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# Measuring Enterprise Performance in China: Do Better Enterprises Get More Resources?

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**Abstract**

This paper develops an analytic framework and related methods for measuring performance of large and medium-sized industrial enterprises in China. The performance is measured on several dimensions including profitability, debt-paying capacity, and productivity. The analytic methods are then applied to a sample of recent firm-level panel data covering the universe of large and medium-size industrial enterprises of all types of ownership in China. A large amount of results have been generated to show detailed patterns and behavior of the enterprises in China. Our preliminary results indicate that better-performing industrial enterprises in China do not seem to get more resources. Our results have important policy implications for China's market-oriented reform. The results reported in this paper illustrates the usefulness of the methods and focuses on a broad issues, such as whether and to what extent China's economic reform so far has improved resource allocation by attracting assets and labor to better performing groups of enterprises. Detailed results on specific topics will be reported in separate papers.

## 1. INTRODUCTION

This paper develops a framework for measuring the performance of China's industrial enterprises based on firm-level accounting data. It focuses on comparing the relative performance across various groups of enterprises as defined by size, industry, region, affiliation, ownership etc. The performance here is examined comprehensively from various dimensions including profitability, financial returns, debt-serving capacity, and productivity. By examining these performance measures, we intend to find out whether better-performing enterprises get more resources.

We develop a set of performance indicators based on the annual accounting statistics of all large and medium-sized industrial enterprises in China. These accounting statistics are submitted to the National Bureau of Statistics of China for the purpose of calculating Gross Domestic Product (GDP) and other industrial statistics by all industrial enterprises classified

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by the government as large and medium-sized. The Chinese government issues standards on how to classify industrial enterprises into different size groups. These standards are based mainly on assets and outputs, vary across industry, and change over time. The National Bureau of Statistics publishes the aggregate statistics, including total number of enterprises and other statistics, for this group of large and medium-sized industrial enterprises. Our study relies effectively on a data set that covers almost the population of a particular group of enterprises and also the most recent data available.

In addition to the performance indicators measured by ratios or other one-dimensional scale variables, we attempted to group enterprises by their profitability, debt-paying capacity, and productivity. By doing so, we are able to examine the changing distribution of the number of enterprises, total assets, and employment among performance groups over time. We have also been able to trace the movement of enterprises from one performance group to another from year to year. The results help us to draw a rich and clear picture of China's large and medium-sized industrial enterprises sector. It should be noted that all performance measures in our study are based on current prices due to the lack of reliable deflators. This would not be a problem for calculating financial indicators. However, it does prevent us from drawing any conclusions about productivity growth or changes in relative productivity over time.

Before using the survey data for analysis, we checked each enterprise in the data set for data inputting error, accounting inconsistencies, and less-than-full operation status. Enterprises with data problems are dropped from our sample. This data cleaning reduces our sample size by about 10%.

We use the cleaned sample to calculate various performance indicators for each enterprise. For a particular enterprise, one or several of the indicators may have extreme values caused either by poor data quality or by other unidentifiable factors. If these extreme values were included in the calculation of the group average of the indicators, the group average could be severely biased. To ensure the robustness of aggregate statistics derived from statistics of each individual enterprise, we identified the influence of the extreme values and coded them as missing values. For observations with missing values, the missing variables will be excluded from the calculation of aggregate statistics; the none-missing values will be used in generating the other aggregate statistics. Therefore, we dropped variables with extreme values, but kept the observation in the data set for analysis. On the other hand, we could further improve the quality of the data by dropping the observations with missing values in one or several performance indicators, this would cut our sample size to about 16,000 per year from 24,000 per year, a drop of about one-third. We consider this approach too costly.

Some performance indicators such as asset-liability ratio and capital-labor ratio are constructed using readily available production or accounting variables, and therefore there is few missing values. Other performance measures such the debt-serving capacity indicator is derived from detailed accounting variables and has many missing values. Therefore, the sample sizes differ for different performance measures. For example, the asset-liability ratio and the capital–labor ratio have the largest sample size of 84,359 over four years (on average, about 21,090 a year); the debt-serving capacity indicator (the ratio of quasi-cash inflow over outflow) has the smallest of 66,544 over four years (on average, about 16,636 a year), which is about 23% less than the largest sample.

Since the sample sizes differ for different performance measures, we may not compare directly the aggregate statistics of two indicators. For example, we are unable to divide the wage bill by number of employees to get average wage rate for a locality when the sample sizes of wage bill and number of employees are different.

We have also attempted to document the pattern and distribution of missing values for each variable. This is important and useful for further study on the robustness of our results.

The primary purpose of this study is to lay out a foundation for further detailed analysis and testing on the behavior and performance of Chinese industrial enterprises. Prior studies on Chinese enterprises have generated contradictory results. We believe that some of the contradictory results may result from the fact that some of the studies used fragmented samples. This study improves our knowledge of the Chinese industrial enterprises by providing a more systematic and robust platform for analyzing firm-level data collected by the National Bureau of Statistics of China.

## 2. MEASURING ENTERPRISE PERFORMANCE

### *2.1 Composition of Value Added Components*

The primary objective of industrial enterprises is to produce output by effectively employing inputs such as capital, labor, and intermediate inputs. In this production process, enterprises create value added which is defined in this study as the following:

VA = YCURR – M + VAT = YCURR – (MINPUT – FC) + VAT;

- VA: value added;
- YCURR: gross value of industrial output;
- VAT: value added tax bill;
- M: intermediate inputs excluding financial charges;
- MINPUT: intermediate inputs including financial charges;
- FC: financial chares including mainly interest payments.

The above equation presents value added from the production perspective. The value added is created by the joint efforts of participants of the enterprises and they are distributed according a set of incentives and accounting rules to the participants. From the distribution perspective, the value added can be divided into a few basic payment components.

VA = ATP + TAX + CURRD + FC + W;

- ATP: after-tax-profits as an income flow to owners;
- TAX: taxes as a revenue flow to the governments;
- CURRD: current depreciation as a flow to maintain owners' equity value;
- FC: financial charges as payment to banking and financial services;
- W: wage and other benefits as payment to labor services.

We believe that the above presentation on the composition of value added provides a useful framework for measuring and analyzing the performance of the Chinese industrial enterprises since it traces each of the key components of the value added of a enterprise.

There are slight differences between the common practices in China and our definition. For example, we include the value-added taxes, in addition to other taxes, and financial charges, which contains mainly the interest payments, in our definition of value added since we treat all tax payments and financial charges as part of the basic payment components of value added. But in the accounting for the Gross Domestic Products, both the value added taxes and financial charges are excluded in the calculation of the value added. Instead, to avoid double counting these two components in GDP, they are included in the GDP of the fiscal and financial sectors. Since our study focuses on the industrial enterprises, it seems reasonable to include the contribution to taxes and the use of financial services by enterprises in the measurement of the enterprise performance.

The other three basic payment components of value added in the above equation include after-tax-profits, current depreciation and wage bill. Wage bill includes all costs related to labor. We also add various types of taxes to form the variable--total tax payments.

Table 2.1 in the technical appendix contains summary statistics for the above five basic payment components of value added for our sample by year. Because of the missing values, the sample sizes of each of the accounting terms vary. This suggests that the aggregate components do not add up to the aggregate value added; and we are unable to directly compare one aggregate component with one another either.

### *2.2 Profitability*

Based on the above basic payment components of value added, we derive a few commonly used accounting items including:

| | | |
|---|---|---|
| Value Added: | VA = | ATP + TAX + CURRD + FC + W; |
| Gross Profits: | GP = VA – W = | ATP + TAX + CURRD + FC; |
| Gross Cash Flow: | GCF = GP – FC = | ATP + TAX + CURRD; |
| Profits: | P = GCF – CURRD = | ATP + TAX; |
| After-Tax-Profits: | ATP = P – TAX = | ATP; |

It should be noted that the above five accounting items can take a value of positive, zero, or negative. Their values qualitatively indicate a firm's profitability.

Profitability is one of the most important measures of financial performance. Unfortunately it is also the least understood concept both in statistics and policy-making in China. The enterprises in our sample do report a statistics called total profits (TP). But few understand how that statistics is derived. There is large amount of anecdotal evidence that managers of Chinese enterprises engage in earnings/profit manipulation. Since it is difficult for outsiders to obtain information regarding the real earnings/profit of a firm, earnings/profit manipulation may be hard to detect. We suspect that the reported total profits in our data set are also prone to manipulation, intentionally and unintentionally.

Moreover we attempt to go beyond the single dimension statistics of profits. We argue that profitability is a richer concept than about firms making profits. Based on the five payment components of value added, we classify enterprises into eight profitability groups:

| | |
|---|---|
| GFIN=[-4] –M-W-FC-D-T | if VA <= 0; |
| GFIN=[-3] –W-FC-D-T | if GP <= 0 AND VA > 0; |
| GFIN=[-2] –FC-D-T | if GCF <= 0 AND GP > 0; |
| GFIN=[-1] –D-T | if P <= 0 AND GCF > 0; |
| GFIN=[+1] –T | if ATP <= 0 AND P > 0; |
| GFIN=[+2] | if ATP > 0 AND NROTA <= 5% |
| GFIN=[+3] | if NROTA > 5% AND NROTA <= 15%; |
| GFIN=[+4] | if NROTA > 15% |

In the above classification we use M (MINPUT), W, FC, D (CURRD), and T (TAX) as shorthand labels to represent the payment components of value added or gross output. The negative sign before these shorthand labels can be read as "cannot pay all of". The classification is explained as follow:

- Group [+4]: Enterprises in this group are highly profitable with their after-tax return on total assets (NROTA) higher than 15%.

- Group [+3]: Enterprises in this group are very profitable with their after-tax return on total assets (NROTA) greater than 5% but less than or equal to 15%.

- Group [+2]: Enterprises in this group are profitable with positive after-tax profits but their after-tax return on total assets is less than 5%.

- Group [+1]: Enterprises in this group would make profits if they did not have to pay all the taxes. They have negative after-tax profits (ATP=VA-W-FC-CURRD-TAX) but positive profits (P=VA-W-FC-CURRD). The shorthand -T reminds us that these enterprises care not able to pay all taxes but can pay depreciation, financial charges, wages, and intermediate inputs. This group of enterprises is profitable before paying taxes. Although they make losses after paying taxes, they still create net positive value for the society and could survive in both short and long run if they remain profitable.

- Group [-1]: Enterprises in this group would make profits if they did not have to pay all the taxes and depreciation. They have negative profits (P=VA-W-FC-CURRD) but positive gross cash flow (GCF=VA-W-FC). The shorthand -D-T reminds us that these enterprises are unable to pay all the taxes and depreciation but can pay all financial changes, wages, and intermediate inputs. This group of enterprises has no problems in paying their variable or working capital costs of production such as the costs of materials, labor, and even financial charges. In another words, they can survive in the short-run. However they are not profitable after paying current depreciation and may not be able to survive in the long-run since their existing capital will be depleted rapidly.

- Group [-2]: Enterprises in this group would make profits if they did not have to pay all the taxes, depreciation and financial charges. They have negative gross cash flow (GCF=VA-W-FC) but positive gross profits (GP=VA-W). The shorthand –FC-D-T reminds us that these enterprises are unable to pay all the taxes, depreciation, and financial charges but can pay wages and intermediate inputs. This group of enterprises is able to cover their variable or working capital costs of production related to labor and materials but can pay only part of their financial charges and none of their current depreciation. They could survive in the short-run if their creditors tolerate their non-performing short-term debts. But they may have to be shut down in the long-run since they cannot recover their fixed cost of capital.

- Group [-3]: Enterprises in this group would make profits if they did not have to pay all the taxes, depreciation, financial charges, and wages. They have negative gross profits (GP=VA-W) but positive value added (VA=Y-MINPUT). The shorthand -W-FC-D-T reminds us that these enterprises are unable to pay all the taxes, depreciation, financial charges and wages but can pay intermediate inputs. This group of enterprises could still create some positive value added but could only cover part of their labor costs. If the enterprises could cut their employment and improve labor productivity, they may survive a while in the short-run. If they are unable to cut their labor costs, they may have to be shut down even in the short-run. These enterprises cannot survive in the long run since they cannot recover their fixed cost of capital.

- Group [-4]: Enterprises in this group would make profits if they did not have to pay all the taxes, depreciation, financial charges, wages and intermediate inputs. They have negative value added (VA=Y-MINPUT). The shorthand -M-W-FC-D-T reminds us that these enterprises cannot pay all the taxes, depreciation, financial charges, wages and intermediate inputs. This group of enterprises creates zero or negative value added. They cannot survive without net subsidies and may have to be closed down as soon as possible.

Table 2.2 shows the distribution of enterprises among the eight profitability groups and the group with missing values from 1995 to 1998. As shown in Table2.2, the share of number of enterprises with missing values in our sample increases from 5.5% in 1995 to 6.0% in 1996, 7.7% in 1997 and 8.8% in 1998, reflecting the deteriorating financial data in recent years. The mean of the share of enterprises with missing value in GFIN over the four years is 7.0% in number of enterprises, 8.2% in total assets and 4.6% in labor.

Table 2.2 also shows the distribution excluding enterprises with missing values. The proportion of enterprises for each group is quite stable over the four years from 1995 to 1998. The averages (over the sample period) of the distribution for number of enterprises, total assets, and labor across the profitability groups are shown in the following table.

**Table GFIN**
**Shares of Assets and Labor across Profitability Groups (GFIN)**
(Pooled sample 1995-1998)

| GFIN | No. of Enterprises | Assets | Labor | Assets/No. of Enterprises | Labor/No. of Enterprises |
|---|---|---|---|---|---|
| [-4] | 04.2 | 03.3 | 02.6 | 0.786 | 0.619 |
| [-3] | 14.3 | 08.7 | 14.8 | 0.608 | 1.035 |
| [-2] | 09.6 | 06.3 | 08.7 | 0.656 | 0.906 |
| [-1] | 08.1 | 07.7 | 09.1 | 0.951 | 1.123 |
| [+1] | 12.2 | 15.0 | 15.4 | 1.230 | 1.262 |
| [+2] | 22.5 | 30.4 | 25.5 | 1.351 | 1.133 |
| [+3] | 18.4 | 19.3 | 16.1 | 1.049 | 0.875 |
| [+4] | 10.6 | 09.2 | 07.8 | 0.868 | 0.736 |
| [All] | 100 | 100 | 100 | 1.000 | 1.000 |

Taking from the above statistics, we find that the distributions of number of enterprises, total assets, and labor among the eight profitability groups of the entire industrial sector are very similar over the investigated period. This may sound disappointing. We expect that better-performing enterprises obtain more resources, such as assets and labors if the market reform improves resource allocation. Nonetheless, our evidence suggests that more profitable firms are not getting resources, such as assets and labor.

Our results have important policy implication. To improve resource allocation is one of the most important goals of China’s twenty-year long market-oriented reform. China has experimented various policies to improve its industrial sector’s productivity. Although at the macro level, China’s industrial sector has strengthened significantly in the past twenty years; many of China’s industrial enterprises are still performing unsatisfactory.

To simplify the analysis, we may reduce the number of profitability groups from eight to four in future analysis:

GF =2 or profitable if GFIN=[+3] or [+4];
GF =1 or marginally profitable if GFIN=[+1] or [+2];
GF=-1or light loss-maker if GFIN=[-1] or [-2];
GF=-2 or heavy loss-maker if GFIN=[-3] or [-4];

***2.3 Debt-Serving Capacity***

In this section we construct measures of debt-serving capacity of enterprises, such as liquidity and solvency. Liquidity is a measure of the enterprise's ability to pay its current or short-term debts; while solvency is a measure of the enterprise's ability to honor all of its short-term and long-term debts. Liquidity and solvency is particularly important to a firm's creditors and other stakeholders. In China, state-owned banks are almost the exclusive source of loans to China's enterprises.

In theory, we can separate liquidity from solvency problems for each enterprise. In reality, it is difficult. Solvency is much more difficult to measure than liquidity constraint, but the two are certainly related. In this study, we measure liquidity by the ratio of cash inflow over cash outflow. Since the Chinese enterprises do not usually have cash flow accounts, we use quasi-cash inflow and quasi-cash outflow to define a liquidity index:

Liquidity Index =QFLOW
=quasi-cash inflow / quasi-cash outflow;
=(GP + LIQA-LIQLT)/(TAX+FC+0.2*LTLT);
GP: gross profits = VA – W = Y – MINPUT - W;
LIQA: liquid assets;
LIQLT: short-term liabilities;
TAX: all taxes;
FC: financial charges;
LTLT: long-term liabilities;

In the above equation, the quasi-cash inflow consists of gross profits plus liquid assets minus short-term liabilities. The gross profits are equal to the gross output minus the costs of intermediate inputs and labor.

The quasi-cash outflow consists of all tax obligations, financial charges, and a fraction of long-term liabilities to be paid out in current period. We assume that 20% of the long-term liabilities have to be paid out in the current year.

Based on the above definition, if the liquidity index is above one for a firm, the firm are likely to have no problems in fulfilling its short-term financial obligations. If the index is below one, the firm may have difficulties in honoring its short-term debts.

The liquidity index QFLOW is added to the group of ratio indicators discussed in section 2.1. When we calculate the statistics for QFLOW, we also exclude outliers defined the same as for other ratio indicators.

Because of the importance of this ratio indicator, we separate enterprises into ten groups according to their values of GFLOW and examine the distribution of enterprises across ten groups, defined as follow:

GQFLOW = [-6] if QFLOW < -2;
GQFLOW = [-5] if (QFLOW >= -2) AND (QFLOW < -1);
GQFLOW = [-4] if (QFLOW >= -1) AND (QFLOW < -0.5);
GQFLOW = [-3] if (QFLOW >= -0.5) AND (QFLOW < 0);
GQFLOW = [-2] if (QFLOW >= 0) AND (QFLOW < 0.5);
GQFLOW = [-1] if (QFLOW >= 0.5) AND (QFLOW < 1);
GQFLOW = [+1] if (QFLOW >= 1) AND (QFLOW < 1.5);
GQFLOW = [+2] if (QFLOW >= 1.5) AND (QFLOW < 2);
GQFLOW = [+3] if (QFLOW >= 2) AND (QFLOW < 3);
GQFLOW = [+4] if QFLOW >= 3;

Table2.3 shows the distribution of enterprises across the ten liquidity groups. The table also shows the group with missing values from 1995 to 1998. As shown in Table 2.3, the share of the number of enterprises with missing values in our sample increases from 19.0% in 1995 and 19.3% in 1996 to 21.7% in 1997 and 24.7% in 1998. The mean of the share of enterprises with missing value in GQFLOW over four years is 21.1% in number of enterprises, 16.9% in total assets and 15.2% in labor. The increases in the missing reflect the deteriorating financial data in more recent years.

Table 2.3 also shows the distribution excluding enterprises with missing value. The proportion of enterprises for each group is quite stable over the four years from 1995 to 1998. The averages (over the sample period) of the distribution for number of enterprises, total assets, and labor across the liquidity groups are shown in the following table.

**Table GQFLOW**
**Shares of Assets and Labor across Debt-Serving Capacity Groups (GQFLOW)**
(Pooled sample 1995-1998)

| GQFLOW | No. of Enterprises | Total assets | Labor | Assets/No. of Enterprises | Labor/No. of Enterprises |
|---|---|---|---|---|---|
| [-6] | 18.5 | 08.4 | 13.9 | 0.454 | 0.751 |
| [-5] | 08.6 | 05.6 | 07.9 | 0.651 | 0.919 |
| [-4] | 06.2 | 04.2 | 05.5 | 0.677 | 0.887 |
| [-3] | 07.4 | 06.8 | 07.6 | 0.919 | 1.027 |
| [-2] | 08.9 | 11.3 | 10.2 | 1.270 | 1.146 |
| [-1] | 09.9 | 12.8 | 11.7 | 1.293 | 1.182 |
| [+1] | 09.2 | 13.5 | 11.7 | 1.467 | 1.272 |
| [+2] | 07.7 | 10.2 | 09.3 | 1.325 | 1.208 |
| [+3] | 10.1 | 12.2 | 10.8 | 1.208 | 1.069 |
| [+4] | 13.5 | 15.1 | 11.2 | 1.119 | 0.830 |
| [All] | 100 | 100 | 100 | 1.000 | 1.000 |

As shown by the above statistics, the distributions of the number of enterprises, total assets, and labor across the liquidity groups differ only slightly over the investigated period. Enterprises without liquidity problems (liquidity index greater than one or in group [+1], [+2], [+3], and [+4]) and enterprises with some liquidity problems (liquidity index less than one but greater than zero or in group [-1] and [-2]) have proportionally more assets than enterprises with serious liquidity problems (liquidity index less than zero or in group [-3], [-4], [-5], and [-6]. When calculating QFLOW, we excluded negative values for all the terms except GP (gross profits). This approach ensures that a negative value of QFLOW represents serious liquidity condition.

To simplify the analysis, we reduce the number of liquidity groups from ten to four in future analysis:

GQ =2 or excellent liquidity if GQFLOW=[+3] or [+4];
GQ =1 or good liquidity if GQFLOW=[+1] or [+2];
GQ=-1or constrained by liquidity if GQFLOW=[-1] or [-2];
GQ=-2 or badly constrained by liquidity if GFLOW=[-3], [-4], [-5], [-6];

Liquidity is closely related to solvency. But the most frequently used indicator for solvency is the debt-equity ratio. When an enterprise's debt-equity ration is high, it is more like to get into solvency problems. This ratio is an important indicator on the financial vulnerability of an enterprise.

It should be noted that the debt-equity ratio is not necessarily linked to the possibility of bad debts. It is possible for a firm with high debt-equity ratio to serve well their financial obligations, if the firm is able generate sufficient cash flows. In particular, the normal levels of debt-equity ratios may vary greatly across industries and across firms. It should also be noted that many of the debts on the books of China's industrial enterprises are not being served. Yet, these debts are not classified as bad debts. This problem has become increasingly alarming to the banks and policy-makers in China. It is almost impossible for researchers to obtain reliable information on how serious the bad debt problem in China. Therefore, we are unable to identify exactly how much of the debts are not being served in this study.

We separated firms into eight groups by their debt-equity ratio (DER).

GDER = [-4] if DER > 8
GDER = [-3] if (DER >= 6) AND (DER < 8)
GDER = [-2] if (DER >= 4) AND (DER < 6)
GDER = [-1] if (DER >= 2) AND (DER < 4)
GDER = [+1] if (DER >= 1.5) AND (DER < 2)
GDER = [+2] if (DER >= 1) AND (DER < 1.5)
GDER = [+3] if (DER >= 0.5) AND (DER < 1)
GDER = [+4] if DER < 0.5

Table 2.4 shows the distributions of enterprises across the eight solvency groups and the group with missing values in the investigated period. As shown in Table 2.8, the share of number of enterprises with missing values in our sample increases from 8.7% in 1995 to 9.2% in 1996, 10.6% in 1997 and 11.5% in 1998, reflecting the deteriorating financial data in recent years. Average over the four years the share of enterprises with missing value in GFIN is 10.0% in number of enterprises, 4.3% in total assets and 6.3% in labor.

Table 2.4 also shows the distribution excluding enterprises with missing value. The proportion of enterprises for each group is quite stable over the four years from 1995 to 1998. The distributions of the number of enterprises, total assets, and labor are shown in the following table.

**Table GDER**
**Shares of Assets and Labor across Debt-Equity Ratio Groups (GDER)**
(Shares of the average during 1995 to 1998)

| GDER | No. of Enterprises | Total assets | Labor | Assets/No. of Enterprises | Labor/No. of Enterprises |
|---|---|---|---|---|---|
| [+4] | 07.4 | 10.6 | 05.0 | 1.432 | 0.676 |
| [+3] | 13.1 | 16.8 | 13.7 | 1.282 | 1.046 |
| [+2] | 13.6 | 16.9 | 17.4 | 1.243 | 1.279 |
| [+1] | 11.8 | 13.4 | 14.8 | 1.136 | 1.254 |
| [-1] | 26.3 | 25.3 | 27.9 | 0.962 | 1.061 |
| [-2] | 10.1 | 07.3 | 08.8 | 0.723 | 0.871 |
| [-3] | 05.1 | 03.0 | 03.7 | 0.588 | 0.725 |
| [-4] | 12.6 | 06.7 | 08.6 | 0.532 | 0.683 |
| [All] | 100 | 100 | 100 | 1.000 | 1.000 |

The table shows that the distribution of total assets is skewed toward low debt-equity enterprise groups in [+1], [+2], [+3] and [+4]. The implication of the above evidences is that for the large and medium-sized industrial enterprises in China (including both state and non-state enterprises) better performing enterprises seem able to secure more assets

To simplify the analysis, we reduce the number of solvency groups from eight to four groups in future analysis:

GD =2 or very low debt-equity ratio if GDER=[+3] or [+4];
GD =1 or low debt-equity ratio if GDER=[+1] or [+2];
GD =-1or high debt-equity ratio if GDER=[-1] or [-2];
GD =-2 or very high debt-equity ratio if GDER=[-3], [-4];

### *2.4 Technical Productivity and Financial Efficiency*

In this section we construct measures for total factor productivity, which can be defined broadly as output divided by a weighted average of all inputs. Profitable firms can have very low total factor productivity. This happens when a firm pays very low wages and receives low return on assets. On the other hand, firms with high total factor productivity may not be profitable. This happens when a firm pays high wages or/and high interest expenses on borrowed assets.

We rank enterprises by their relative performance in total factor productivity for each year based on the following production function regression:

Equation (1):

$$Ln(YCURR_i)=\alpha+(\Sigma_j\beta_j\bullet I_j)\bullet Ln(NVFIXA_i)+(\Sigma_j\delta_j\bullet I_j)\bullet Ln(LABOR_i)+(\Sigma_j\gamma_j\bullet I_j)\bullet Ln(MINPUT_i)+\varepsilon_i;$$

i denotes each of the enterprises in the sample;
i = 1, 2, ..., N. N=number of enterprises in the sample;
j denotes each industry in the sample;
j = 1, 2, ..., M. M=number of industries;
$\alpha$, $\beta_j$, $\delta_j$, and $\gamma_j$ are regression coefficients;
$\alpha$ is the coefficient for the constant;
$\beta_j$ is the estimated output elasticity of capital for industry j;
$\delta_j$ is the estimated output elasticity of labor for industry j;
$\gamma_j$ is the estimated output elasticity of intermediate inputs for industry j;
$I_j$ is the industry dummy variable;
$I_j$ = 1, if enterprise i belong to industry j; otherwise $I_j$ = 0;
$\varepsilon_i$ is the regression residual for enterprise i;
$\alpha+\varepsilon_i$ is the log of total factor productivity for enterprise i.

Regression equation (1) provides estimates of output-input elasticity ($\beta_j$, $\delta_j$, and $\gamma_j$) for each industry. The industry average total factor productivity can be obtained by taking the average of the regression residuals. We use the regression residual of each enterprise as a proxy for its relative level of total factor productivity among the sample enterprises. The varying output-input elasticity is to capture the production technology across industries.

The productivity index $GYM_i$ for enterprise i in each year is defined as the standardized residual for enterprise i from the regression equation (1) or:

Equation (2):

$$GYM_i = \frac{\varepsilon_i - \bar{\varepsilon}}{\sqrt{\frac{\sum (\varepsilon_i - \bar{\varepsilon})^2}{n-1}}};$$

The mean and standard deviation for $GYM_i$ are zero and one respectively because of the standardization. In each year, we will use $GYM_i$ to order and categorize enterprises in our sample into different productivity groups.

It should be noted that $GYM_i$ is effectively an annual ranking of relative productivity level for our sample enterprises. The value of $GYM_i$ from different years should not be compared directly to draw any conclusions about the growth of the total factor productivity for each enterprise. As we pointed out earlier, the study of productivity growth is complicated by the lack of reliable price deflators and need further study in the separate papers.

On the other hand, the value of $GYM_i$ does inform us a little about the position of a particular firm's relative total factor productivity levels. For example, $GYM_i = 2$ means that the productivity score for enterprise i is two standard deviations above the sample mean.

To identify the outliers, we run regressions Equation (1) twice. The first run uses all observations in our sample and generates a productivity index according to formula (2). If this index is greater than 4.5 or less than –4.5, we treat that observation as an outlier and exclude it from the second run of the regression. This procedure eliminates the impact of outliers on the estimation of production function coefficients in the second run of regression. The second run of the regression generates the productivity index $GYM_{i,}$ and we code observations with GYM greater than 3 or less than –3 as outliers as well. All outliers and missing values are then excluded from our study in this paper.

We group firms into eight productivity groups by their GYMs for each year as follow:

GTFPYM = [+4] if GYM >= 2 AND GYM <= 3;
GTFPYM = [+3] if GYM >= 1 AND GYM < 2;
GTFPYM = [+2] if GYM >= 0.5 AND GYM < 1;
GTFPYM = [+1] if GYM >= 0 AND GYM < 0.5;
GTFPYM = [-1] if GYM >= -0.5 AND GYM < 0;
GTFPYM = [-2] if GYM >= -1 AND GYM < -0.5;
GTFPYM = [-3] if GYM >= -2 AND GYM < -1;
GTFPYM = [-4] if GYM >= -3 AND GYM < -2;

Table 2.5 shows the distribution of enterprises across the eight productivity groups and the outliers from 1995 to 1998. The outliers include both low and high productivity outliers defined earlier as well as the enterprises with negative value added, which are excluded from the production function regressions.

As shown in Table 2.5, the negative value added outliers are about 4.0% of the sample in number of enterprises, 3.1% in total assets, and 2.4% in number of employees.

The low productivity outliers are about 2% in number of enterprises, 1.3% in total assets, and 1.4% in number of employees.

The high productivity outliers are about 1.7% in number of enterprises, 2.5% in total assets, and 1% in number of employees.

After excluding the outliers, the distribution of enterprises across the eight productivity groups is similar to the normal distribution. Table 2.5 also shows the cross-tabulation of the productivity grouping with year without the outliers.

**Table GTFPYM**
**Shares of Assets and Labor across Technical Productivity Groups [GTFPYM]**
(Shares of the average during 1995 to 1998)

| GTFPYM | No. of Enterprises | Total assets | Labor | Assets/No. of Enterprises | Labor/No. of Enterprises |
|---|---|---|---|---|---|
| [-4] | 01.4 | 01.4 | 01.2 | 1.000 | 0.857 |
| [-3] | 07.6 | 06.3 | 08.1 | 0.829 | 1.066 |
| [-2] | 14.9 | 11.3 | 12.6 | 0.758 | 0.846 |
| [-1] | 28.0 | 24.5 | 26.0 | 0.875 | 0.929 |
| [+1] | 25.7 | 25.6 | 26.1 | 0.996 | 1.016 |
| [+2] | 12.7 | 17.4 | 15.5 | 1.370 | 1.220 |
| [+3] | 07.7 | 11.2 | 08.7 | 1.455 | 1.130 |
| [+4] | 01.9 | 02.3 | 01.8 | 1.211 | 0.947 |
| [All] | 100 | 100 | 100 | 1.000 | 1.000 |

About one fourth of the enterprises fall into the middle groups [+1] and [-1] (the regression residuals for these enterprises are within 0.5 of the standard deviation away from the mean). The distributions of the number of enterprises, total assets, and labor in total assets are very similar for productivity groups. This is similar to the case in the profitability groups and indicates that technically more productive groups of enterprises have not attracted proportionally more assets than the less productive.

We reduce the number of groups to four by combining the high and low productivity groups in the future analysis:

GTYM =2 or high productivity if GTFPYM=[+2] or [+3] or [+4];
GTYM =1 or above average productivity if GTFPYM=[+1];
GTYM =-1 or below average productivity if GTFPYM=[-1];
GTYM =-2 or low productivity if GTFPYM=[-2] or [-3] or [-4];

Detailed discussion on the comparison of productivity performance of the Chinese enterprises across ownership, size, region, industry etc based on the methodology developed in this study is beyond the scope of this paper. We will address it in separate papers.

***2.5 Efficiency Index and Grouping by Efficiency***

In addition to the productivity index, we also estimate an index of efficiency based on value added and equal output elasticity across industries. The efficiency index is derived from the following regression:

Equation (3):

$$Ln(VA_i) = \chi + \phi \bullet Ln(NVFIXA_i) + \eta \bullet Ln(LABOR_i) + \theta_i;$$

i denotes each of the enterprises in the sample;
i = 1, 2, ..., N. N=number of enterprises in the sample;
$\chi$, $\phi$, and $\eta$are regression coefficients;
$\chi$ is the coefficient for the constant;

$\phi$ is the estimated average output elasticity of capital for the whole industrial sector;
$\eta$ is the estimated average output elasticity of labor for the whole industrial sector;
$\theta_i$ is the regression residual for enterprise i;

The efficiency index $GVA_i$ for enterprise i is defined as the standardized residual for enterprise i from the regression equation (3) or:

Equation (4):

$$GVA_i = \frac{\theta_i - \bar{\theta}}{\sqrt{\frac{\sum(\theta_i - \bar{\theta})^2}{n-1}}};$$

Equation (3) estimates an aggregate production function for the entire industrial sector without allowing variations in output elasticity of each factor input across industries. China's National Bureau of Statistics and other Chinese research institutes prefer to use Equation (3) for estimating the total factor productivity index for its simplicity. This is however not in line with the standard practices outside of China where Equation (1) is commonly used for estimating the total factor productivity. To avoid confusion, we give another name, efficiency index, to the performance index estimated from Equation (3).

The productivity index defined in Equation (2) and the efficiency index defined in Equation (4) are closely related but have different economic implications. The productivity index indicates which enterprises generate more gross value of output given their industry-specific production function and the same inputs. It measures essentially the technical productivity. On the other hand, the efficiency index indicates which enterprises generate more value added given the same average production function and the same inputs. It measures essentially the financial productivity.

The benefit of using productivity index is that it is a standard measure in the literature and does not cause confusions among researchers outside China. But it does have a few problems in China's context. The productivity index is useful for comparing technical efficiency among enterprises within the same industry but may not be proper for comparing technical efficiency among enterprises from different industries.

The efficiency index captures the idea that the reallocation of factor inputs across industries generates more output not only from higher total factor productivity but also from higher output elasticity of inputs. To show this, we rearrange Equation (3):

Equation (5):

$$\begin{aligned}\chi+\theta_i &= Ln(VA_i) - \phi\bullet Ln(NVFIXA_i) - \eta\bullet Ln(LABOR_i)\\ &=[Ln(VA_i) - (\Sigma_j\phi_j\bullet I_j)\bullet Ln(NVFIXA_i) - (\Sigma_j\eta_j\bullet I_j)\bullet Ln(LABOR_i)]\\ &\quad + [\{(\Sigma_j\phi_j\bullet I_j) - \phi\}\bullet Ln(NVFIXA_i) + \{(\Sigma_j\eta_j\bullet I_j) - \eta\}\bullet Ln(LABOR_i)];\end{aligned}$$

Suppose an enterprise i=1 belongs to industry j=1, equation (5) can be reduced to the following:

Equation (6):

$$\begin{aligned}\chi + \theta_1 &= Ln(VA_1) - \phi\bullet Ln(NVFIXA_1) - \eta\bullet Ln(LABOR_1)\\ &=[Ln(VA_1) - \phi_1\bullet Ln(NVFIXA_i) - \eta_1\bullet Ln(LABOR_i)]\\ &\quad +[\{\phi_1 - \phi\}\bullet Ln(NVFIXA_1) + \{\eta_1 - \eta\} \bullet Ln(LABOR_1)];\end{aligned}$$

The first line in Equations (5) and (6) is the measure of efficiency or financial productivity as defined in Equation (3). The sum of the second and third lines is the same as the first line but is presented in two terms. The first term or the second line measures productivity similar to the total factor productivity defined in Equation (1), where we allow output elasticity to vary across industries. The second term or the third line measures the contribution to value added by the industry-specific output elasticity and the economy-wide average output elasticity.

Apparently the productivity index and efficiency index should be correlated but the correlation should not be very high. Table 2.15 shows the Pearson Correlation statistics between GYM and GVA is 0.557 for the pooled four-year sample of these two indicators, as expected.

Similar to the estimation of productivity index, we identify outliers in estimating the efficiency index by running Equation (3) twice. The first run uses all observations in our sample and generates a preliminary efficiency index defined by Equation (4). If this index is greater than 4.5 or less than –4.5, we treat that observation as an outlier and exclude it from the second run of the regression. This procedure eliminates the impact of the outliers on the estimation of production function coefficients in the second run of the regression. The second run of the regression generates the efficiency index $GVA_i$. We will code observations with GVA greater than 3 or less than –3 as outliers as well. All outliers and missing values are then excluded from our study in this paper.

Based on the value of $GVA_i$, we group the enterprises into the following eight efficiency groups for each year:

GTFPVA = [+4] if GVA >= 2 AND GVA <= 3;
GTFPVA = [+3] if GVA >= 1 AND GVA < 2;
GTFPVA = [+2] if GVA >= 0.5 AND GVA < 1;
GTFPVA = [+1] if GVA >= 0 AND GVA < 0.5;
GTFPVA = [-1] if GVA >= -0.5 AND GVA < 0;
GTFPVA = [-2] if GVA >= -1 AND GVA < -0.5;
GTFPVA = [-3] if GVA >= -2 AND GVA < -1;
GTFPVA = [-4] if GVA >= -3 AND GVA < -2;

Table 2.6 shows the distribution of enterprises among the eight efficiency groups and the outliers from 1995 to 1998. The outliers include both low and high efficiency outliers defined earlier as well as enterprises with negative value added, which are excluded from the production function regressions.

As shown in Table 2.6, the negative value added outliers are about 4.0% of the sample in number of enterprises, 3.1% in total assets, and 2.4% in number of employees. This is the same as for the productivity index.

The low efficiency outliers are about 1.4% in number of enterprises, 0.7% in total assets, and 1.0% in number of employees.

The high efficiency outliers are about 0.6% in number of enterprises, 1.4% in total assets, and 0.4% in number of employees.

The shares of low and high efficiency outliers are much lower than those of low and high productivity outliers. This may be due to the data problems in the intermediate input, which is included in the estimation of productivity index but is excluded in that of the efficiency index.

Table 2.6 also shows the cross-tabulation of the efficiency grouping by year without the outliers. The distribution of enterprises across the eight efficiency groups is less close to the normal distribution than that across the productivity groups.

**Table GTFPVA**
**Shares of Assets and Labor across Financial Efficiency Groups [GTFPVA]**
(Shares of the average during 1995 to 1998)

| GTFPVA | No. of Enterprises | Total assets | Labor | Assets/No. of Enterprises | Labor/No. of Enterprises |
|---|---|---|---|---|---|
| [-4] | 02.8 | 01.4 | 01.8 | 0.500 | 0.643 |
| [-3] | 09.9 | 05.3 | 07.6 | 0.535 | 0.768 |
| [-2] | 12.0 | 07.9 | 11.8 | 0.658 | 0.983 |
| [-1] | 20.2 | 14.6 | 21.1 | 0.723 | 1.045 |
| [+1] | 24.6 | 25.6 | 28.6 | 1.041 | 1.163 |
| [+2] | 17.8 | 22.5 | 18.1 | 1.264 | 1.017 |
| [+3] | 11.5 | 18.9 | 09.8 | 1.643 | 0.852 |
| [+4] | 01.3 | 03.9 | 01.2 | 3.000 | 0.923 |
| [All] | 100 | 100 | 100 | 1.000 | 1.000 |

More enterprises are concentrated in efficiency groups [+1], [+2] and [+3] than in [-1], [-2] and [-3]. The distribution in total assets is particularly skewed toward high efficiency groups. When interpreting the results, we should be cautious. It seems that the implication of the t evidence is that for the large and medium-sized industrial enterprises in China (including both state and non-state enterprises) more efficient enterprises seem able to secure more assets. This may be due to the fact that value added becomes more and more important than technical productivity as China moves from a centrally planned economy towards a market economy. However, the results can also be caused by measurement errors. Given the way GVA is constructed, hence the way the efficiency groups are formed, it is likely that large firms with more assets are clustered in sectors with large output elasticities. If this is the case, the estimated coefficients in Equation (3) are underestimated, resulting in inflated regression residuals and higher GVAs. In this study, we are unable to differentiate the two explanations.

To simplify the analysis, we reduce the number of efficiency groups from eight to four by combining the high and low efficiency groups in future analysis:

GTVA =2 or high efficiency if GTFPVA=[+2] or [+3] or [+4];
GTVA =1 or above average efficiency if GTFPVA=[+1];
GTVA =-1 or below average efficiency if GTFPVA=[-1];
GTVA =-2 or low efficiency if GTFPVA=[-2] or [-3] or [-4];

Detailed discussion on the comparison of efficiency performance of the Chinese enterprises across ownership, size, region, industry etc based on the methodology developed in this paper is beyond the scope this paper. We will address it in separate papers.

### *2.6 Financial Performance Indicators*

We also derive a set of basic indicators of enterprise performance using simple ratios. Ratio indicators related to return on assets include the following:

Net return on equity: NROE = ATP/ (TA – TL); TA: total assets; TL: Total liabilities;
Net return on sales: NRONS = ATP / SR; SR: sales revenues;

Net return on total assets: NROTA = ATP / TA;
Return on total assets: PROTA = P / TA;
Total return on total assets: TROTA = (P + RFEE) / TA; RFEE: interest outlay;
Ratio of sales revenue over gross output: MKTR = SR / YCURR;

Ratio indicators related to debt-serving capacity include the following:

Asset-liability ratio: ALR = TL / TA;
Current Ratio: CR = LIQA / LIQLT;
LIQA: liquid assets; LIQLT: short-term liabilities;
Debt-equity ratio: DER = TL / (TA – TL);
Ratio of earning (gross profit) over interest outlay: EIR = GP / RFEE;
Raito of GCF over TL: GCFTLR = GCF / TL;

We also calculate wage, labor productivity and capital intensity for each enterprise:

Wage: WAGE = W / LABOR; LABOR: number of employees;
Labor productivity: VAL = VA / LABOR;
Capital Intensity: KL = NVFIXA / LABOR;
NVFIXA: net value of fixed assets yearly average.

Throughout this study, unless otherwise noted, the unit for all value variables is 1000 Yuan and the unit for employees is number of persons.

The above ratio indicators are standard measures of enterprise financial performance in the market economies. But most of them are not frequently used in China primarily due to the difficulty in accessing firm-level accounting data as well as lack of a systematic framework to define and calculate the ratio indicators. In this study, we attempt to provide a systematic framework to a comprehensive firm-level data set.

We calculate the above ratio indicators for each enterprise in our sample. However as shown by the range of the ratio indicators in Table 2.20, the outlier problem for the ratio indicators is quite serious. In our four-year pooled sample with outliers, the range of the statistics PROTA (return on total assets) is (–2818%, 739%). Without outliers, the range of PROTA is reduced to (-44%, 77%). We identify the outliers for each ratio indicator by regressing the indicator on a set of industry dummies for each year. Then we code an enterprise's indicator as an outlier if its regression residual is 4.5 times the standard deviation of the residuals. The mean and median for PROTA in our four-year pooled sample decreased from 5.87% and 3.45% to 4.84% and 3.28% respectively. The standard deviation also dropped from 20.8% to 12.4%.

### *3. Conclusion*

In this paper we develop an analytical framework and the associated operational procedures for measuring the performance of the Chinese industrial enterprises. We then test our methodology using the annual industrial census on large and medium sized enterprises. The results presented are primarily for illustrating our methods. We focus on data cleaning, presentation of consistent accounting framework, construction of simple ratio indicators and other more sophisticated performance measures, and ranking and grouping by various performance criterions such as profitability, liquidity, solvency, productivity and efficiency. This paper lays a foundation for reliable and systematic studies of the performance and behavior of the Chinese industrial enterprises. Many important issues can be examined using our methods and the data collected by the National Bureau of Statistics. We have already generated a large amount of results on various issues. Some of the results are included in the appendix of this paper in the form of tables. This methodological paper provides basic information and conceptual framework for you to understand these tables. However we will illustrate the implications of these results in separate topic papers. In particular we will use some of the data sets developed in this project to examine the conditions of loss-making state-owned and non-state-owned enterprises in China in one of the separate papers.

**Table 1.1 Description of Sample Coverage**
**(By year, enterprises, employees, and output)**

| | Unit | 1995 | 1996 | 1997 | 1998 |
|---|---|---|---|---|---|
| **Number of firms in the cleaned sample** | Number | 21,115 | 21,592 | 21,488 | 20,164 |
| **Number of firms in the raw sample** | Number | 22,870 | 23,568 | 23,690 | 23,284 |
| **Number of all industrial enterprises in China** | Number | 7,341,500 | 7,986,500 | 7,922,900 | 7,974,600 |
| **Gross value of industrial output at current prices for the cleaned sample** | Billion yuan | 2,860 | 3,160 | 3,380 | 3,430 |
| **Gross value of industrial output at current prices for all industrial enterprises in China** | Billion yuan | 9,189 | 9,960 | 11,373 | 11,905 |
| **Number of employees for the cleaned sample** | Million | 36.4 | 35.4 | 34.4 | 30.3 |
| **Number of employees in all industrial enterprises in China** | Million | 66.1 | 64.5 | 62.2 | 47.5 |
| **Number of employees in urban China** | Million | 190.9 | 198.8 | 202.1 | 206.8 |
| **Number of employees in China** | Million | 679.5 | 688.5 | 696.0 | 699.6 |

**Table 1.2. Employment and Output of the Cleaned Sample as Compared to the Total of China's Industrial Sector: 1998**

| | | Unit | (1) The Cleaned Sample | (2) China's Industrial Sector | (1)/(2) |
|---|---|---|---|---|---|
| 1 | Number of Enterprises | Number | 20164 | 7974600 | 0.25% |
| 2 | Number of Employees | Million | 30. 3 | 47.5 | 63.79% |
| 3 | Gross Value of Industrial Output at Current Prices | Billion | 3430 | 11905 | 28.81% |
| 4 | Value Added + Financial Charges | Billion | 1201 | 3343 | 35.93% |
| 5 | Value Added | Billion | 1056 | 3343 | 31.59% |
| 6 | Value Added / GDP | % | 13. 30% | 42.10% | |

Note: Financial Charges are included as a component of a broadly defined concept of value added in this study.

**Figure GFIN.A**
**Shares of Assets and Labor across Profitability Groups (GFIN)**
(Pooled sample 1995-1998)

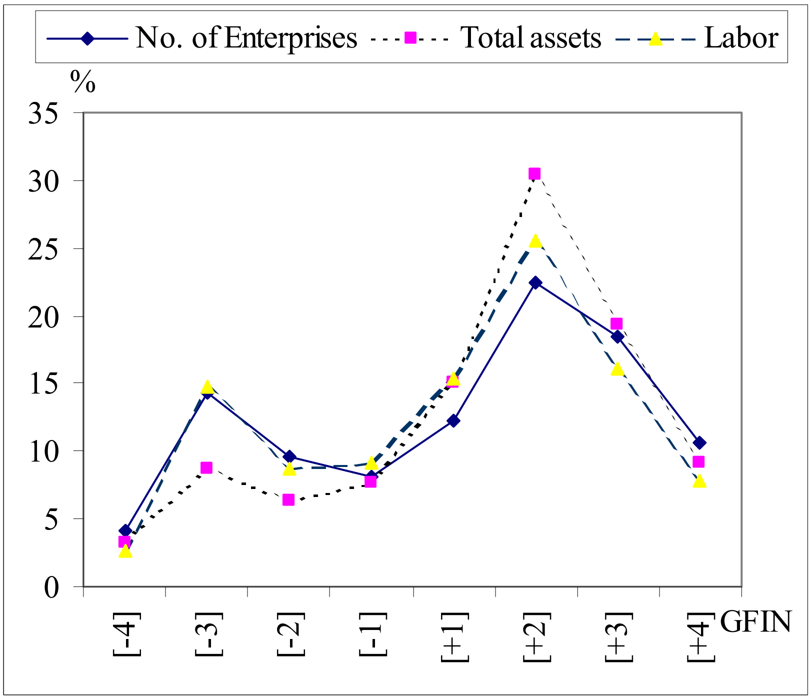



**Figure GFIN.B**
**Relative Enterprise Scale by Assets and Labor**
**across Profitability Groups (GFIN)**
(Pooled sample 1995-1998)

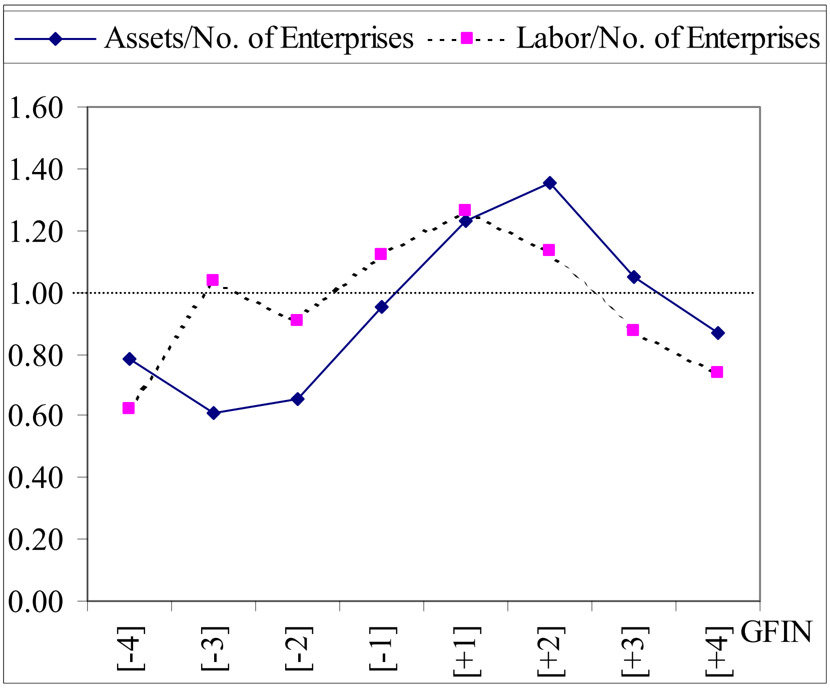


**Figure GQFLOW.A**
**Shares of Assets and Labor across Debt-Serving Capacity Groups [GQFLOW]**
(Pooled sample 1995-1998)

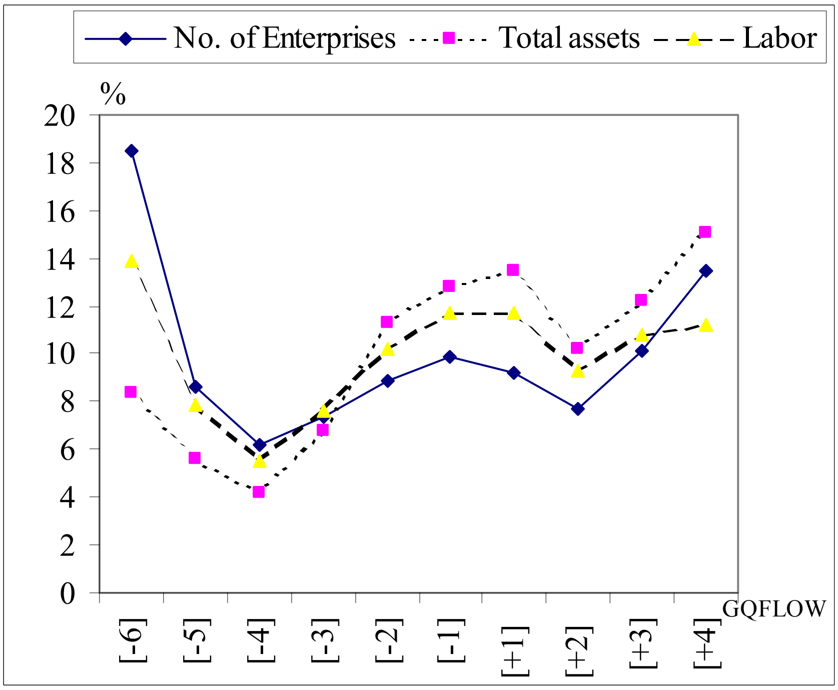



**Figure GQFLOW.B**
**Relative Enterprise Scale by Assets and Labor**
**across Debt-Serving Capacity Groups (GQFLOW)**
(Pooled sample 1995-1998)

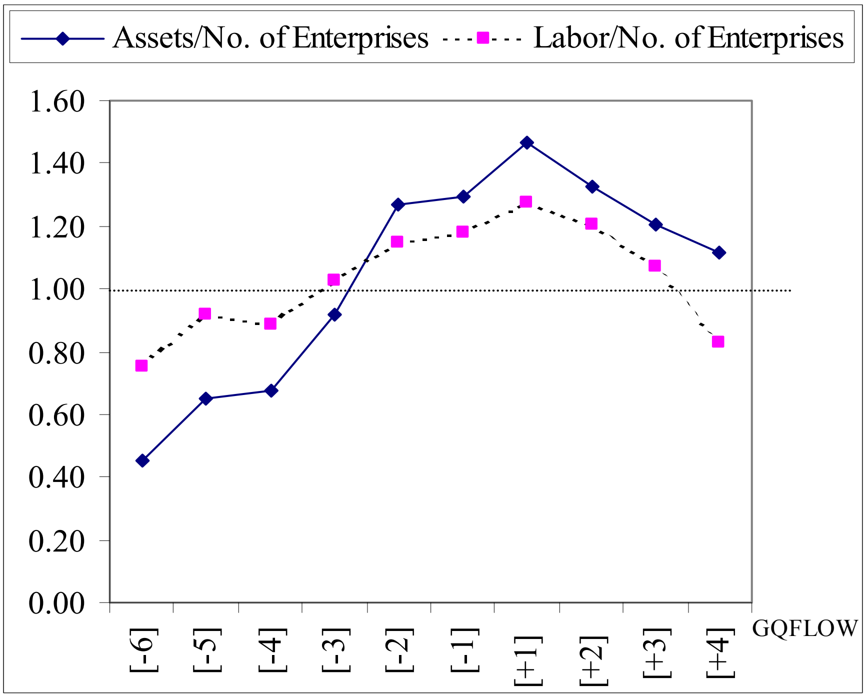


**Figure GDER.A**
**Shares of Assets and Labor across Debt-Equity Ratio Groups [GDER]**
(Pooled sample 1995-1998)

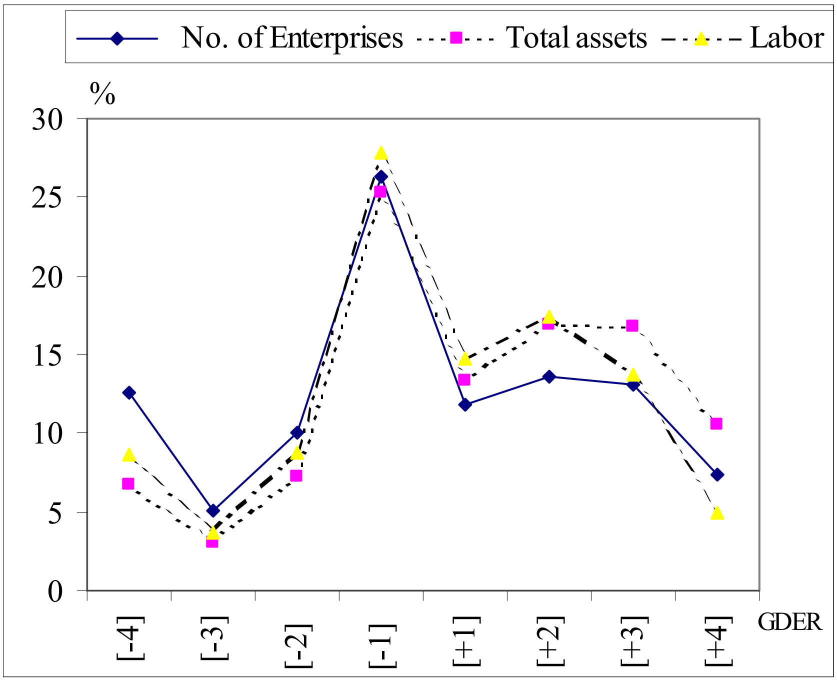



**Figure GDER.B**
**Relative Enterprise Scale by Assets and Labor**
**across Debt-Equity Ratio Groups (GDER)**
(Pooled sample 1995-1998)

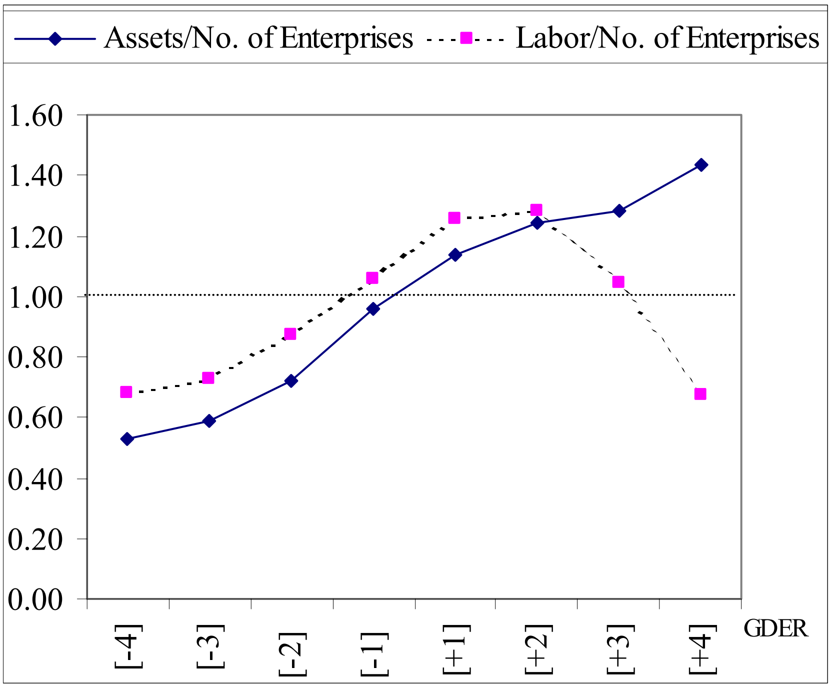


**Figure GTFPVA.A**
**Shares of Assets and Labor across Financial Efficiency Groups [GTFPVA]**
(Pooled sample 1995-1998)

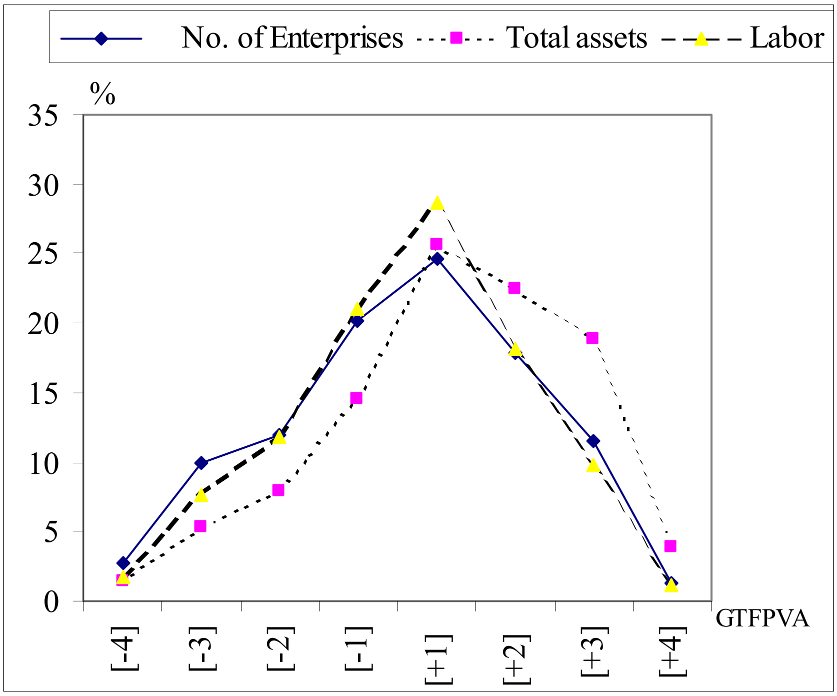



**Figure GTFPVA.B**
**Relative Enterprise Scale by Assets and Labor across Financial Efficiency Groups (GTFPVA)**
(Pooled sample 1995-1998)

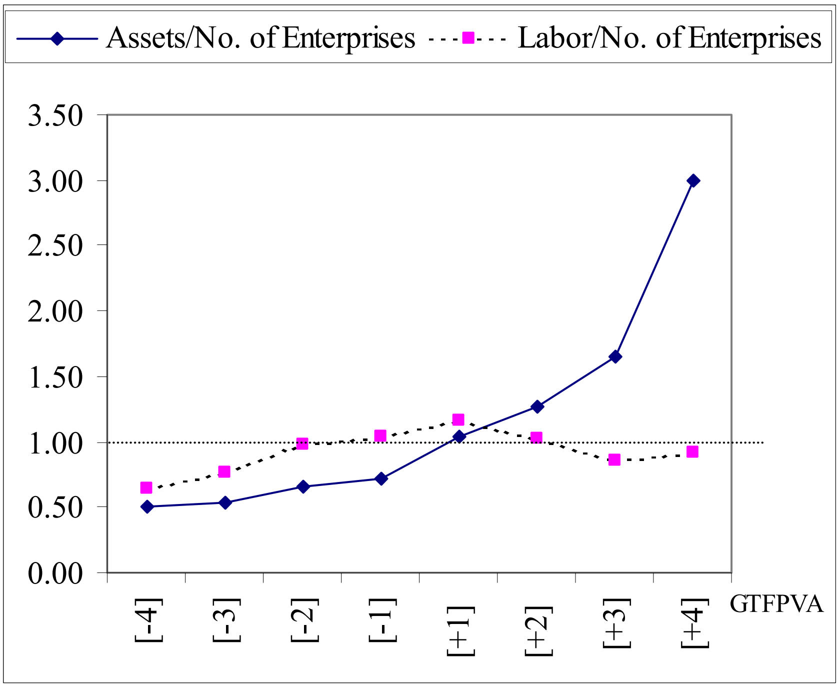


**Figure GTFPYM.A**
**Shares of Assets and Labor across Technical Productivity Groups [GTFPYM]**
(Pooled sample 1995-1998)

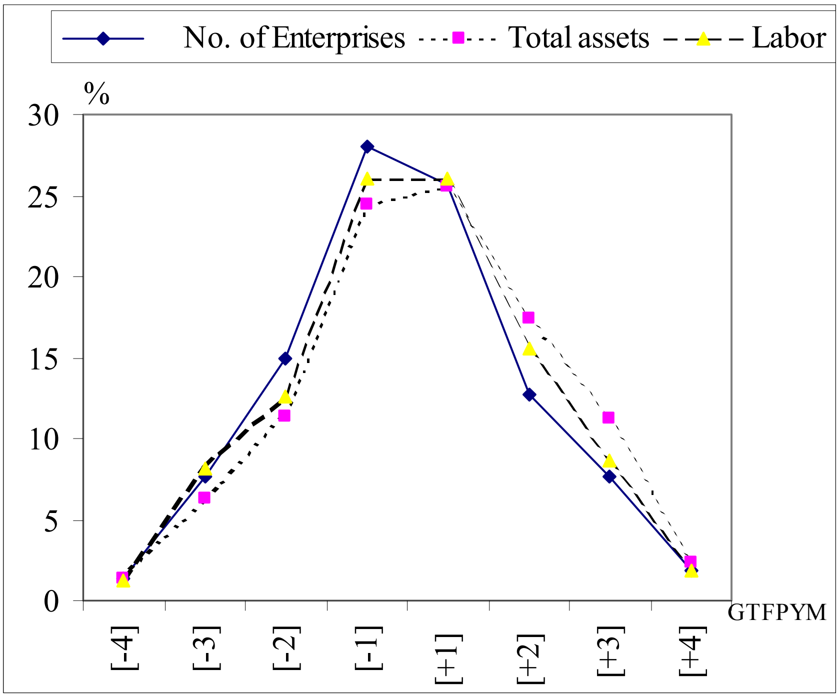
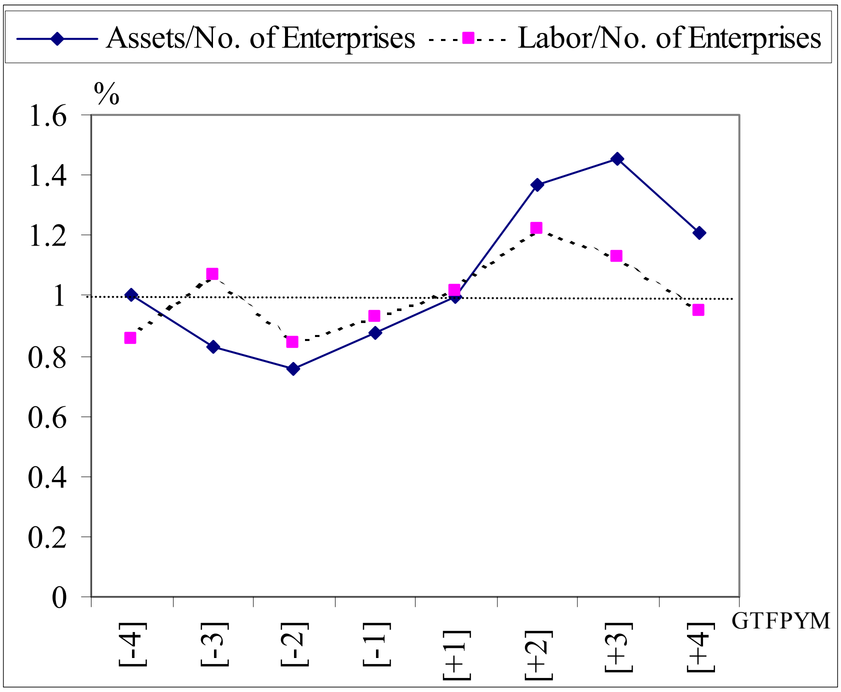



**Figure GTFPYM.B**
**Relative Enterprise Scale by Assets and Labor across Technical Productivity Groups (GTFPYM)**
(Pooled sample 1995-1998)



## Appendix A. DATA AND DATA CLEANING

### *A.1 Data Sources*

This study relies primarily on the annual brief accounting reports filed by all of the large and medium-sized industrial enterprises with the National Bureau of Statistics (NBS) of China during 1995-1998. Before 1995, firm-level industrial statistics collected by NBS were fragmented and sometimes inconsistent due to changes in accounting systems and collection methods. In 1995 ,China conducted its third nation-wide industrial census. The statistical reporting system for data used in this study was built during the 1995 industrial census. The quality of data collection and management has been improve significantly since 1995 thanks for the resources and efforts put into the 1995 census by NBS.

NBS uses these firm-level annual accounting data primarily for calculating components of the Gross Domestic Product (GDP). Hence, this data set contains critical and comprehensive information on the calculation of value added for the sector of the large and medium-sized industrial enterprises. The name, label, and explanation of variables used in this study are contained in Table C.1 in Appendix C and will be explained where necessary.

### *A.2 Unbalanced Sample*

Each enterprise covered by this data set has an independent legal identity with a unique legal identity number filed with the government. The total number of enterprises covered by this data set is about 24,000 in recent years. Enterprises may leave or enter this data set when they create, cancel, or change their legal identity number and/or when the scale of the enterprises are reclassified by the government. The changing composition of the enterprises covered by this data set reflects the dynamics of the Chinese industry and deserves careful study. However, there is little information in this data set on the nature of the changes in enterprise composition. For example, if an enterprise covered in 1995 but disappeared in 1996, we do not know whether it went bankrupt, or was acquired by another enterprise, or was classified as a small enterprise, or changed its legal identity number for other reasons. It is a major limitation of the data set. As a result, we are unable to investigate one of the most interesting set of questions regarding the birth and death of industrial enterprises in an emerging market. In summary, the firm-level data used in this study is an unbalanced sample. But because the sample covers the population of all large and medium-sized industrial enterprises, the aggregate variables such as the total number of firms, total value of gross output, and value of total assets do not change so much over the years.

The sample used in this study covers four years from 1995 to 1998. The composition of enterprises in each of the four years varies for one year to another. Table A.1 shows how the composition of enterprises changes from year to year. Table A.1 also shows that only 10,460 enterprises stay in our sample continuously for four years from 1995 to 1998. This is only 32.2% of the total enterprises that appeared in our sample in one or more years.

In our sample, among 21,115 enterprises existed in 1995 only 15,501 enterprises stay in 1996 and 4,614 enterprises did not show up in 1996, representing an exit rate of 21.9%. On the other hand, among 21,592 enterprises appeared in 1996, 5,091 enterprises did not exist in 1995 and had new legal identification numbers, representing an entry rate of 23.6%. The exit and entry rates have dropped to 15.6% and 15.2% respectively from 1996 to 1997 but risen to 28.0% and 23.3% from 1997 to 1998.

It should be noted that enterprises that appear to be leaving our sample in a particular year might re-enter our sample in the same year with a new legal identification number. It is also possible that the leaving enterprises may be merged or acquired by other enterprises. In any case, the exit and entry rates should not be interpreted as bankruptcy rate or birth rate of new enterprises.

Given the fast pace of structural change and reform in China, the high exit and entry rates are expected and normal. The problem is that we do not have information on why enterprises exit or enter our sample. We believe that availability of that information would help us to examine more closely the behavior of the Chinese enterprises and the impact of economic reform.

The fact that our sample coverage changes from year to year suggests that we should compare changes in the sample aggregates from one year to another with caution. However, in principle we can calculate the growth rate of economic variables for individual enterprises and then calculate the average growth rate for the sample as a whole or for a sub-group in our sample. Because of the difficulties in estimating price index we do not attempt to examine the growth of economic variables in this study.

### *A.3 Data Cleaning*

To ensure the reliability of our study, we screened the original firm-level data for problematic observations. One observation is defined as all statistics for one enterprise in a particular year. The problem observations are identified by the following five screening rules:

1. Enterprises which are not in full operation.
2. Enterprises which have apparent data entry errors.
3. Enterprises with too small scale in inputs.
4. Enterprises with inconsistent accounting data.
5. Enterprises with suspicious accounting data.

On average, the percentage of enterprises caught by each of the screening rules is 5.0% by Rule 4 (inconsistent accounting data), 3.4% by Rule 3 (too small scale in inputs), 2.4% by Rule 5 (suspicious accounting data) and 2.2% by Rule 1 (not in full operation).

Measured by the number of enterprises, the share of problematic observations in original data set is 7.7% for 1995, 8.4% for 1996, 9.3% for 1997, and 13.4% for 1998. The shares fall significantly when each enterprise is weighted by its total assets: 6.2% in 1995, 7.7% in 1996, 7.5% in 1997, and 10.2% in 1998. This indicates that many problematic observations are from enterprises with low levels of total assets. Basing on these results, we conclude that the benefits of more reliable screened data are much larger than the reduction of sample size by around 10%.

Many researchers concern that the state-owned enterprises may have poorer data quality than the non-state ones. To our surprise, the evidences reject this prior impression. The share of problematic observations in the state-owned enterprises is much lower than that in the non-state enterprises: 8.6% versus 11.5% measured by number of enterprises and 6.5% versus 12.1% measured by total assets.

On the other hand, the impression that the quality of data from the loss-making enterprises is worse than those from the profit-making ones is weakly confirmed by the evidences. The share of problematic observations for loss-making enterprises is slightly higher than that for profit-making enterprises: 10.5% versus 9.3% measured by the number of enterprises and 10.2% versus 7.4% measured by the total assets. The relatively small difference in the distribution of problem observations across profitability groups lead us to conclude that we can exclude the problematic observations from our study without generating much systematic bias in the analysis of enterprise performance.

### *A.4 Sample Size and Coverage Relative to Population*

In this study, we use the screened sample for analysis. Table 1.2 shows the size of the screened sample relative to China's industrial aggregates and GDP for the year 1998. The screened sample has 20,164 large and medium-sized enterprises or 0.25% of total industrial enterprises in China in 1998. The enterprises in the screened sample employed 30.3 million workers or 63.8% of the total in China's industrial sector. They produced 3,430 billion Yuan of industrial output or 28.8% of the total industrial output and 1,056 billion Yuan of the value added or 31.6% of the value added from the industrial sector. The number of workers hired by enterprises in this sample is only 4.3% of China's total rural and urban labor force but generated 13.3% of China's GDP.

### *A.5 Management of Outliers*

This study attempts to develop a reliable framework for measuring the performance of China's core industrial enterprises. We have paid particular attention to identifying and outliers while measuring performance. With such a large sample, it is likely that we are unable to identify and exclude all problematic observations Some of the data errors however may generate outliers in performance indicators. These outliers, if included in our analysis, may not only distort the comparison of performance across sectors but also affect directly the measurement of relative performance. When we estimate the total factor productivity of each enterprise, we need to estimate production functions by industry. A data error may create outliers in the production function regression and then distort significantly the estimation of the total factor productivity.

Unfortunately, we are unable to tell whether the outliers are due to data errors or due to real exceptionally good or bad performance of a few enterprises. We decide to exclude all outliers from our measurement of performance, we believe it is important to obtain a reliable measure of performance for the majority of the Chinese industrial enterprises. Since we have a large sample, we are not so much worried about the reduction in sample size.

The methods we used in identifying outliers are explained in detail in the next section. After identifying the outliers for each performance indicator, we code them as missing. This is different from how we deal with problematic observations--we simply delete problematic observations from our sample. Coding an outlier for one particular performance indicator as missing value does not lose the rest of performance indicators for that observation. For the problematic observations, we assume that all the data for that enterprise are not reliable and should not be used for estimation of any performance indicators.

### *A.6 Missing Values and Sample Selection Bias*

Missing values also exist in the original data set. Since missing values can not be used for calculating any performance indicators, the sample size and coverage for each indicator vary. Missing values may lead to serious biases in estimating performance indicators if their distribution is correlated with performance variables. Take the productivity index GYM as an example, as shown in Table A.2, the loss-making enterprises have proportionally more missing values (about 15%) in GYM than the profit-making enterprises (about 3.5%). This leads to a sample selection bias. The profit-making enterprises are over-represented relative to loss-making enterprises in the estimating of the productivity index GYM. This sample selection bias should be taken into account when we interpret the results or carry out further studies. At this stage, we only document the distribution of missing values across various groups for each performance indicator. Further study is needed to assess the implications of the possible sample selection bias.

### *A.7 Weighting Indicators by Total Assets and Employment*

In this study we derive a number of performance indicators for each enterprise. Based on these indicators for individual enterprises, we are able to estimate the performance indicators for various groups of enterprises. In some cases, simple average is be good enough. But in many other cases, it makes more economic sense to use weighted average with total assets or employment as the weight.

For example, the shares in the number of loss-making enterprises across sectors are the most frequently used statistics in China's official documents and research reports. But they may not make much economic sense, since in theory, the share of the number of loss-making enterprises can be reduced to almost zero by merging all loss-making enterprises into one firm. On the other hand, if we use total assets to weight the number of loss-making enterprises, we get the share of total assets in loss-making enterprises and this share does not change when all the loss-making enterprises are merged into one firm.