includes: vectors of firm-specific variables (FS_{it}), and environmental variables (EN_{it}), and a term to correct for sample selection bias (IMR_{it}). This IMR_{it} is the inverse Mill's ratio ("hazard rate") computed from a binary probit model of survival (see Equation 8). This model for the cross-section ($i = 1, \dots, N$) is written:

$$y^*_{it+\tau} = \mathbf{Z}_{it} \boldsymbol{\gamma} + v_{it} \quad (8)$$

where $y^*_{it+\tau}$ is a latent variable defined by the binary variable $y = 1$ ('survival') if the firm has survived until the second-stage interview at time $t + \tau$ (and $y = 0$ otherwise). \mathbf{Z}_{it} is a row vector containing the main variables thought to affect the survival of Chinese private firms over the period 2004-06 (e.g. preceding growth rate, gearing, cash flow problems, customer orientation, size in terms of sales and

¹⁷ This involves evaluating the ratio of the normal density function to the cumulative normal density function, see below.

employment and sector). γ is a conformable vector of coefficients to be estimated, and v_{it} is the error term. An estimate of γ is reported in Table 2 below.

5 Estimation

This section reports on: a survival equation (cf. Equation 8) for selectivity bias corrections; a basic size-age-growth model (cf. Equation 5) as a reference point (for current literature, and further developments); and then our own ‘comprehensive’ growth model (cf. Equation 7), which extends the scope of the basic model to strategic and (commercial not biological) environmental variables. Heckman’s (1979) two-step selection model is employed to estimate the growth equations. We proceed as follows. First, using size/age and growth data between 2004 and 2006, and other pertinent variables (e.g. gearing, cash flow, customer orientation), maximum likelihood estimates of a binary probit model of small firm survival (Equation 8) provide us with a satisfactory selection equation ($N = 83$). Second, the ‘basic’ size-age-growth model, in ‘stripped down’ form (Equation 5), is estimated by generalized least squares (GLS), with sample selection bias correction, using the data of surviving firms ($N = 76$). Third, our ‘comprehensive’ growth model (Equation 7) is estimated by similar methods, but using a more general framework than the previous model, incorporating both firm-specific variables (e.g. *Planning*, *R&Dorient*, *CustomerOrient*) and environmental variables (e.g. *Elasticity*, *Competition*, *Location*).

5.1 The Survival Model

The selection model (the probit model of small firm survival, as in Equation 7) is estimated by the method of maximum likelihood, using quadratic hill climbing, with (Huber/White) standard errors and covariance. The explanatory variables are: previous annual employment growth rate since inception (*GrowthEmploy0*); equity gearing (*Gearing*); cash flow problem since inception (*CashFlowProb*); customer

orientation (*CustomerOrient*); full-time employment at the time of first-stage interview (*SizeEmploy04*); total net sales in 2003 (*sales03*); and *Sector* (see Table 2).

Table 2 The Probit (Survival) Model (N=83)

Variable	Coefficient	Std. Error	z-Statistic	Prob
Constant	-60.566	17.502	-3.460	0.0005**
<i>GrowthEmploy0</i>	59.111	17.083	3.460	0.0005**
<i>Gearing</i>	-26.728	9.0462	-2.954	0.0031**
<i>CashFlowProb</i>	-46.014	16.292	-2.824	0.0047**
<i>CustomerOrient</i>	6.5743	1.9394	3.389	0.0007**
<i>SizeEmploy04</i>	0.2910	0.1025	2.836	0.0046**
<i>Sales03</i>	-0.0008	0.0006	-1.287	0.1979
<i>Sector</i>	15.652	7.5728	2.066	0.0387*
Log likelihood		-2.5741		
Restr. Log likelihood		-19.712		
McFadden R-squared		0.8694		
LR statistic (6 df)		34.275		
Probability (LR stat)		0.0000		

*Note: Significant at less than 1% (**), 1-5% (*).*

In Table 2, we observe that the overall fit of the model is good. Using the restricted and unrestricted log likelihood of Table 2 to perform a Lagrange multiplier (LM) test of the significance of the full coefficient set, produces a test statistic (34.275) which is highly statistically significant (prob value = 0.000). It is also

noteworthy that all the variables, with the exception of *Sales03* are statistically significant¹⁸.

Since Penrose (1955) it has been suggested that past growth can generate future growth. Similar arguments have since been advanced by Anslow (1994) and Abouzeedan (2001), suggesting that survival itself might be predicated on prior growth rates. These findings are confirmed in our study by the positive and highly significant coefficient on the employment growth variable (*GrowthEmploy0*), which itself is expressed in terms of the annual growth rate since inception. Nonetheless, the effect of size *in general* on survival is equivocal. When the size is measured by full-time employment, as in the early study of Mansfield (1962), then the smaller is the firm, the more likely it is to fail. However, this result does not seem to be robust to changes in the size measure e.g. if the size measure is sales, like total net sales. In our model of Table 2, the coefficient on sales, measured as total net sales in the year 2003, (*Sales03*), is positive but not statistically significant. This may be because of the difficulty that arises in collecting accurate data on receivables from Chinese private firms. Chinese entrepreneurs/owner-managers are notoriously shy (even evasive) about revealing the level of their receivables. It is also possible that with larger receivables come larger risks, especially if the private firms in this situation are 'over trading'. Along with this can come cash flow problems, debt servicing crises, quality degradation, and so on, all of which will lower the chances of survival.

It is observed that *Gearing* (viz. debt/equity as measured at the first-stage interview) has a significant (prob value = 0.003) and negative coefficient (-26.7). High gearing may put a firm in a higher risk class, which will raise the price of

¹⁸ Finally, using the Expectation-Prediction matrix for the probit of Table 2, the % Correct is as high as 96.92% and the Percent Gain from default (constant probability) specification reaches the level of 66.67%, which suggests that the specification of the selection model is statistically satisfactory. See Yi (2002) on diagnostic interpretation.

finance capital by a rise in the risk premium, and may also lead to rationing of finance capital, which can make matters worse, by exposing firms more to cash flow crises. In a different context, a similar result was reported by Reid (1991), who found that a 1% reduction in gearing would increase the survival rate of a typical Scottish small firm by 0.19%.

Apart from financial health (e.g. low gearing), Table 2 indicates that competitive strategy is of importance to the survival of Chinese private firms. Good customer orientation (*CustomerOrient*), as emphasized by Porter (1980, 1985), is found to have a positive (+6.57) and highly significant (prob value = 0.0007) impact on survival. Although we know from Table 1 that these Chinese private firms are not yet highly 'customer driven' in their conduct, these estimates indicate that what *is* going on is having a positive impact already: firms which meet customers' expectations *are* more likely to survive. The industrial sector (*Sector*) has a positive and significant (at the 5% level) impact on survival. This suggests that firms in the manufacturing industries may have a higher probability of surviving than do those in non-manufacturing sectors. This is not always so in models of this sort (cf. Power et al, 2005), and is noteworthy, given that this region has a high reputation in manufactures.

However, the main purpose of the selection equation is not as a sophisticated and complex survival model, but as a statistical device to detect, and to correct for, sample selection bias. To this end, the inverse Mill's ratio was calculated from the probit estimate of Table 2, and added to the regressors of (X_{it}) in the growth Equation (7).

5.2 The Basic Size-Age-Growth Model

Our ‘basic’ size-age-growth model was estimated using the data from 76 surviving firms at the second-stage interview. Initially, our independent variables included, in addition to the employment size (*SizeEmploy04*) and age (*Age04*), the squared and interaction terms of these size and age variables (*SizeSq*, *AgeSq*, *SizeAge*). The latter performed badly in estimates. A correlation matrix analysis revealed that the first order (i.e. levels) of size and age were highly correlated with their second order (i.e. squared) and interaction terms: e.g. $\rho(\text{LnAge04}^2, \text{LnAge04}) = 0.956^{**}$; $\rho(\text{LnSizeEmploy04}, \text{LnSizeEmploy04}^2) = 0.979^{**}$; $\rho(\text{LnSizeEmploy04} \times \text{Age04}, \text{LnAge04}^2) = 0.839^{**}$, where $\rho(\cdot)$ denotes correlation coefficient, and ** denotes significant at less than 1%. Therefore interaction (i.e. cross product) variables and quadratic variables were dropped.

[Table 3 near here]

In Table 3 we report a basic size-age-growth model, which, because of high multi-collinearity between the size and age interaction and the quadratic terms, has been ‘stripped down’ to size and age variables alone, which are just in levels, plus further variables. The R^2 is satisfactory (0.255) for a cross-section model of this sort, and the F-statistic (3.506) is highly significant (prob value = 0.008), indicating a good overall fit of this model. The significance levels for the coefficients are unambiguously indicative, and therefore very revealing, in an empirical sense. The inverse Mills ratio (*IMR*)¹⁹, derived from the probit of Table 2, is not statistically significant, suggesting, as often with cross-section models of this type, that bias due to sample selectivity is not important here.

¹⁹ In general, the IMR is computed as $\varphi(\mathbf{Z}\gamma)/\Phi(\mathbf{Z}\gamma)$ for $y = 1$, and the same expression minus unity for $y = 0$, where φ is the normal pdf and Φ is the normal cdf, from the probit $y = \mathbf{Z}\gamma + v$

Table 3 The ‘Basic’ Size-Age-Growth Model (N = 76)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
<i>Constant</i>	0.3896	0.1212	3.213	0.0023**
<i>LnSizeEmploy04</i>	-0.0376	0.0175	-2.148	0.0365**
<i>LnAge04</i>	-0.0745	0.0362	-2.056	0.0449**
<i>Sector</i>	0.0477	0.0634	0.752	0.4555
<i>Location</i>	-0.1161	0.0557	-2.084	0.0422*
<i>IMR</i>	-0.0033	0.0033	-0.985	0.3292
R-squared	0.255	F-statistic	3.506	
Adjusted R-squared	0.182	Prob (F-statistic)	0.0084	

*Note: Significant at less than 1% (**), 1-5% (*).*

Most obvious, in terms of interpretation of the results in Table 3, are the negative and highly significant coefficients on size and age. These results refute the simple Gibrat Law (1931) and support the Javonovic (1982) learning model. Thus the smaller and younger private firms are observed to grow faster than the older and larger private firms. Again, as is common in such cross-section models, the sectoral dummy is not significant, suggesting high mobility of capital and labour between sectors.

Of particular note, given the observation (see Table 1) that about 40% of the private firms are in manufacturing (i.e. with a one-digit CNSIC code of C), is the negative (- 0.116) and significant (prob value = 0.02) coefficient on the *Location* variable. This suggests that these private firms grow faster if they are located outside the capital city of Guangzhou. This kind of effect is not unknown. For example, Smallbone *et al.* (1993) have found that location influenced the growth rates of small firms significantly. Storey (1994) has argued that British firms located in accessible

rural areas have higher growth rates than those in urban or remote rural areas. In our case, the reasons for this may be as follows. First, running a business in Guangzhou, the political and economic centre of the Province, entails the highest operating cost. To illustrate, land has become so expensive that most manufacturing firms have had to move out of the capital city. Second, the small and medium sized cities around Guangzhou (e.g. Shenzhen, Dong Guan) have successfully developed industry clusters within their locale. For example, the city of Shenzhen is now the leading financial centre of southern China, and the city of Dong Guan is now the principal manufacturing centre for electronics in China. Therefore, it is perhaps not surprising to see firms outside Guangzhou experiencing growth benefits arising from cheaper operating costs and external economies of agglomeration.

5.3 The 'Comprehensive' Growth Model

Finally, and most importantly, we conclude this section on Estimates by reporting on what we have labelled a 'comprehensive' growth model. This incorporates not only the familiar size and age specification deriving from Equation (4), which we have found to be robust for our sample of Chinese private firms, but also: (a) firm-specific (FS) variables like planning (*Planning*), the degree of R&D orientation (*R&Dorient*), and the degree of customer orientation (*CustomerOrient*); as well as (b) commercial and business environmental (EN) variables like the customers' sensitivity to price cutting (*Elasticity*), the degree of market competition (*Competition*), industrial sector (*Sector*) and locational choice within the Province (*Location*). Last, the inverse Mill's ratio (*IMR*) computed from Equation (7), as reported in Table 2, is included as a regressor to correct for possible sample selection bias. These additional independent variables, FS and EN, are gathered into the

partitioned vector of variables (FS_{it} , EN_{it} , IMR_{it}) which is consolidated into the vector X_{it} in general. The latter is pre-multiplied by the conformable vector of coefficients β in the cross-section model specified by Equation (9):

$$(\ln S_{i,t+\tau} - \ln S_{it})/\tau = \alpha_0 + \alpha_1 \ln S_{it} + \alpha_2 \ln A_{it} + \beta^T X_{it} + u_{it} \quad (9)$$

Where $i = 1, 2, \dots, N$ with N being the number of firms in the cross-section, $t = 2004$ and $\tau = Age04$ that is, time from inception to the year 2004. However, as the coefficients of nine regressors are estimated in this growth equation using the relatively small sample size of $N = 76$, one must be alert to potential problems arising from multicollinearity. Our diagnostic approach is to regress, in turn, each of the regressors on the remaining regressors to obtain values of R^2 from which we can calculate the so-called ‘variance inflation factor’ (VIF)²⁰ to measure the degree of multicollinearity. The values of VIF for each regressor are as follows: *SizeEmploy04* (3.9669), *Age04* (2.6008), *Planning* (2.4669), *R&Dorient* (1.6963), *CustomerOrient* (2.4257), *Elasticity* (1.3536), *Competition* (3.0947), *Sector* (1.3837), *Location* (1.7820), and *IMR* (1.6397). As all the VIF values are well below 10 (see Yi, 2002, on diagnostic interpretation), multicollinearity is not viewed as a major problem here.

[Table 4 near here]

²⁰ The variance inflation factor (VIF) for the i 'th regressor X_i is $1/(1 - R_i^2)$, where $i = 1, 2, \dots, K$. When X_i is highly correlated with the remaining regressors, its variance inflation factor will be very large. When X_j is orthogonal to the remaining regressors, its variance inflation factor will be 1.

Table 4 The ‘Comprehensive’ Growth Model (N = 76)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
<i>Constant</i>	0.2570	0.1788	1.437	0.1618
<i>LnSizeEmploy04</i>	-0.0682	0.0327	-2.085	0.0463*
<i>LnAge04</i>	-0.1014	0.0368	-2.755	0.0102*
<i>Ln(Planning)</i>	0.1095	0.0892	1.227	0.2298
<i>Ln(R&Dorient)</i>	-0.1445	0.1215	-1.188	0.2446
<i>Ln(CustomerOrient)</i>	0.2498	0.1012	2.468	0.0200*
<i>Ln(Competition)</i>	0.1850	0.1674	1.104	0.2787
<i>Ln(Elasticity)</i>	-0.0792	0.0585	-1.354	0.1863
<i>Location</i>	-0.1689	0.0691	-2.444	0.0211*
<i>IMR</i>	-0.0007	0.0041	-0.191	0.8497
R-squared	0.510	F-statistic		3.248
Adjusted R-squared	0.353	Prob (F-statistic)		0.0079

Note: Significant at less than 1% (**), 1-5% (*).

Thus, we may put aside concerns about multicollinearity and proceed to consider our ‘comprehensive’ growth model, as estimated with White’s heteroscedasticity-consistent standard errors and covariance. The regression estimates, and associated diagnostics, are displayed in Table 4. With additional regressors, compared to the ‘basic’ size-age-growth model of Table 3, it is perhaps no surprise that the fit of the comprehensive growth model of Table 4 is much better ($R^2 = 0.51$), with over 50% of variation being explained. The overall fit of the model, as indicated by the F-statistic (3.25), is highly significant (prob value = 0.0008). Given that *Sector* is not significant in the ‘basic’ model (of Table 3), this variable has now been dropped in the ‘comprehensive’ model of Table 4. We note again that the *IMR* is not significant in

this model: there is no evidence for sample selection bias in the ‘comprehensive’ model of Table 4.

As in the ‘basic’ model, the coefficients on the logs of the size and age variables (*SizeEmploy04*, *Age04*) in the ‘comprehensive’ model are negative and highly significant. This finding is very robust. Given the log-linear specification for all but the *Location* and *IMR* variables, the corresponding estimated coefficients are interpretable as elasticities. We therefore can conclude also that the negative impact of age (*Age04*) on growth (- 0.10) is somewhat stronger than is the negative impact (- 0.07) of size (*SizeEmploy04*). However, the variables age and (to some extent) size, are not entirely controllable, whereas most of the firm-specific (*FS*) and commercial environment (*EN*) variables are highly controllable.

We find that of the additional variables we have proposed for the comprehensive model, only one, namely customer orientation (*CustomerOrient*), has a significant impact (Prob. Val. = 0.02) on the growth of these private firms, and this impact is positive (+ 0.25). Further, the impact of this variable is the greatest of all the variables in this model, adopting the interpretation that coefficients in this log-linear model can be interpreted as elasticities. Thus, from Equation (9) and Table 4 the elasticity of growth with respect to customer orientation is given by:

$$\eta_{co} = [\partial (GrowthEmploy0) / \partial (CustomerOrient)] \div [(GrowthEmploy0)/(CustomerOrient)] = 0.25 \quad (10)$$

For example, if a private firm’s customer orientation were to improve from weak to strong (a fifty per cent improvement on our calibration) this would result in an increase of growth of nearly thirteen per cent. Indeed, for some SMEs, this magnitude may even be sufficient to offset, restrain or defer, in the short run, the relatively irresistible effects of age and size, in the long run, of reducing growth. This has

important policy implications from the standpoint of small business counselling. For example, it suggests introducing new training regimes which aim to increase the customer orientation of owner-managed Chinese private firms in Guangdong Province (and, if this area proves to be an exemplar case, in other Provinces).

In other respects, the conclusions derived from Table 4 resemble those of Table 3, in that size and age have negative and highly significant impact on growth, that location in the capital city is negatively associated with growth, and that there is no evidence of sample selectivity bias (with the prob. value on the *IMR* coefficient being 0.85).

Although business planning (*Planning*), R&D orientation (*R&D orient*), competition (*Competition*) and price elasticity of demand (*Elasticity*) do not have significant coefficients, they are both useful as control variables in our ‘comprehensive’ model, and indicative of what sort of model formulation could be relevant in a larger sample study than we have been able to undertake on our limited research budget.

Meanwhile, our findings on the significance of being a customer orientated private firm if you wish to grow is noteworthy for its high statistical significance, high elasticity of impact on growth, and its ‘controllability’ (in that it is an aspect of small firm management that is amenable to training, and thereby to change of attitude, and ultimately of outcome).

6 Conclusion

This paper has examined the impact of key variables on the growth of a sample of 83 Chinese private firms. The data were collected by fieldwork conducted in the Guangdong Province, arguably the most market oriented province of China. This fieldwork involved face-to-face interviews with owner-managers, using an

administered questionnaire. Owner-managers were approached using personal connections, in the 'guang xi' tradition of business networking. The fieldwork was undertaken over the three months of September to December 2004, and then a set of brief follow-up interviews was conducted with the surviving firms in February 2006, in order to acquire additional data necessary for correcting for potential sample selectivity bias. Two cross-section models were estimated on the fieldwork data: a 'basic' size-age-growth model inspired by current research in this area; and a 'comprehensive' growth mode, with (in addition to the size and age variables) two types of control variables, firm-specific (e.g. use of planning, customer orientation) and commercial environmental variables (e.g. intensity of competition, degree of price sensitivity of demand). Estimation was by log-linear regression using the two-step model of Heckman (1979) to deal with sample selection bias, and with adjustment for heteroskedasticity undertaken using the procedure of White (1980).

Broadly, our findings are: (a) to refute the simple Gibrat (1931) ('law of proportionate effects') model; (b) to support the Jovanovic (1982) ('learning by market experience') model; and (c) to extend the class of models that has emerged from the two above to a 'comprehensive' model of small firm growth, with additional control variables that augment the 'basic' size-age-growth model with variables which are both *firm-specific*, like the use of business planning, and customer orientation, and *environmental* (in a business or commercial sense), like the intensity of competition, choice of location, and the magnitude of price elasticity of demand.

Our 'comprehensive' model has good statistical properties, and suggests two things of importance, which go beyond what the basic size-age-growth model offers. First, it points to the importance of locational choice for small firm growth. Other

things being equal, moving from a location in the capital city of Guangzhou to another location in the province (which typically would be to a city like Shenzhen, or Dong Guan) would raise the prospective growth rate of a private business in this Province. Second and probably more important quantitatively and strategically (e.g. from a policy standpoint), improving the customer orientation of a firm has a significant and positive impact on growth.

The reasons for this first effect are probably a mixture of internal economies (e.g. lower input costs, like rental costs and wages) and external economies (e.g. positive spillovers, as is evident in a city like Dong Guan specializing in microelectronics). As regards the second effect, it is a notorious shibboleth of enterprise policy makers that firms which are planning-led do not sufficiently take account of their customer's interest. This is still evident in Europe, with the 'new accession' countries to the EU (e.g. Hungary, the Czech Republic) still shaking off the shackles of dirigisme; and it was previously a feature of Western countries emerging from the planning regimes of World War II (e.g. the UK) which arguably suffered 'entrepreneurial failure' until the 1980s. In looking at, and learning from, such historical experience, private firms in China will need to adapt to a more customer-driven approach if they are to achieve greater growth – otherwise they face an inexorable tendency for their growth rates to fall as they age and/or their size increases.

Appendix

Definition of Variables Used in Main Text

ENDOGENOUS VARIABLES

<i>GrowthEmploy1</i>	Annual growth rate of employment between 2004 and 2006
<i>GrowthEmploy0</i>	Annual growth rate of employment from inception to 2004
<i>GrowthSales0</i>	Annual growth rate of sales from inception to 2003
<i>GrowthAsset0</i>	Annual growth rate of assets from inception to 2003
<i>Survival</i>	=1 survivor in 2006, 0 otherwise

EXOGENOUS VARIABLES

<i>SizeEmploy04</i>	Number of full-time employees in 2004
<i>Age04</i>	Number of years from inception to 2004
<i>Sales03</i>	Total net sales in 2003
<i>SizeEmploy0</i>	Size in terms of full-time employees at financial inception
<i>SizeSales0</i>	Size in terms of total net sales at financial inception
<i>SizeAssets0</i>	Size in terms of total net assets at financial inception
<i>IMR</i>	The inverse Mill's ratio
<i>Planning</i>	Number of plans undertaken
<i>R&Dorient</i>	The degree of R&D orientation: strong (3), weak (2), none (1)
<i>CustomerOrient</i>	The degree of Customer orientation: strong (3), weak (2), none (1)
<i>CashFlowProb</i>	=1 if experiencing cash flow problems since inception, 0 otherwise
<i>Elasticity</i>	The price elasticity of demand when price decreases 5%, <i>ceteris paribus</i> , elastic (4), unitary (3), inelastic (2), perfectly inelastic (1)
<i>Competition</i>	Description of market competition: weak (1), medium (2), strong (3)
<i>Sector</i>	=1 if a firm locates in manufacturing industries (one-digit CNSIC code is C), 0 otherwise
<i>Location</i>	=1 if firm located in Guangzhou, 0 otherwise

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