The Size Distribution of Chinese Manufacturing Firms: From the Perspective of Industry Life Cycle

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Abstract

Using panel data of Chinese manufacturing firms between 2003 and 2008, this paper aims to examine the evolution of firm size distribution (FSD) as the industry goes through its life-cycle. The results reveal that during the life-cycle process, China's manufacturing firms' average size becomes larger then shrinks, and the degree of firm size heterogeneity and industry concentration increases all the time. Empirical results also indicate that the change rate of FSD is affected by firms' net entry rate into industry. When net entry rate is higher, average firm size's growth rate is smaller, while size heterogeneity and industry concentration rises more dramatically.

Keywords: firm size distribution, industry life cycle, manufacturing industry

1. Introduction

Firm size distribution (FSD) has attracted increasing focus of attention in the research of industry dynamics, as it can shed some light into the market structure of the industry, and aids in understanding the mechanism of industry evolution.

Researches on FSD are concentrated on developed countries. There exist two classical theories, which are the Giblrat's law and Pareto law (Gibrat, 1931; Simon, 1958). They respectively conclude that FSD will approach the lognormal distribution or a Pareto distribution in a long term. Many empirical studies using data of different counties are carried out to testify the above theories. Some suggest that the Pareto index is close to 1 in free competitive market, which called Zip'f distribution (Fujiwara, Di Guilmi, Aoyama, Gallegati, and Souma, 2004). However, recent empirical tests claim that the above facts does not hold true when taking more complete data and more sophisticated analyzing tools into consideration. Characteristics of firm growth are more complicated than a random walk process, and behaviors of firm entry and exit in industry evolution are influenced by many factors. Based on this, more and more elements affecting FSD is explored. Lotti and Santarelli (2004), as well as Reichstein and Jensen (2005), after investigating different industries in Italy and Denmark, both point out that convergence of FSD are significantly affected by features of industries. Cabral and Mata (2003), basing on the study of Portuguese manufacturing firms, argues that in the early period of industry development, growth of small firms are impeded by financial constrains, which leads FSD a deviation from the lognormal. However, the impact of financial constraints weakens gradually as the industry develops. Kang, Jiang, Cheong, and Yoon (2011) observe the FSD for Korean firms, and find that the upper tail of the Korean FSD can be described as power-law distributions, but it derives in financial crisis period. Thus the paper concludes that the FSD changes over time, and Zipf's law is not universal but does hold as a special case.

Due to data constraints, domestic studies about FSD appear only these years. Shi (2010) examines the size distribution of Chinese industrial firms, and indicates that the Chinese FSD is mostly belonged to lognormal, being consistent with the Gibrat theory. However, there shows new characteristics in China's FSD, like lacking of large firms, low degree of market concentration, and unbalance development between different industries. Yang, Li, and Fang (2010) estimate the Pareto index of FSD using different provinces' data in China. They suggest that FSD in China is significantly deviated from Zipf's Law, and the main reason is some large-scale stated-owned firms fostered by government distort market's competition mechanism. Using samples of China's large and medium size manufacturing enterprises (LMEs), Fang and Nie (2010) tests the size distribution of Chinese firms, and the results show that the FSD deviates Zipf's law, mainly owing to the existence of state-owned enterprises (SOEs).In detail, the entry and exit barriers set by government, the unfair competition between SOEs and private enterprises, together weaken the competition mechanism in industry, and lead to FSD a deviation from Zipf's law. Zhang and Meng

(2010), by using the data of all the listed companies from 1997 to 2008, study the Burr distribution and the generalized extreme value distribution, and find that the FSD of Chinese firm follows Burr distribution.

From the above studies, we find that the shape and convergence trend of FSD has been a focus of attention. However, most studies above only casually chose a period of time to observe FSD, and researches mainly assume that the industry has developed into a stable and mature stage, so testing the convergence shape of FSD statically is paid high attention on. Nevertheless, this is far from enough to describe the actual evolution of FSD during the whole life-cycle of an industry. In fact, the industry life-cycle theory clearly states that when the industry goes through stages of its life-cycle, firm behaviors and industry characteristics will show obvious periodic features, such as firm entry and exit behavior. Hence, by influencing the number of firms inside industry and firms' growth rate, these features will certainly lead to a significant evolution of FSD along with the general evolution of the industry. Dinlersoz and MacDonald(2009) analyzes the distribution of output and employment across firms in US manufacturing industries from 1963-1997, and confirm that the FSD evolve in a way that depends on the phrase of the industry life cycle, and the evolution of the distributions are more dramatic when life cycle itself unfolds more dramatically. However, due to the different industry environment between developed and developing countries, this principle does not necessarily hold true in China. Therefore, this paper uses panel data from 2003 to 2008 of Chinese manufacturing firms to survey the evolutionary trend of FSD in China.

The rest of the paper is organized as follows. The methodology and data are described in section 2. Statistical results describing characteristics of FSD evolution is represented in section 3, and section 4 demonstrates an empirical test. In Section 5, we conclude with a discussion of statistical and empirical results with policy implications.

2. Data and Methodology

2.1 Data

This paper uses data of 4-digital industries according to "Industrial classification for national economic activities". Data of firm size are gathered from "China Industry Business Performance Database". This database contains a big range of data in firm level, such as output value, total assets, and employment number, which provides original data we need for our study.

However, because the "Industrial classification for national economic activities" was revised in 2002, the 4-digit industry classification was different after 2003. Hence, in order to retain more data and keeping data up-dated, samples from 2003-2008 are chosen for research. After excluding samples that lacking data or maintain illogical data, about 170,000 observations in 6 years are finally taken to use. In addition, some data in industry level, such as annual industrial output value, are directly collected from the National Bureau of Statistics of China.

2.2 Identification of the Industry Life-cycle Stage

Industry life cycle can be divided into 4 stages, including initial stage, growth stage, maturity stage and decline stage. However, it takes a long time for a single industry to go through all these stages, and it's difficult to get data for such a long duration. With the aim of solving this problem, the article adopts the method used by Dinlersoz and MacDonald (2009), which divides all samples in to 4 groups including initial, growth, mature and decline group according to the life-cycle stage the industries are experiencing during the sample period, then characteristics showed by different groups are used to represent the features when industry goes through this stage. Electronic computer industry is used to test the robustness in Dinlersoz and MacDonald's article, and it has confirmed that the method gives reasonable results while solving the problem of lacking data for a long duration.

Identification of industries' life-cycle stage refers to Fan (2002), recognizing industry life-cycle stage by relative output growth rate. In detail, from 2003 to 2005 and from 2006 to 2008, average annual growth rate of each 4-digit industry sample' output is compared to that of national total industrial output respectively. If an industry's output grows more slowly than total national industry output in the first 3 years, then faster in the last 3 years, it can be recognized as in initial stage. On the opposite, if grows faster in first 3 years then grows more slowly later, in mature stage. If grows faster in both period, in growth stage, and if more slowly in both, in decline stage.

Average annual growth rate of national total industry output from 2003-2005 and 2006-2008 is 12.57% and 11.94% respectively. Average annual growth rate of samples are summarized in Table 1.

Stages	Number of	Average annual growth rate of Chinese 4-digit manufacturing industries (%)						
Industries are in	4-dıgıt Industries	Fror	From 2003 to 2005 From 2006 to 2008					
uic in	maastries	Mini	Max	Mean	Mini	Max	Mean	
Initial	49	-30.13	11.69	1.47	13.77	191.97	36.15	
Growth	268	12.14	204.90	38.99	12.72	115.55	31.56	
Mature	22	15.40	83.39	41.01	-11.14	12.47	7.30	
Decline	9	-21.46	7.18	-1.07	-2.07	10.97	7.01	

Table 1.	Identification	results of Ch	ninese manu	afacturing	industries'	life-cycle stage

Table 1 shows that, after removing some samples not in clear stage,348 samples are ultimately available, including 49 in initial stage, 268 in growth stage, 22 in mature stage, and the rest 9 in decline stage. Industries in growth stage account for over 3/4 of all the samples, which hints characteristics of Chinese manufacturing industries in growth stage is worth of paying attention.

Apart from identifying by growth rate, another common identification method of industries' life-cycle stage is based on firm entry and exit. Behavior of firm entry and exit is considered as a significant feature in industry evolution, and firm number is expected to increase first and then decrease (Zhang, 2007). In order to further understand the characteristics of Chinese manufacturing industry, this paper, basing on the results of growth rate classification, calculates the average net firm entry rate from 2003 to 2008 for each group. Results are shown in table 2.

Table 2. Average net firm entry rate of Chinese manufacturing industries in different life-cycle stages

Industry Life-cycle Stage	Initial stage	Growth stage	Mature stage	Decline stage
Net Firm Entry Rate	63.40%	126.11%	55.19%	11.98%

Table 2 shows the average net firm entry rate of Chinese manufacturing industries is always above 0 in 4 stages. Entry rate of growth stage is 126.11%, which is the highest of all. That of initial and mature stage is between 55% and 65%, and that of decline stage is 11.98%. It's supervising to find that Chinese manufacturing industry attracts many firms to enter in when it goes through its decline stage, because traditional life-cycle theory claims that a large number of firms would exit the industry in this stage. Taking into the specialties of the samples into consideration, we think there are two possible reasons as follows: firstly, as shown in table 2, we only get 9 sample industries in decline stage, which only occupies 2.59% of all samples. In other words, samples in decline stage may be too little to reflect the characteristic of decline stage completely. Secondly, we can also discover from table 2 that, average growth rate of declining industries is -1.07% in the first 3 years and 7.01% in the last 3 year. Though declining industries always grow more slowly than national industry, they grow much faster in the last 3 years than the first. The increase of growth rate may profits from firms' innovative activities in order to maintain revenues. The innovation theory points out that the innovative activities may significantly postpone the arrival of decline stage, or may even help some industries get rid of recession and leap into a rapid growing stage again. Hence, an upward turning point of growth rate in declining industry is very likely to suggest that the industry will go into prosperity again, and thus may attracts a number of firms to enter in.

The above reasons make it possible for declining manufacturing industries in China has a positive net firm entry rate. However, comparing growth rate of 4 different stages, growth rate in decline stage is the least, so it is still consistent with the logic of relative decline.

2.3 Measurement of FSD

2.3.1 Measures of Firm Size

Common measurements of firm size can be classified into two categories. One is based on the production scale, like measuring firm size by employment number (Nkurunziza, 2008), total assets (Chen and Xing, 2003), or total production (Datta Mago and Dechenaux, 2009). Another is related to operating scale, like measuring firm size by sales (Zhu, 2006), revenue (Demirel and Mazzucato, 2009), or client numbers (Chowdhury, 2010).

As operating data is vulnerable to accidental factors and is easy to fluctuate in different years, it's not suitable to use operating index to measure comparatively stable firm size. Hence, we finally chose 3 production indexes to measure

firm size, which are total assets, total output value and employment number. Distributions of the three are observed one by one and compared to each other in analysis, which further ensures robustness of our conclusion.

2.3.2 Measures of Size Distribution

Generally, distribution curve map is the most direct way to observe the shape of FSD. However, distribution map is stationary, so it's not an ideal method to explore the evolution of FSD. Another way to demonstrate FSD is to use related statistical indicators. Statistical indicators can reflect tiny changes in FSD precisely, and are also helpful for revealing the essence of FSD. Thus 3 groups containing 2 statistical indicators each as follows are chosen to measure the shape of FSD.

The first group contains the mean (μ) and the median (M), together reflecting the average firm size of Chinese manufacturing industry. Details can be seen in formula (1) and (2), where n represents the number of firms inside industry, Xi represents the size of the ith smallest firm in the industry.

$$\boldsymbol{\mu} = \frac{1}{n} \sum_{i=1}^{n} X_{i} \tag{1}$$

$$M = \begin{cases} X_{(n+1)/2} \text{ when } n \text{ is odd} \\ \frac{(X_{n/2} + X_{n/2+1})}{2} \text{ ; otherwise} \end{cases}$$
(2)

The second group contains the standard deviation (σ) and coefficient of variation (CV), revealing the heterogeneity of firm size within industry. The bigger the σ or CV, the higher the degree of heterogeneity is. Details are as follows.

$$\sigma = \sqrt{\frac{\sum (X_i - \mu)^2}{n - 1}}$$
(3)

$$CV = \frac{\sigma}{\mu} \tag{4}$$

The third group contains the coefficients of skewness (sk) and coefficient of kurtosis (kur).Sk reflects the asymmetry of distribution. If the left tail is more pronounced than the right tail, the function is said to have negative skewness (or skew to left). If the reverse is true, it has positive skewness (or skew to right). A distribution with a greater sk is more tend to be skewed to right. Kur is a measure of whether the data are peaked or flat relative to a normal distribution. That is, distribution with high kurtosis tends to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Combination of the two indicators well reflects the proportion of small or big firms within the industry, and further tells the degree of market concentration of the industry. Details can be seen in formula (5) and (6).

$$sk = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{X_i - \mu}{\sigma}\right)^3 \tag{5}$$

$$kur = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{X_i - \mu}{\sigma} \right)^4 \tag{6}$$

Take 2008 for example, we calculate these 6 indicators of FSD for all 2-digit manufacturing industries. Results of assets distribution are in table 3, and output and employment distribution are in table 7 and 8 in appendix.

	Table 3. Asset Distribution of	2-digit Chinese	manufacturing industries	in 2008 (Assets: million	RMB)
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2-digit industries	μ	М	σ	CV	sk	kur
Agricultural and Sideline Products Processing	48.15	13.56	204.35	4.24	22.18	728.17
Food Manufacturing	64.68	17.24	247.01	3.82	16.14	374.61
Beverage Manufacturing	109.89	19.51	627.85	5.71	30.39	1218.32
Tobacco Processing	2838.78	199.63	7716.48	2.72	4.82	28.28
Textile Industry	46.29	13.38	314.95	6.80	107.08	15590.44
Textile Garments, Shoes and Caps Products	31.01	10.62	156.15	5.03	34.01	1538.39
Leather, Furs, Down and Relate Products	35.09	11.25	126.12	3.59	30.23	1519.18
Timber Processing, Bamboo, Cane, Palm Fiber and Straw Products	26.61	8.50	138.06	5.19	44.77	2854.61
Furniture Manufacturing	36.04	12.56	91.71	2.54	10.05	155.77
Papermaking and Paper Products	74.41	13.87	561.91	7.55	27.42	977.99
Printing and Record Medium Reproduction	40.78	14.00	113.21	2.78	11.92	213.77
Cultural, Educational and Sports Goods	33.26	12.23	84.36	2.54	10.71	476.24
Petroleum Processing, Coking and Nuclear Fuel Processing	480.67	33.04	2387.74	4.97	11.06	151.01
Raw Chemical Materials and Chemical Products	97.67	16.14	573.14	5.87	23.75	849.62
Medical and Pharmaceutical Products	120.81	36.39	405.14	3.35	14.73	332.40
Chemical Fiber	165.89	16.24	664.55	4.01	11.29	203.10
Rubber Products	71.05	13.84	371.14	5.22	13.29	209.21
Plastic Products	36.03	11.57	146.48	4.07	24.23	784.22
Nonmetal Minerals Products	58.73	16.48	254.26	4.33	24.09	937.43
Smelting and Pressing of Ferrous Metals	439.30	24.33	4210.93	9.59	25.23	805.70
Smelting and Pressing of Nonferrous Metals	171.68	20.06	1196.72	6.97	22.14	633.28
Metal Products	39.07	12.45	148.61	3.80	24.96	1054.97
General Equipment	52.71	12.76	410.70	7.79	63.41	5925.35
Special Purpose Equipment	68.78	16.30	406.72	5.91	26.89	973.54
Transport Equipment	155.67	18.21	1325.12	8.51	29.21	1156.32
Electric Equipment and Machinery	80.65	16.87	543.62	6.74	39.08	2115.66
Telecommunications, Computer, and Other Electronic Equipment	195.78	26.48	1476.71	7.54	43.27	2671.09
Instruments, Meters, Cultural and Clerical Machinery	67.88	17.57	229.19	3.38	12.66	243.12
Handicraft Article and Other Manufacturing	28.60	9.81	110.01	3.85	25.77	1080.53
Waste Resources and Materials Recovering	50.50	15.30	295.24	5.85	23.93	655.59

Remarks: because of data missing, data of "Smelting and Pressing of Nonferrous Metals" industry is replaced by data of 2007.

Table 3 shows 70% of the Chinese manufacturing industries have an average asset size between 2.5 million to 100 million RMB. Only 9 industries exceed 100 million in u, and only 1 exceeds 100 million in M, which illustrates that Chinese manufacturing firms are too small in scale. As to σ , the minimum is 84.36 and the maximum is 7716.48. Three-fourths of the industries have σ between 100-1000, and most have a CV between 3 to 6, which demonstrates the heterogeneity of Chinese manufacturing industries. Sk and kur are all positive, and we find there exist some connections between the two indicators. The industry which has a higher sk tends to have a higher kur too, but a lower average size. As a high sk and a high kur together reflects a high degree of concentration, it confirms that an industry with a high degree of concentration contains many small-scaled firms inside. We can get similar conclusion when referring to output and employment distributions from table 7 and 8 in appendix.

2.3.3 Analysis Method of the Trend of Distribution Evolution

The goal of this paper is to reveal the evolution trend of FSD when the industry goes through its life cycle. Hence, in order to show the variation tendency directly, we further calculate the change rate of all the 6 FSD indicators from 2003 to 2008, and then make average of industries in the same group so as to describe the characteristic of the corresponding life-cycle stage. Details are as follows.

$$\overline{\Delta Y_k} = \sum_{i=1}^n \left(\frac{Y_{k,i}^{2008} - Y_{k,i}^{2003}}{Y_{k,i}^{2003}} \right) / n \tag{7}$$

Subscript k identifies different indicators of FSD. When k=1~6, Y represents μ , M, σ , CV, sk and kur respectively. The i identifies different 4-digit manufacturing industry. Superscript of Y indicates the year. $\overline{\Delta Y_k}$ finally represents the average growth rate of the kth indicator from 2003 to 2008.

3. FSD Evolution of Chinese Manufacturing Industry

With data of Chinese manufacturing industry from 2003 to 2008, taking assets, output and employment as measurement of firm size one by one, growth rate of 6 indicators in every life-cycle stage are calculated according to formula (1) to (7). The results are shown in table 4.

Table 4. Growth rate of 6 indicators in every life-cycle stage (%)

	Δμ	ΔM	$\Delta \sigma$	ΔCV	Δsk	Δkur
			Based	on asset distr	ibution	
Initial Stage	31.30	21.81	33.42	1.62	29.23	90.50
Growth Stage	50.81	31.85	71.83	13.93	43.73	124.79
Mature Stage	19.90	34.84	33.31	11.19	33.63	91.45
Decline Stage	-19.79	-0.37	8.64	35.44	35.60	46.03
			Based	on output dis	tribution	
Initial Stage	69.85	55.30	63.19	-3.92	7.37	28.10
Growth Stage	104.92	90.05	125.56	10.07	45.45	153.06
Mature Stage	20.52	30.29	31.48	9.09	17.78	46.72
Decline Stage	-11.22	18.53	17.26	32.08	30.48	74.40
			Based	on employme	ent distributio	n
Initial Stage	19.84	-22.91	-20.19	-0.44	11.60	20.53
Growth Stage	-20.14	-30.84	-3.94	20.29	42.66	147.80
Mature Stage	-0.68	-25.22	14.59	15.38	31.68	78.06
Decline Stage	-25.89	-25.83	-6.98	25.52	23.34	75.25

3.1 Changing Trend of Average Firm Size

Average firm size measured by assets and outputs evolve in similar trend. Both demonstrate an upward trend in initial growth and mature stages and a downward trend in decline stage. Both μ and M increases fastest in the growth stage, especially $\Delta\mu$ of assets in growth stage is 104%, which means asset scale of firms in growing industry doubles in 6 years. We have mentioned in table 1 that most of Chinese manufacturing industries are in growth stage, so it means most of the industries have a rapid growth rate of firm size, which is a positive signal for China to resolve the problem of lacking large firms while crowded with too many small firms.

However, employment result is very different from the above two. μ only increases in initial stage, but decreases in all remaining stages. $\Delta\mu$ in growth and decline stage both exceeds -20%. Δ M is always negative for all stages. As China now is in a period of transition, we believe that this is related to the structure upgrading of China's manufacturing industry. Although traditional labor-intensive comparative advantage make Chinese manufacturing industry a rapid development in the last decades, we all believe that in the long term, only firms with high-technology and creativity will have a promising future. Hence, manufacturing firms begin to change from

labor-intensive to technology-intensive or even knowledge-intensive. Consequently, demand for talents or high-skilled employees will increase but the total number of employment may decline at the same time. Therefore, it's no more difficult to understand why Chinese manufacturing firms increase in assets and outputs size, but decrease in employment size.

3.2 Discrete Degree of FSD

Standard deviation (σ) and coefficient of variation (CV) describe the discrete degree of a distribution. Results of $\Delta\sigma$ measured by asset, output and employment differ significantly. σ of asset and output distribution continuously increases when Chinese manufacturing industry goes through its life cycle. Both rise fastest in the growth stage, showing a growth rate of 71.83% and 125.56% respectively. $\Delta\sigma$ in initial and mature stage maintain between 30% and 65%, and that in decline stage is the lowest, which bellows 20%. However, the result of employment is entirely different. σ of employment distribution always demonstrates negative change rate in initial, growth and decline stage, which are -20.19%, -3.94% and -6.98% respectively.

However, it's supervising to find that three sets of CV results are quite similar to each other. As compared to σ , CV excludes the influence of mean, so we conclude that difference of 3 sets of σ derives from unusual variation of average employment number.

Excluding uncommon variation of employment, rest σ s and CVs all maintain positive change rate, indicating the degree of firm size heterogeneity in Chinese manufacturing industry deepens continuously when it goes through its life cycle. Heterogeneity is an important topic in evolutionary economics, which concerns about the impact of heterogeneity on industry innovation. Nowadays, researches reach an agreement that heterogeneity encourages firms to invest in R&D, and will contribute to industry innovation and performance (Greunz, 2004; Sun, 2010). Therefore, it's appropriate to further stimulate and promote the deepening of the heterogeneity degree inside China's manufacturing industries.

In all life cycle stages, rising of heterogeneity is very fast in the second stage. It owes to two characteristics of this stage. First, industry in growth stage always has a promising prospect and attracts many firms to enter. Existing of a variety of firms makes it possible for a high degree of heterogeneity. Second, firms in growing industry are facing more and more fierce competition, so they pay increasing attention on process innovation and firm expansion so as to make most of benefits from economics of scale. During this time, a self-reinforcing mechanism appears. It means the firms beginning earlier to enlarge scale are prone to earlier get benefits which provide enough money to expansion further. Consequently, the big firm becomes large or huge while small firms remain still small. In other words, the gap between small and large firms widened gradually. The above reasons together lead to a rapid increase in degree of firm size heterogeneity when Chinese manufacturing industry in its growth stage. To the contrary, decline stage is considered to narrow down firm heterogeneity. In this stage, many firms are expected to exit the industry, while the survival ones are considered to be all the similar type, which are efficient and full of vitality. However, table 4 shows that Chinese manufacturing firms don't demonstrate negative change rate in standard deviation or coefficient of variation in decline stage. One possible explanation is that Chinese manufacturing industry doesn't show extensive firm exit in decline stage as usual which we have mentioned when explaining table 2, so it denies the premise of reducing heterogeneity. Another reason may be from the efforts of firms trying to increase heterogeneity of their products, service or firms in order to maintain competitive advantage in the decline stage.

3.3 Asymmetry of FSD

Both skewness and kurtosis of Chinese manufacturing FSD change in the similar trend. All results of Δ sk and Δ kur in four stages are above zero and the two indicators show certain of positive correlation. Both sk and kur grow fastest in growth stage, with Δ sk at about 43% and Δ kur between 120% and 155%. Change rate in initial stage is the smallest. Apart from Δ sk of asset distribution, all rest 5 indicators are below 30%. Besides, mature and decline stage show a mild change rate, with Δ sk at about 30%, and Δ kur between 45% and 90%.

Kur and sk increase together means there are increasing small firms in the industry while the impact of few large or giant firms do not diminish, so the concentration rate of industry will increase accordingly. It's generally recognized that there are two modes for an industry to increase the degree of industry concentration. One is to let firms experience full competition, so under the survival of the fittest mechanism, the most outstanding firms develop and expand while the inefficient ones shrink or eliminates. This mode is considered to create a virtuous cycle in development of industry. On the other hand, under some circumstance, government support can also provide opportunities for some state-owned firms to expand quickly. However, this type is not expected to improve performance of the firms or industry, because when supported by government, these firms are no longer necessary to compete with others fiercely, and will lose motivation to reform or innovate. The second method to increase industry

concentration degree is certainly undesirable. In order to investigate the increasing mode of concentration degree of Chinese manufacturing industry, two groups of sample industries are chosen for comparison. The first group contains the industries having a high proportion of state-owned company in sales, which are Tobacco Producing; Petroleum Processing, Coking and Nuclear Fuel Processing; and Smelting and Pressing of Ferrous Metals. Another contains the industries in opposite condition, including Textile Industry; Leather, Furs, Down and Relate Products; and Furniture Manufacturing Industry. According to table 3, we calculate average u, sk and kur for each group. The average u, sk and kur of the first group are 1252.91, 13.70 and 328.33. But when it comes to the second group, the story is quite different. Average u of the second group is 39.14, much lower than the first group, while average sk and kur are 49.12 and 5755.13, much higher than the first group. It means that the highly-concentrated manufacturing industries in China are little invented by government. It confirms the increasing in concentration degree of Chinese manufacturing industry is mainly derived from healthy competition, which is good news for China that wishes to increase concentration degree of manufacturing industry further.

We find that the change trend of concentration degree in decline stage is different from the conclusion in USA (Dinlersoz and MacDonald, 2009), which says that in decline stage, degree of monopoly and concentration drop down. We still consider it relevant to abnormal entry of Chinese manufacturing firms into the industry in this stage.

4. Influence of Firm Entry and Exit to the Change Rate of FSD

From above, we have concluded that FSD evolves when the industry goes through its life-cycle. However, what will affect the evolution speed of FSD? As firm entry and exit is a significant feature in industry's life-cycle, and directly affects firm number of an industry, so we wonder will it have some impact on the change rate of FSD? When an industry has a higher firm entry rate, will it also has a greater change rate in FSD?

In order to clarify the relation between the two, this paper makes a regression described in formula (8). ΔN represents the net firm entry rate of the 4-digit industry from 2003 to 2008. ΔY indicates change rate of above 6 FSD indicators one by one, that are $\Delta \mu$, ΔM , $\Delta \sigma$, ΔCV , Δsk and Δkur . Samples include all 348 industries mentioned in section 2.

$$\Delta Y = b_1 \Delta N + b_0 + \mu \tag{8}$$

The descriptive statistics of the samples are in table 5:

	Δμ	ΔΜ	$\Delta \sigma$	ΔCV	Δsk	Δkur	ΔΝ
Obs	348	348	348	348	348	348	348
			Base	d on asset d	istribution		
Mini (%)	-65.93	-69.53	-75.86	-70.14	-74.93	-950.06	-55.78
Max (%)	409.37	1128.28	1646.58	269.15	1116.37	194377.61	760.31
Mean (%)	31.73	24.54	74.63	26.42	63.05	813.18	120.54
S.D. (%)	52.14	72.73	136.53	49.58	109.18	10419.59	99.24
			Based	l on output o	distribution		
Mini (%)	-49.96	-63.01	-78.82	-70.01	-66.77	-1091.17	
Max (%)	523.76	438.09	4122.32	576.92	1008.97	14617444.13	
Mean (%)	80.66	62.35	137.88	23.61	52.77	42222.09	
S.D. (%)	67.97	57.22	254.41	51.83	94.66	783565.70	
			Based or	n employme	nt distribution		
Mini (%)	-74.75	-91.73	-82.73	-52.44	-3786.21	-396.00	
Max (%)	312.49	75.76	563.77	231.00	636.64	4368.15	
Mean (%)	-18.73	-22.86	-1.16	17.91	40.83	208.66	
S.D. (%)	30.05	19.07	60.20	38.50	222.24	411.30	

Table 5. Descriptive Statistics

Based on E-views 6.0, this paper uses OLS method to make regression one by one. When White heteroskedasticity test is made to avoid heteroscedasticity problem in cross-section regression, we find 5 sets of regression are bothered by the problem, which are $\Delta Y = \Delta \mu$, $\Delta \sigma$, ΔCV , Δkur (under assets distribution) and $\Delta Y = \Delta sk$ (under employment

Table 6. Regression Results

	Δμ	ΔM	Δσ	ΔCV	Δ sk	∆kur
			Based on asset d	istribution		
ΔN	0.0269**	-0.0802*	0.3685**	0.1482**	0.3891**	14.7663**
	(8.8591)	(-2.0475)	(57.8064)	(81.5833)	(7.0339)	(18.8088)
\mathbb{R}^2	0.1849	0.0120	0.9062	0.9506	0.1251	0.5056
			Based on output of	listribution		
ΔN	-0.0808*	-0.1384**	0.1208	0.1090**	0.2613**	195.8434
	(-2.2095)	(-4.6010)	(0.8778)	(3.9684)	(5.2984)	(0.4615)
\mathbb{R}^2	0.0139	0.0577	0.0022	0.0435	0.0750	0.0006
		Ba	used on employment	nt distribution		
ΔN	-0.0498**	-0.0297**	-0.0320	0.0320	-0.4292**	0.8904**
	(-3.1025)	(-2.9138)	(-0.9834)	(1.5375)	(-39.2683)	(4.0916)
\mathbb{R}^2	0.0271	0.0240	0.0028	0.0068	0.8167	0.0462

distribution). Therefore, WLS method is used to modify these results, and the final regression results are shown in table 6.

Notes: Standard deviations in parentheses, significance levels: *<5%, **<1%.

In table 6, 12 groups of regression get effective results under significance level of 5%. Conclusions based on asset, output and employment are similar, and consistent with our expectation, revealing a particular relation between firm entry rate and FSD change rate. In detail, change rate of average firm size is negative to firms' net entry rate. The coefficients are between -0.15 and -0.02, indicating that the more the small firms enter into the industry, the slower the industry's average firm size grows. Second, coefficients of $\Delta\sigma$ and Δ CV are positive, which means an industry with a high firm entry rate, will enjoy a rapid increase in firm heterogeneity. Last but not the least, coefficients of Δ sk and Δ kur are all positive except Δ sk of employment distribution. It suggests that the sooner the firm enters into the industry, the faster the increase of the degree of industry concentration.

5. Conclusion and Suggestions

With data of Chinese manufacturing industry from 2003-2008, this paper examines the evolution of firm size distribution (FSD) as the industry goes through stages of its life cycle. We find that Chinese manufacturing firms' average size increases and then fall down, the degree of firm size heterogeneity and industry concentration increases all the time. Chinese manufacturing industries are crowded with too many small firms but have a low degree of concentration, so it's cheerful to find that most Chinese manufacturing industries are in growth stage, during which, average firm size, firm heterogeneity and degree of concentration are expected to increase quickly. What's more, empirical results also indicate that the FSD change rate is influenced by firms' net entry rate into the industry. When net entry rate is higher, average firm size raises more lowly, while size heterogeneity and industry concentration increases more dramatically. Besides, characteristics of employment distribution are found different from asset and output distribution. It demonstrates new features in transition period when Chinese manufacturing industries are upgrading from labor-intensive to technology-intensive or even knowledge-intensive.

In order to further promote the development of Chinese manufacturing industry, relative measures should be taken by government. The first is to encourage innovation, especially to encourage process innovation of the firms in growing industry so that they can expand quickly and stimulate the increase of average firm size of Chinese manufacturing industry. The second is to reduce administrative barriers for firms to enter into Chinese manufacturing industry. The degree of heterogeneity and concentration will both increase soundly under a high net firm entry rate. The last is to pay attention on education, to foster high-skilled employees, because human-resources are of crucial importance for the upgrading of Chinese manufacturing industry.

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Appendix

Table 7. Output distribution	of 2-digit Chinese	manufacturing industries in	n 2008(Output:million RMB)
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			<u> </u>	-		
2-digit industries	μ	М	σ	CV	sk	kur
Agricultural and Sideline Products Processing	104.90	34.90	413.79	3.94	25.52	1009.96
Food Manufacturing	95.17	27.89	326.48	3.43	13.55	262.23
Beverage Manufacturing	115.51	28.07	495.85	4.29	27.45	1151.19
Tobacco Processing	2877.48	114.13	6618.37	2.30	3.36	12.52
Textile Industry	64.57	24.56	456.42	7.07	133.29	21355.90
Textile Garments, Shoes and Caps Products	51.74	20.62	190.63	3.68	32.92	1592.43
Leather, Furs, Down and Relate Products	68.10	25.12	175.37	2.58	12.52	251.71
Timber Processing, Bamboo, Cane, Palm Fiber and Straw Products	46.57	20.85	144.55	3.10	37.41	2037.07
Furniture Manufacturing	57.05	23.30	134.92	2.36	13.74	337.76
Papermaking and Paper Products	78.65	24.21	343.51	4.37	23.20	775.09
Printing and Record Medium Reproduction	41.43	15.42	96.68	2.33	9.55	136.18
Cultural, Educational and Sports Goods	52.08	20.60	129.78	2.49	12.72	503.28
Petroleum Processing, Coking and Nuclear Fuel Processing	936.56	63.37	5058.40	5.40	10.24	123.10
Raw Chemical Materials and Chemical Products	120.31	30.22	650.93	5.41	37.29	2072.09
Medical and Pharmaceutical Products	120.71	38.51	398.16	3.30	17.84	520.73
Chemical Fiber	195.67	34.03	797.60	4.08	12.00	200.67
Rubber Products	90.96	22.98	437.32	4.81	17.50	396.19
Plastic Products	50.80	19.47	146.48	2.88	22.22	883.49
Nonmetal Minerals Products	68.61	26.60	176.78	2.58	15.59	416.55
Smelting and Pressing of Ferrous Metals	558.26	58.07	3577.26	6.41	19.16	505.81
Smelting and Pressing of Nonferrous Metals	269.64	50.76	1240.87	4.60	19.20	523.10
Metal Products	61.23	21.14	215.46	3.52	30.41	1599.50
General Equipment	66.87	20.15	339.44	5.08	45.72	3239.56
Special Purpose Equipment	75.92	20.61	395.19	5.21	29.92	1307.00
Transport Equipment	173.18	25.84	1502.79	8.68	35.88	1831.04
Electric Equipment and Machinery	118.28	26.06	753.02	6.37	58.68	5070.89
Telecommunications, Computer, and Other Electronic Equipment	323.23	31.73	2876.10	8.90	37.16	1965.81
Instruments, Meters, Cultural and Clerical Machinery	88.89	19.67	409.90	4.61	15.76	334.41
Handicraft Article and Other Manufacturing	52.27	18.09	174.54	3.34	17.83	456.38
Waste Resources and Materials Recovering	104.67	34.87	322.74	3.08	14.73	297.01

Remarks: because of data missing, data of "Smelting and Pressing of Nonferrous Metals" industry is replaced by data of 2007.

Table 8. Employment distribution of 2-digit Chinese manufacturing industries in 2008

2-digit industries	μ	M	σ	CV	sk	kur
Agricultural and Sideline Products Processing	138.19	63.00	395.92	2.87	27.95	1401.86
Food Manufacturing	190.64	86.00	457.31	2.40	13.88	313.28
Beverage Manufacturing	208.91	84.00	693.56	3.32	25.88	1007.14
Tobacco Processing	1267.44	430.00	2549.15	2.01	4.87	30.69
Textile Industry	196.80	89.00	931.31	4.73	119.15	18346.59
Textile Garments, Shoes and Caps Products	251.52	146.00	548.27	2.18	27.45	1312.08
Leather, Furs, Down and Relate Products	316.98	129.00	931.31	2.94	18.11	597.09
Timber Processing, Bamboo, Cane, Palm Fiber and Straw Products	127.30	80.00	251.26	1.97	25.67	1125.90
Furniture Manufacturing	193.85	95.00	383.53	1.98	8.68	118.99
Papermaking and Paper Products	151.76	75.00	347.81	2.29	13.31	276.90
Printing and Record Medium Reproduction	126.57	66.00	318.74	2.52	40.29	2453.86
Cultural, Educational and Sports Goods	276.67	120.00	654.10	2.36	12.09	185.87
Petroleum Processing, Coking and Nuclear Fuel Processing	352.52	68.00	1198.17	3.40	8.90	97.07
Raw Chemical Materials and Chemical Products	152.22	62.00	439.98	2.89	16.97	510.73
Medical and Pharmaceutical Products	231.07	109.00	604.55	2.62	17.65	476.84
Chemical Fiber	222.10	60.00	765.55	3.45	10.27	135.48
Rubber Products	209.26	85.00	551.40	2.64	11.42	193.21
Plastic Products	131.09	65.00	479.93	3.66	67.55	6276.66
Nonmetal Minerals Products	163.39	89.00	313.76	1.92	13.04	303.12
Smelting and Pressing of Ferrous Metals	391.29	81.00	2420.25	6.19	27.06	1058.60
Smelting and Pressing of Nonferrous Metals	233.68	70.00	1036.15	4.43	19.02	492.98
Metal Products	133.28	70.00	282.95	2.12	14.99	432.85
General Equipment	133.59	65.00	332.94	2.49	19.18	667.32
Special Purpose Equipment	154.87	70.00	502.55	3.24	27.13	1099.55
Transport Equipment	237.61	86.00	752.63	3.17	14.71	317.45
Electric Equipment and Machinery	205.15	80.00	699.40	3.41	33.33	1994.03
Telecommunications, Computer, and Other Electronic Equipment	488.16	135.00	2426.94	4.97	47.96	3516.99
Instruments, Meters, Cultural and Clerical Machinery	207.51	78.00	532.87	2.57	9.32	122.70
Handicraft Article and Other Manufacturing	186.21	96.00	342.03	1.84	9.91	192.24
Waste Resources and Materials Recovering	130.64	49.00	1049.94	8.04	31.71	1030.81

Remarks: because of data missing, data of "Smelting and Pressing of Nonferrous Metals" industry is replaced by data of 2007.