

Innovation and Productivity of China Textile Industry

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Abstract

Using the textile firm data from the census of National Bureau of Statistics, this paper observes the effect of 3 innovation factors to productivity at industrial level and 3 different classifications in an extended Cobb-Douglas production function. The 3 factors are self-research and development, absorbing and introducing techniques and labour training to adapt new techniques. They are significant at industrial level and different under the classification of firm size, ownership and region. The analysis shows that a combined innovation way is helpful for productivity. Self-Research and Development has higher influence in middle firms, private and HMT firms. It is not significant in foreign firms. Absorbing and introducing techniques has better influence in national firms and foreign firms. For developed area of textile industry, all the influences in Shandong are higher than Jiangsu and Zhejiang.

Keywords: Innovation, Productivity, Enterprise group, Stepwise comparison

JEL Classification: D24 L67 O33

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1. Introduction

Innovation has been considered as the most important promotional power in the next 20 years development of China after a long period of rapid growth. Enterprises and industries are the basic elements of economic growth. They carry out new research and development work, absorb new techniques and product lines, train their employees to improve their productivity and gain more profits. This paper will discuss innovation and productivity in different innovation behaviour and various firm characters based on firm data of China textile industry as an example.

Productivity is a long-term topic for discussion. Capital and labour are the main factors of production function. Cobb and Douglas (1928) established the theory of production and tested it in two US series, i.e. time series of total industrial production and cross-section series of various industries in a same year. Tinbergen (1942) discussed the theory and suggested adding a time variable in the function. Solow (1957) improved the function with uncertain factors to examine technical change in productivity besides capital and labour. It gives us a wide field to define and study the uncertainty. Jorgenson (1986) added intermediate input as a variable and got a different level of influence of technology on productivity in US historical data. Many different methods and results developed after that and most of them were based on macro data and time series of countries and regions, e.g. Romer 1986 and Lucas 1988.

It is a new direction to use micro data to analyze innovation and productivity in recent years and UNU-MERIT provides a good platform to discuss technological change and development in firm level, especially in developing countries. Goedhuys et al. (2006) analyzed Tanzanian firm data in technology and institution factors by using firm survey data and separated innovation into two ways. We will introduce technological factors in boosting productivity of China firm in a similar way.

By using firm data of China textile industry comes from an annual census by National Bureau of Statistics of China (NBS) in 2005, we measure influence of innovation on productivity by 2

variables. The first one is R&D expenditure which assesses the influence by self-research and development. The second is new production value as a result of R&D or/and of absorbing and introducing techniques. Both of them are analyzed under firm size, ownership and regional classifications. Labour training expenditure is added to help figure out the process of firms to adapt to new techniques. The database contains classification variables and inputs and outputs of firm's finance accounting items.

The paper organizes as follows. Section 2 introduces the regression model and a stepwise comparison method. Section 3 describes data and firm classification ways. Section 4 explains innovation behaviour of different enterprises groups in industrial level and those under different classification. Section 5 draws the conclusion.

2. Method

2.1 Model

To well understand the effects of innovation variables on labour productivity of firm level, we use a simple function extended from Cobb-Douglas production function. A group of innovation variables are added as the third factor except labour and capital in formula

$$VA_i = A(Z_i) C_i^a L_i^b e_i \quad (1)$$

in which firms value added VA_i is an explained variable, physical capital C_i and labour employed L_i are traditional explanatory variables, Z_i is a group of technological variables explaining only total factor productivity, and e_i is the random error. We get a linear function after taking logarithms

$$\ln(VA_i) = \ln A(Z_i) + a \ln C_i + b \ln L_i + e_i \quad (2)$$

and rewritten in terms of labour productivity

$$\ln P_i = \ln A(Z_i) + a \ln(C_i/L_i) + (a + b - 1) \ln L_i + e_i \quad (3)$$

in which $P_i = VA_i/L_i$.

Our interest is not in equation and estimation method, but the comparison of innovation

variables' coefficients under different enterprises groups. So all the models under different classifications are estimated in Ordinary Least Squares (OLS) method.

2.2 Innovation Variables and Comparison Method

We can understand firm innovation behaviour by using Figure 1. There are two ways in technology innovation in firm level. The first one is to do self-research and development and the direct result may be new technology and new product, or no result. The second one is absorbing from outside with the aim to get new products. New technology or product can reduce costs or increase price, so that firm can gain more profit and improve productivity. But we could not say a no-result R&D has no influence on productivity. Labour training is a way to adapt to new technology to produce new products and the training can also improve productivity directly.

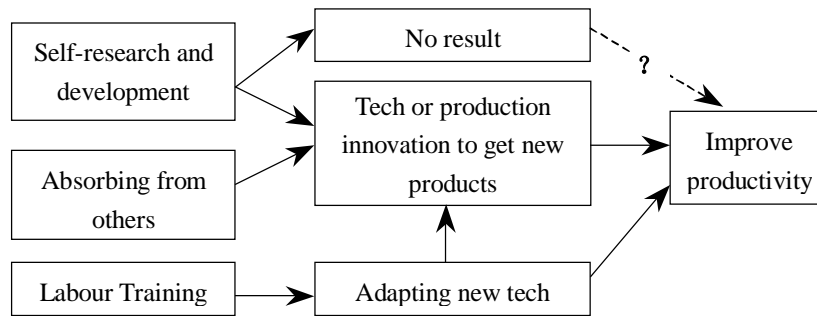


Figure 1: Technology Innovation Path of Firms

We use three explanatory variables in Z_i to explain innovation effects, i.e. R&D Expenditure (RDE) to explain self-research and development, New Product Value (NPV) to understand output of either two ways of innovation, and Labour Training Expenditure (LTE) to show adapting process of innovation. These three variables are adding in the model step by step and 7 models are estimated to find the significant coefficient. The 7 models have different meanings figured out in table 1.

After the 7 models are estimated in one group of firm data, all the significant models are included in analysing the influence of innovation. That is so called stepwise comparison. It is not a stepwise regression for we do not find a single better model to explain the variables, but

to find various characters in different enterprises groups by different models. We can explain it by figure 2: Different cycles means different firms have different characters in innovation like A (e.g. RDE) or B (e.g. NPV). One-variable regression can help to understand behaviour of enterprise group with character A and two-variable regression can help to understand behaviour of enterprise group with character $A \cap B$. It is the first dimension of comparison called Innovation Behaviour Comparison of Enterprises Groups.

Table 1: Explanation of Different Innovation Variables in Models

Level	Significant Variable	Explanation of Innovation Behaviour
Single variable	RDE	Self-research and development influence productivity.
	NPV	Absorbing from others influence productivity. *
	LTE	Labour capacity influence productivity.
Combined variables	RDE & NPV	Innovation influence productivity, but we can not make sure which way it is.
	RDE & LTE	Self-research and Labour capacity influence productivity.
	NPV & LTE	Absorbing and Labour capacity influence productivity.
	RDE, NPV & LTE	Innovation and Labour capacity influence productivity, but we can not make sure which way it is.

* The significance of NPV may come from former R&D. But we suppose the influence mainly comes from absorbing way based on the frequently changes of Chinese firms in the past years.

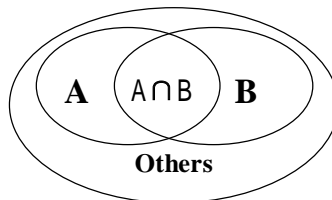


Figure 2: Explanation of Stepwise Comparison Method by Innovation Behaviours

3. Data and Classification Method

The data is released by NBS's annual industry survey of all the national owned firms and other firms whose sales value of products is more than 5 million RMB Yuan. In fact it is a census of large firms with high sales of products. Three types of indicators are included in the

database. The first is classification variables to identify different characters of firms, e.g. sub-industries, regions, ownerships. The second is gross value of production, sales, labour force and so on. The third is financial accounting data include different kinds of assets, liabilities, profits and costs. More than 200 thousands firms are included in the database. Textile industry is a labour-intensive industry with the largest employees among other industries in China. We select it to analyze for it has the largest amount of firms and it is one of the most important and competitive industries in China.

Value added (VA) can be calculated from value of production, value added tax and intermediate input. Capital (CA) is the total assets including fixed assets, current assets and intangible assets. Labour (LA) is the number of employees on production. And labour productivity comes from value added divided by labour. Innovation factors are 3 direct indicators in the database, i.e. RDE, NPV and LTE. Table 2 describes summary statistics of these variables and all of them changed into logarithm in the models. Zero value is not included in the estimation, i.e. different observations are included in different models, which has been pointed out in figure 2.

Table 2: Statistical Description of Relevant Variables in the Model

	Number	Zero Value	Mean	Std. Deviation	0.25 Percentile	Median	0.75 Percentile
Productivity	21716	0	73643	110968	26120	44956	81845
Capital	21716	0	46363	232826	6180	12781	32425
Labour	21716	0	267	874	63	120	250
NPV	1420	20296	45370	149751	1837	8328	31325
RDE	1105	20611	1148	5025	33	110	457
LTE	7842	13874	58	329	6	15	42

Descriptions of innovation indicators do not include zero value cases.

In order to understand different effects under different firm characters, after an industrial level estimation of all textile firms, we extend three classification variables to show different effects of innovation in different kinds of firms. The first is firm size divided into large, middle and small by number of employees. The second is ownership and we pay attention to some of four

kinds, i.e. national owned, Hong Kong, Macao and Taiwan (HMT) owned, foreign owned and private owned. The third is region of firms and we show 3 most competitive provinces in textile industry, i.e. Jiangsu, Zhejiang and Shandong in the east of China (ZHEN, 2005). Table 3 shows the description of innovation behaviour and classification variables. The scatter plots (appendix figures 1 to 9) in appendix show relations between innovation indicators and labour productivity classified by 3 variables.

Table 3: Description of Classification Variables

Innovation			Ownership		
Character of Variables	Cases	%	Owner	Cases	%
RDE>0	1105	5.09	National	262	1.21
NPV>0	1420	6.54	HMT	2795	12.87
LTE>0	7842	36.11	Foreign	2081	9.58
RDE & NPV>0	282	1.30	Private	12524	57.67
RDE, NPV & LTE>0	231	1.06	Others	4054	18.67
Size			Area		
Employees	Cases	%	Province	Cases	%
<100	9050	41.67	Jiangsu	4510	20.77
100-1000	11732	54.02	Zhejiang	6207	28.58
>=1000	934	4.30	Shandong	2646	12.18
Total	21716	100.00	Others	8353	38.46

The meaning of firm classification can be explained by figure 3: All firms can be separated into different groups in one classification standard like A (e.g. National owned), B (e.g. Foreign owned), C (e.g. Private owned), etc. We can compare different coefficients to understand different power of influence between groups in models with the same innovation variable(s). It is the second dimension of comparison called Enterprise Classification Comparison of Enterprises Groups.

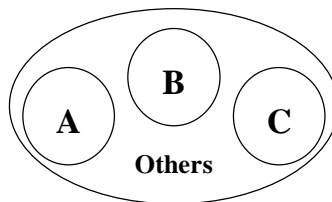


Figure 3: Explanation of Stepwise Comparison Method by Enterprises Classification

By using stepwise comparison of innovation behaviour and enterprise classification, two dimensions could be explained by different variable(s) in the same group and the same variable(s) between groups. In the same group (e.g. large firms), one singular significant explanatory variable represents by one way of influence of innovation, two or more significant variables means a combined effect of innovation. Models with the same significant variables in different groups (e.g. large and middle firms with RDE as the only significant variable in technology part) can help to explain different power of influence between groups.

In addition, we do not introduce dummy variables as Goedhuys et al. (2006) done in analyzing Tanzanian data, nor do we include zero value in the models. For dummy variable (e.g. RD), we found it difficult to explain when the symbols are opposite in the same factor, e.g. RD and R&D Expenditure, and the samples are enough to estimate in different group. With a hypothesis of zero value for independent variables after a logarithmic transform, the estimation of parameter will also be significant but small, for the large amount of zero. It is no better in understanding the effects of firms with innovation factors. On the other hand, we could not use the stepwise comparison method by hypothesizing zero after a logarithmic transform.

4. Results

The regression results are summarized in tables 4 to 7. Table 4 shows influence of innovation indicators in industrial level. Tables 5 to 7 report the influence under different classification levels. As presented in table 4, all the 7 equations are estimated in each table, i.e. each one of indicator, each two of indicators and all the 3 indicators. Only significant equations with significant coefficient(s) are included in the forms.

For all the textile firms, only 5.09 percent of them have R&D expenditures. Their spending has a significant influence on productivity as M3.2 shows in table 4. The effect is enhanced when new product outputs or/and labour training are added. New product value and labour

training are changing in the same way. Model M3.8 with the highest adjusted R square shows combination of innovation with labour training is better for productivity of textile firms in China, but the sample size reduces to 231.

Table 4: Regression Models on Industrial Level

	Basic	One Explanatory Variable			Two Explanatory Variables			Overall
Code	M3.1	M3.2	M3.3	M3.4	M3.5	M3.6	M3.7	M3.8
Traditional								
L(CA/LA)	0.423***	0.473***	0.630***	0.663***	0.511***	0.797***	0.727***	0.471***
LLA	-0.210***	-0.295***	-0.295***	-0.330***	-0.238***	-0.508***	-0.391***	-0.408***
Technology								
LRDE		0.162***			0.184***	0.133***		0.202***
LNPV			0.104***		0.127***		0.120***	0.131***
LLTE				0.145***		0.198***	0.172***	0.164**
Adjusted R²	0.262	0.332	0.278	0.283	0.443	0.399	0.358	0.468
Observations	21716	1105	1420	7842	282	763	710	231

Dependent Variable: $L(VA/LA)=\text{Log}(\text{Labour Productivity})$

Significant Level: 0.01(***), 0.05(**), 0.1(*)

Classified by firm size in table 5, only 3 models are significant for small and large firms. To small firms, NPV is significant only when it's together with RDE. It shows the difficulty for small firms to absorb new techniques entirely without any change. It may be expensive for them to buy a new technique entirely. So absorbing by copy with a little research can change into new products and uses a long time. Large firms group cares only one field of innovation and no combined indicators are significant. They have a high situation in gross output and market. Caring only one field is enough for a short-time development for most large firms. This group did not pay enough attention to the benefit of multiple ways of innovation to productivity growth. Middle size firms have various behaviours. The productivity gets benefits from separate innovation indicators. The combined 2 indicators are helpful and most of them enhanced with another indicator. On the other dimension, R&D innovation way has a better influence on productivity in middle firms, rather than large and small firms. But the influence of labour training in middle firms is the smallest in all the models. New product and

labour training have greater influence in little and large firms. That is to say, in order to adapt to market changes and competition, little firms have great stress to improve productivity by new product and labour training. The stress for large firms may come from the pursuit of sustainable profit and leadership of the industry.

Table 6 shows it is important for national owned firms to absorb high technique since RDE is not significant. The fact is that not much national owned firms are left in textile industry today, i.e. 1.2% of total textile firms is a very small percentage. Most of them do not do their own research and depend on absorbing and acquire new technology from other sources, e.g. institutes of textile, for they have good connection and cooperation since the planned economic system. They spend more on labour training and the two significant factors are much higher than industrial level in table 4. Foreign owned firms also use a straight way to obtain new techniques from external, e.g. foreign sources. Self research and development is significant in private and HMT groups, they are Chinese private owned firms. And all the innovation variables have significant influence on productivity separately in these private owned firms. But private firms need a long-term management and spend more on innovation since its parameters are the smallest.

Divided by region in table 7, Shandong is a traditional region for textile industry and it is near the material producing area. All the innovation factors are significant in one-indicator equations and give a higher explanation than the other two provinces. And the influence is greater than the industrial level presented in table 4. Labour Training and absorbing techniques seems more useful than R&D in improving productivity in Zhejiang. The separate effect of each factor is smaller than the equal level in China, but the only combined effect is greater. There is no significant effect of R&D in Jiangsu, whereas absorbing techniques is more important since its fast development of foreign investment.

Table5: Regression Models Classified by Firm Size

	Small Firms (Employees<100)			Middle Firms (100=< Employees <1000)						Large firms (Employees>=1000)		
Code	M4.1	M4.2	M4.3	M4.4	M4.5	M4.6	M4.7	M4.8	M4.9	M4.10	M4.11	M4.12
Traditional												
L(CA/LA)	0.497***	0.400***	0.399***	0.497***	0.465***	0.483***	0.629***	0.638***	0.615***	0.594***	0.524***	0.552***
LLA	-0.162**	-0.251***	-0.204***	-0.111**	-0.035	-0.082*	-0.214***	-0.221***	-0.212***	-0.149**	-0.095	-0.054
Technology												
LRDE	0.110*	0.118**		0.139***	0.184**		0.166***			0.113*		
LNPV	0.257***				0.126*	0.170**		0.145***			0.170***	
LLTE			0.184***	0.098**		0.094***			0.088***			0.153***
Adjusted R^2	0.417	0.304	0.273	0.321	0.352	0.286	0.277	0.24	0.214	0.405	0.353	0.362
Observations	166	284	2776	437	164	392	633	800	4497	188	212	564

Dependent Variable: $L(VA/LA)=\text{Log}(\text{Labour Productivity})$

Significant Level: 0.01(*), 0.05(**), 0.1(*)**

Table 6: Regression Models Classified by Ownerships of Firms

	National		HMT			Foreign		Private		
Code	M5.1	M5.2	M5.3	M5.4	M5.5	M5.6	M5.7	M5.8	M5.9	M5.10
Traditional										
L(CA/LA)	0.516***	0.419***	0.537***	0.525***	0.497***	0.473***	0.462***	0.455***	0.421***	0.409***
LLA	-0.038	-0.316***	-0.271***	-0.312	-0.182***	-0.146*	-0.156***	-0.270***	-0.180***	-0.262***
Technology										
LRDE			0.142*					0.108*		
LNPV	0.214*			0.153*		0.136*			0.075**	
LLTE		0.233**			0.153***		0.121***			0.138***
Adjusted R ²	0.308	0.311	0.412	0.404	0.333	0.270	0.266	0.280	0.224	0.262
Observations	55	122	117	146	859	124	755	556	665	4391

Dependent Variable: $L(VA/LA)=\text{Log}(\text{Labour Productivity})$

Significant Level: 0.01(***), 0.05(**), 0.1(*)

Table 7: Regression Models Classified by Region

Code	Jiangsu		Zhejiang				Shandong		
	M6.1	M6.2	M6.3	M6.4	M6.5	M6.6	M6.7	M6.8	M6.9
Traditional									
L(CA/LA)	0.356***	0.436***	0.618***	0.664***	0.636***	0.601***	0.319***	0.475***	0.366***
LLA	-0.374***	-0.284***	0.226***	-0.123**	-0.107***	-0.210***	-0.433***	-0.260**	0.434***
Technology									
LRDE				0.098*			0.348***		
LNPV	0.190**		0.131***		0.076**			0.191*	
LLTE		0.130***	0.190***			0.120***			0.201***
Adjusted R ²	0.289	0.264	0.432	0.455	0.402	0.411	0.296	0.300	0.268
Observations	93	1630	327	319	495	2930	161	80	875

Dependent Variable: $L(VA/LA)=\text{Log}(\text{Labour Productivity})$

Significant Level: 0.01(***), 0.05(**), 0.1(*)

5. Conclusion

This study uses micro data to explain 3 innovation factors of China textile industry. All of them are significant in separate or combined at the industrial level in improving productivity. The combination can make the positive influence greater. In classified study, middle firms group are active, national owned firms place greater effect on technique-absorbing and labour training, Shandong has a better expression in 3 factors separately with a stronger influence than the average level in industrial level equation and province level of the other 2 provinces.

From the empirical results, we could get the conclusion that technology innovation and labour training have significant influence on accelerating productivity. But the intensities are variance in different enterprises groups. The empirical study shows a similar result in experiential judgement, e.g. the innovation stress of small firms, the less innovation behaviour of foreign firms and the short term running of private firms. It is helpful for macro policy-making and micro firm management and innovation behaviour selecting.

The study can improve in 2 directions. The first one is the usage of longitudinal data for a multilevel model. The difficulty is that only about 15% firms sustained in the past 6 years and the other 85% changed. The Survey on Enterprise Transfer arranged by NBS since last year can help to improve this study, but the data is not available now. The second direction is the usage of innovation variables is not sufficient to describe firm innovation behaviours like management and so on. The Enterprise Innovation Survey by NBS since 2006 will help to introduce more innovation variables and we may get the data in late this year.

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Appendix

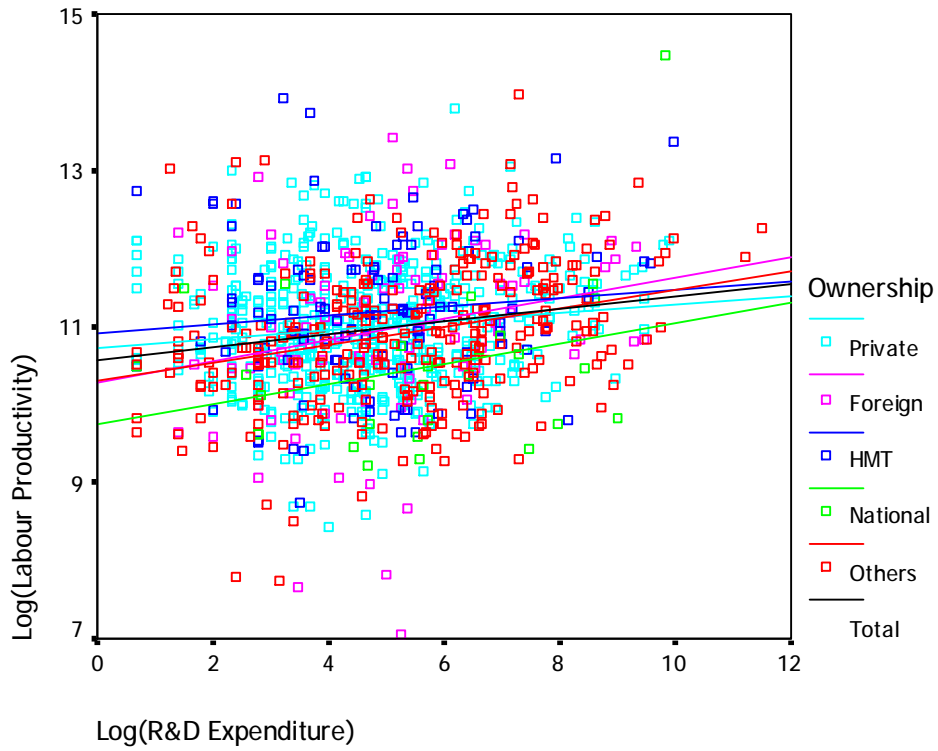


Figure 1: Scatter Plot of R&D Expenditure and Productivity Marked by Ownership

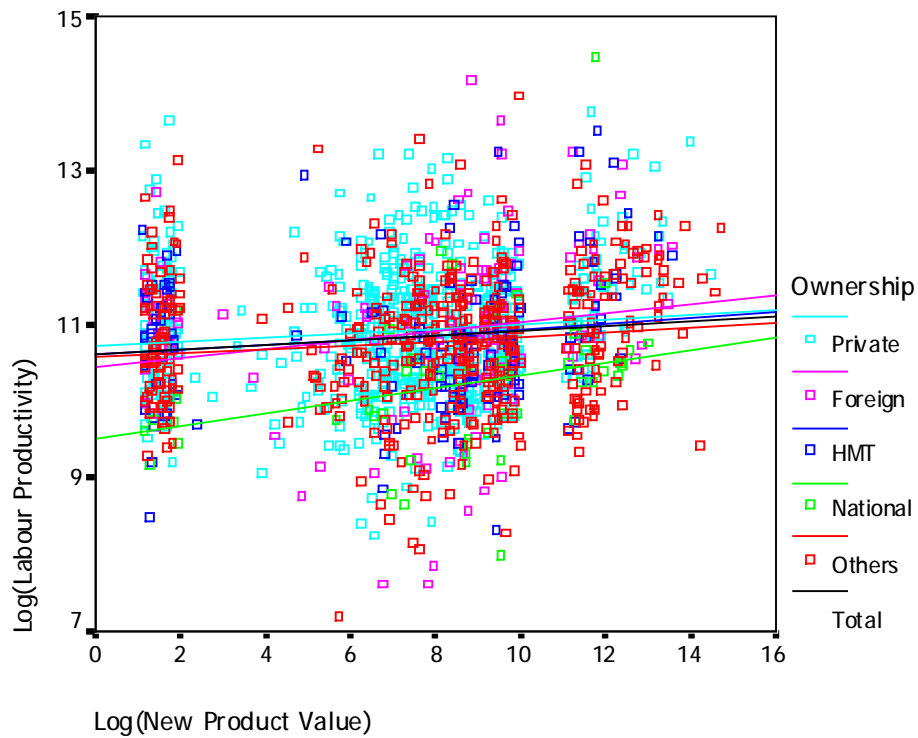


Figure 2: Scatter Plot of New Product Value and Productivity Marked by Ownership

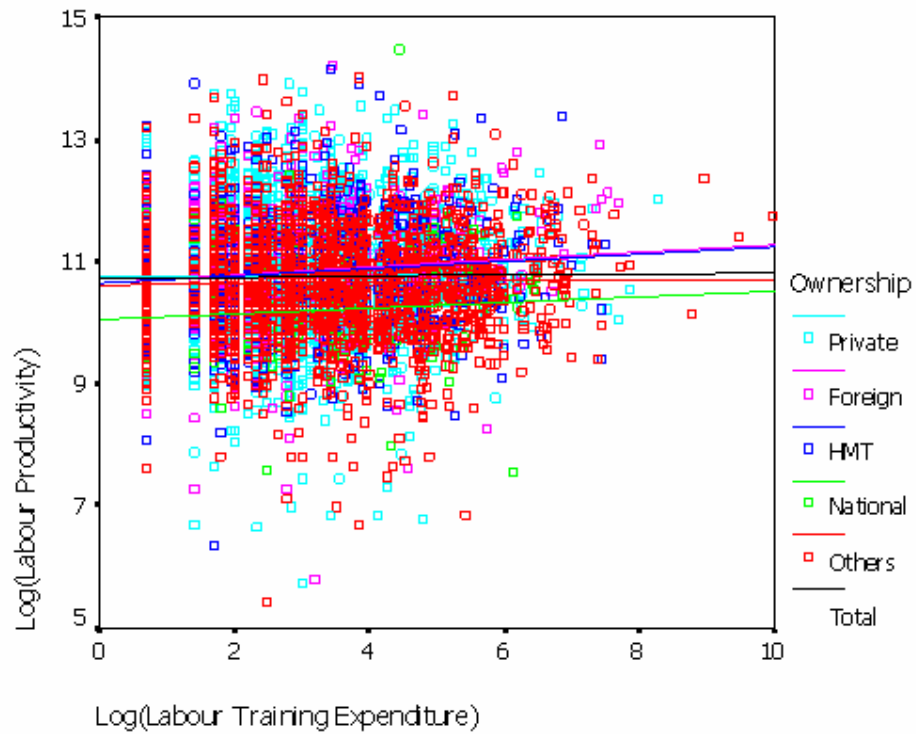


Figure 3: Scatter Plot of Labour Training Expenditure and Productivity Marked by Ownership

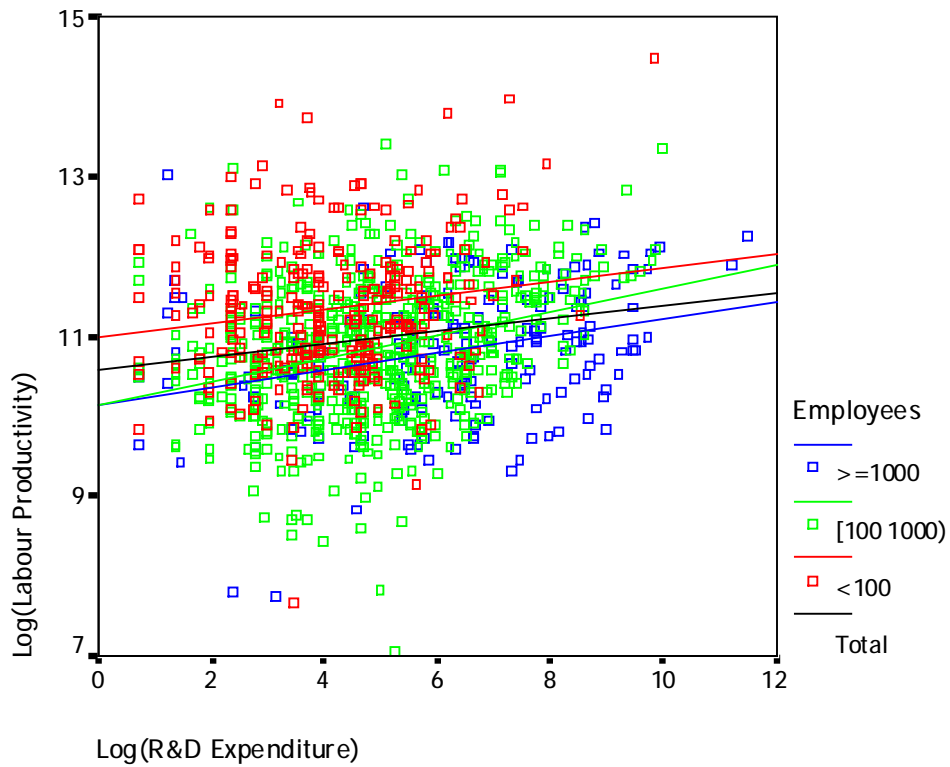


Figure 4: Scatter Plot of R&D Expenditure and Productivity Marked by Employees

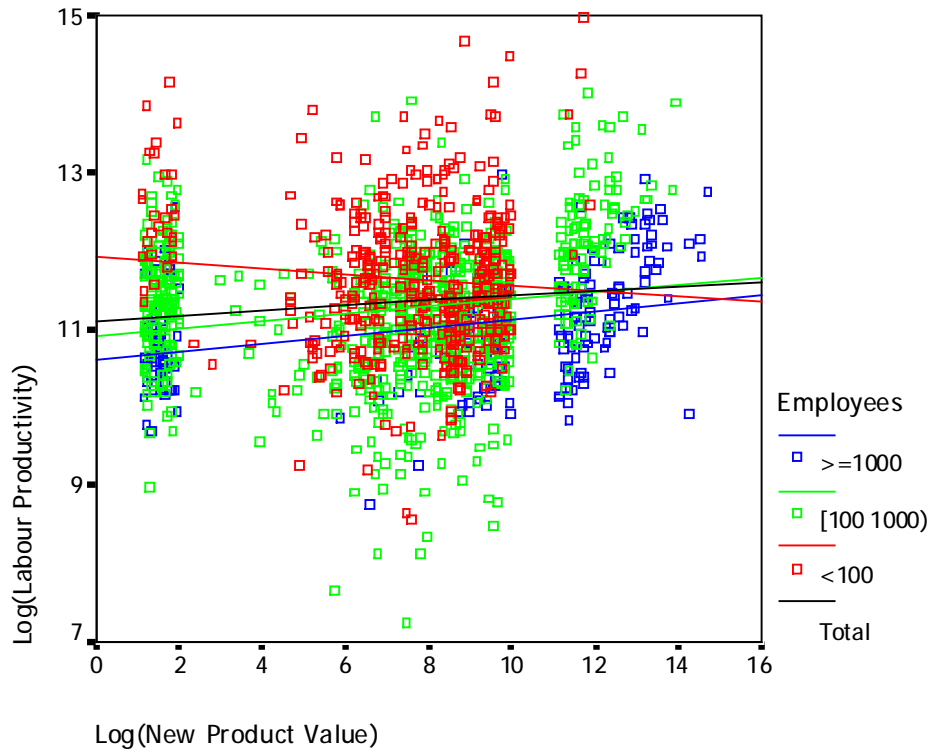


Figure 5: Scatter Plot of New Product Value and Productivity Marked by Employees

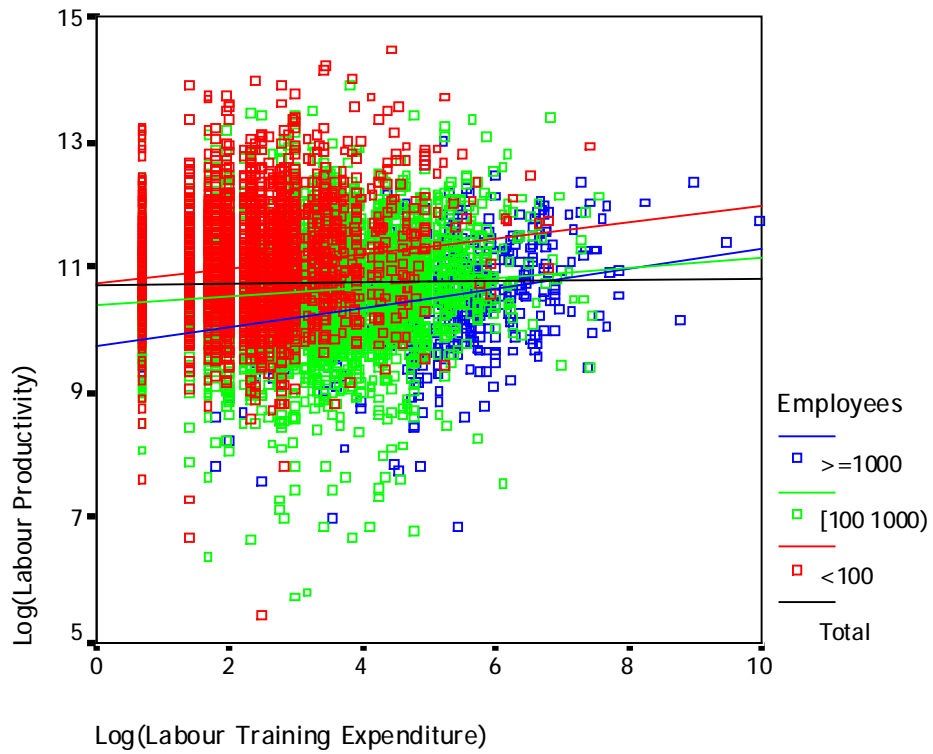


Figure 6: Scatter Plot of Labour Training Expenditure and Productivity Marked by Employees

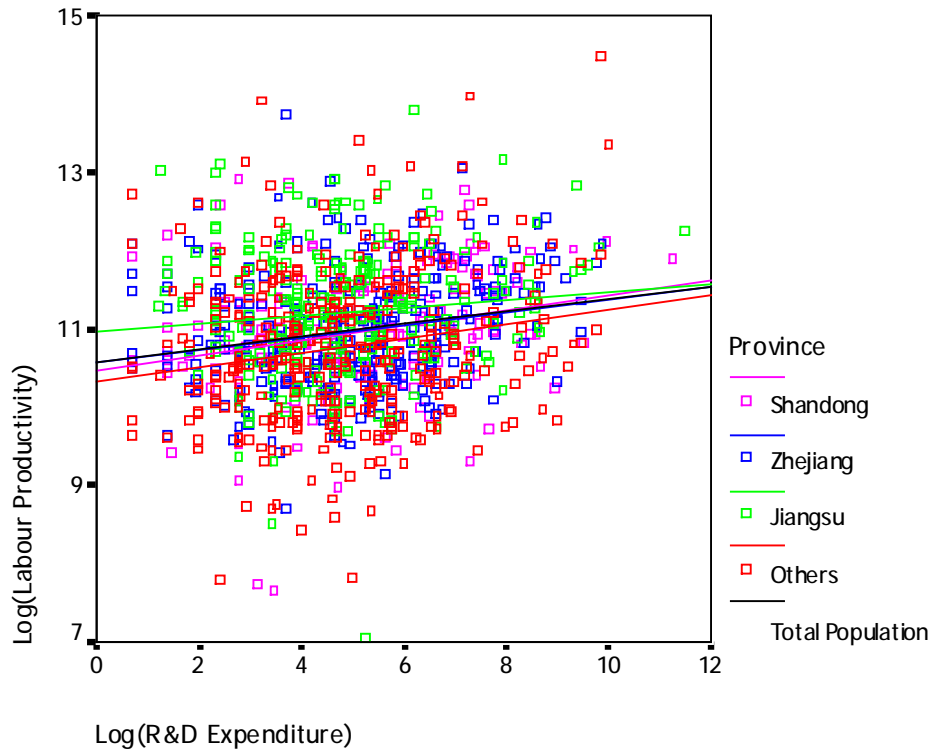


Figure 7: Scatter Plot of R&D Expenditure and Productivity Marked by Province

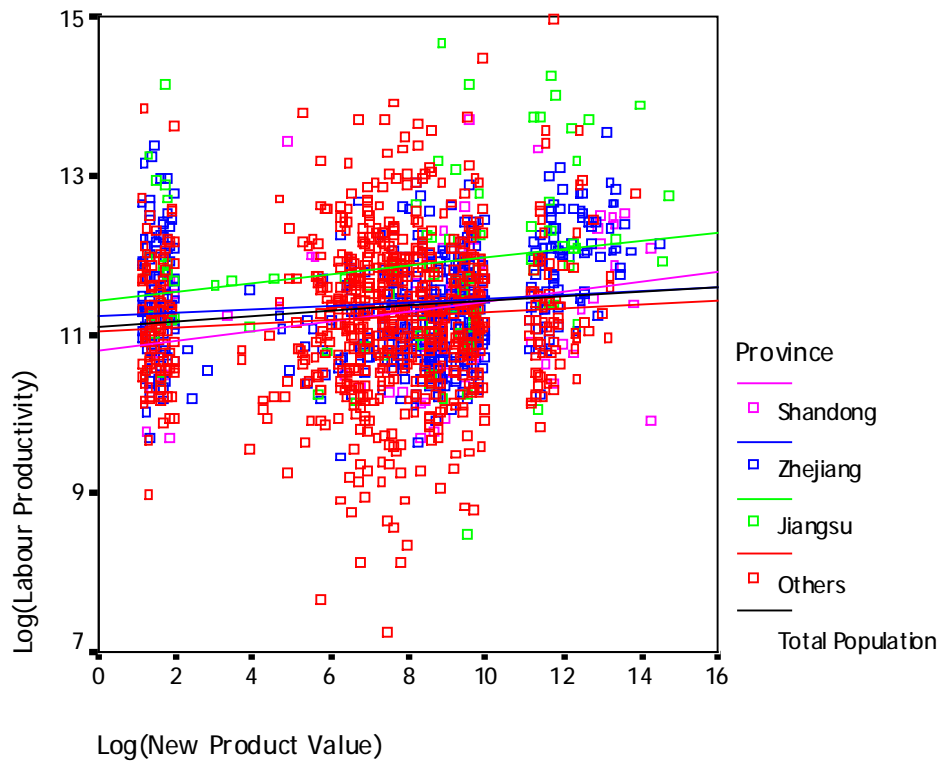


Figure 8: Scatter Plot of New Product Value and Productivity Marked by Province

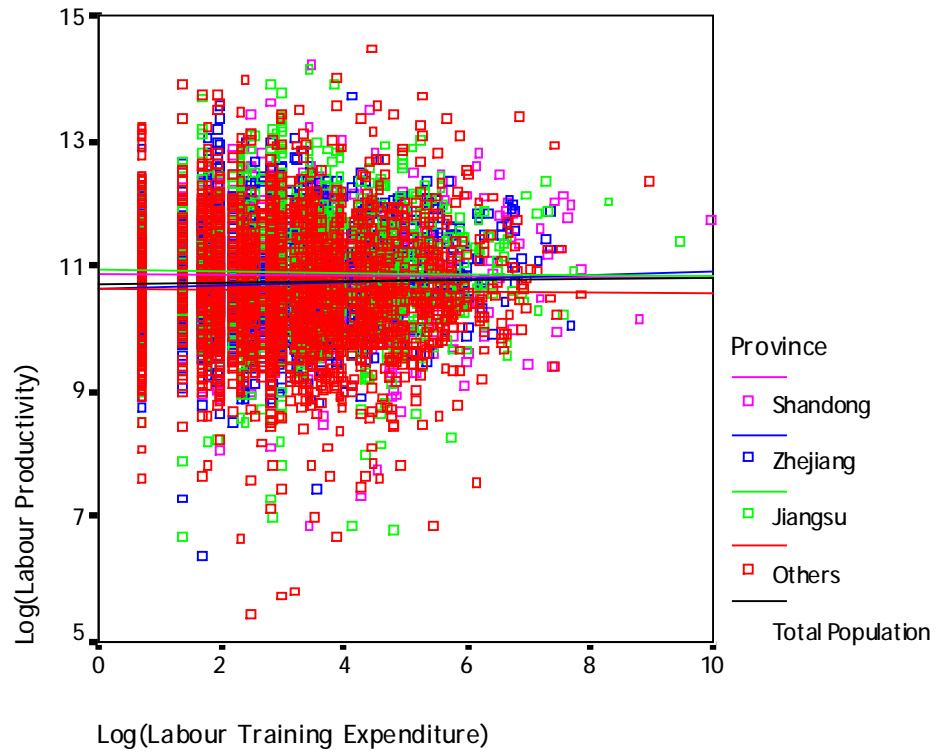


Figure 9: Scatter Plot of Labour Training Expenditure and Productivity Marked by Province