Impact of Technological Innovations on Quantity and Quality of Employment in Beijing: a Micro-Econometric Approach[∗]

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Abstract: According to the relevant theory of employment effect of innovations and Beijing's characteristics in technological innovations, the author hypothesized that technological innovations in Beijing would have positive effect on employment quantity and bias towards high-level tacit professional knowledge and skills. Based on the questionnaires collected from 235 enterprises in Beijing, the author tested the hypothesis. The results show that the firms' technological innovations have significantly promoted not only the increases of total employees, but the proportion increases of expected skilled workers, including R&D staff, technological professionals, white collar workers, highly educated employees and skilled manual workers. In order to alleviate structural unemployment pressure brought by technology change, the local government could promote the development of productive service industries with higher elasticity of employment, improve the sensitivity of college and vocational education to the demand of labor market, and encourage the enterprises to take on the major part of technological innovations.
Keywords: Technological innovation; Employment effect; Skill biased innovation

1 Introduction

Technological innovation has always been the engine for economic growth in Beijing. Attribute to its distinguished advantages in human resources, R & D facilities and hi-tech industrial clusters, Beijing has become the leading innovative city, and was designated as the National Innovation Center of China. Meanwhile, the escalating employment pressure (especially for the college graduates) is attracting more and more concern from the government and scholars. This paper conducts a micro-econometric research on the impact of technological innovations on the quantity and quality of employment in Beijing, based on latest literature on innovation-employment relationships and questionnaires to enterprises in Beijing. The empirical results show a positive effect of technological innovation on employment quantity and strong skill biased orientation.

The remainder of this paper is organized as follows: section 2 briefly reviews literatures on employment effect of technological innovation, including impact on the quantity and quality of employment; section 3 formulates the characteristics of technological innovation in Beijing and its expected employment consequences; section 4 conducts an empirical research based on a questionnaire survey to enterprises in Beijing; section 5 draws conclusions and policy implications.

2 Literature Background

As Pianta (2003) recalls, literature discussing the innovation-employment link has concentrated on two major questions: The first one is related to the classical question "does technology create or destroy jobs", referring to the impact of technological innovation on the *quantity* of employment. The second one focuses on what type of jobs are created or destroyed and whether there're changes in skill structure and wage distribution, referring to the impact of technological innovation on the *quality* of employment.

2.1 The impact of technological innovation on the quantity of employment

In the theoretical literature the differentiation between product and process innovations has been proved important (Stoneman, 1984; Hamermesh, 1993). Product innovations are often associated with employment gain since the new products create new demand, but it may be realized at the expense of loss of its competitors. Process innovations often reduce labor demand by automating or mechanizing processes, but it may lead to positive employment changes elsewhere in the economy via new machines, decrease in prices, increase in incomes, increase in new investments, or decrease in wages (for more details, see Spiezia and Vivarelli, 2000). The overall effect depends on a complicated array of technological, economic and social variables. Empirical researches show that at the firm level, the

overall employment impact of innovation tends to be positive, regardless of product innovation or process innovation, while at industry and aggregate level, the effect of process innovation range from negative to positive according to the specifications (for reviews, see Van Reenen, 1997). This paper focuses on the firm level empirical research.

The model of industry life cycle raised by Utterback (1996) proposes a dynamic perspective to treat the link between innovation and employment. According to the model, in the early 'fluid' stage of the industry life cycle when product is poorly defined, firms tend to be small and compete by radical product innovations to satisfy various customer demands, leading to rapid increases of firms and jobs. After a 'dominant design' emerges, firms seek to introduce minor changes on the design template rather than offer radically different alternatives, and the logic of the industry begins to switch from exploration to exploitation and efficiency; many small firms are kicked out by more efficient and grown-up ones. Hence in this 'transitional phase', radical product innovations turn to incremental product innovations and later process innovations; increase of the firms and jobs slows down. As the industry becomes more mature and enters the 'specific phase', economy of scale and cost-effectiveness rule the competition; firms retreat to minimize cost by process innovation which usually replace labor with capital; amount of firms and jobs begin to decrease.

2.2 The impact of technological innovation on the quality of employment

Besides the quantity of employment change, quality aspects have received increasing attention, especially when Information and Communication Technologies (ICT) are radically changing the techno-economic paradigm of the modern economies. This strand of literature focuses on the changes of skill composition and wage structure. Most empirical researches find that technological innovations especially ICT developments are biased towards skilled workers as it replaces unskilled labor and increases wage inequality (reviewed in Acemoglu, 2002). However, most research overlooked the heterogeneity of innovation, simply representing innovation by proxies like R&D expenditure and patents approved; furthermore, these researched overlooked the heterogeneity of skills biased, simply representing skills by relative proportion of blue/white collar occupations or education levels. Such shortcomings will be improved in this paper.

The taxonomy approach developed by Pavitt (1984) can better understand how the impact of innovation on skill structure differs in different types of sectors. Pavitt identified four different 'sectoral patterns' of technological change. Respectively, they are the pattern of science-based firms, specialist suppliers, scale intensive firms and supplier dominated firms, which differ dramatically in requirements for knowledge and skills. For example, science based firms, typically found in sectors such as pharmaceuticals, biotechnology, and electronics, heavily depend on the knowledge and skills of R&D professionals, scientists and highly educated graduates from academia; while specialist suppliers, with typical products like instrumentation and specialist computer software, require high level vocational and practical skills.

Another useful approach for this paper is the theory of 'defensive skill biased innovation' developed by Thoenig and Verdier (2003). This theory argues that globalization and intensive trade of hi-tech products triggers an increased threat of technological leapfrogging or imitation, firms tend to respond to that threat by increasing the share of tacit knowledge and non-codified know-how embodied in their production processes, which leads to skill biased innovations in both developed and developing regions. This theory can be applied for the region intensively importing or exporting hi-tech products including Beijing.

3 Characteristics of Technological Innovation in Beijing

According to the Annual Reports of Regional Innovation Capability of China (Research Group of the Science and Technology Development Strategy of China, 2002~2011), Beijing has always been ranked top 3 cities of China in terms of regional innovation capability from 2001 to 2010. Compared to other leading innovative regions like Shanghai, Jiangsu province or Guangdong province, technological innovations in Beijing have the following characteristics, which entail specific employment effects:

3.1 Abundant human capital and R&D facilities lead to induced skill biased technological innovation

Beijing has the most universities, research institutes, laboratories and R&D bases in China. For example, Beijing gathers 28% of the State Key Labs, 33% State Engineering R&D Centers, 45% of the National Science Projects and 50.9% of the National Academicians (Research Group of the Science and Technology Development Strategy of China, 2010). Furthermore, Beijing has abundant or even

redundant supply of college students every year. Such abundant human capital, R&D professionals and hence their relative low cost may lead to induced labor augmenting and skill biased innovation.

3.2 Environment of more globalization and openness may easily cause passive and proactive defensive skill biased technology innovation

Compared to other domestic innovative regions, Beijing is more international and open to the developed world, with intensive trade flow of high technology and hi-tech products (including services). On one hand, Beijing consumes large amount of hi-tech products from the developed countries, with intensive tacit knowledge embodied by the producers; In order to compete for the domestic market with international firms, local firms have to take the similar defensive skill biased innovation passively. On the other hand, Beijing is also a major source of R&D, production and exportation of hi-tech products (mainly to underdeveloped regions in China); in order to counter react the threat of imitation and leapfrogging from domestic competitors, local firms tend to take defensive skill biased innovations proactively.

3.3 Hi-tech industrial clusters take on obvious innovation pattern of science-based firms and specialist suppliers

Beijing has advanced industrial structure, characterized by several large scale industrial clusters including Zhong Guan Cun Science Park, Daxing Bio-Medical Base, New Media industry base, Electronics Park, Aerospace Park, etc. These industrial clusters mainly function in ICT, bio-medical, electronics and intelligent transportation sectors. On one hand, these sectors are mostly in the fluid or transitional phase of their life cycles, with amount of jobs on the increasing tracks; on the other hand, these sectors take on obvious innovation patterns of science based firms and specialist suppliers, requiring more scientists, professionals and college graduates with high level of general knowledge and tacit professional skills.

3.4 Strong policy incentives accelerate the development of its unique industrial structure and skill requirements

Beijing has always been receiving strong policy incentives for independent technological innovation and industrial structure upgrading in fiscal subsidy, tax exemption and talent importation, etc. In the newly issued 'the 12th five years' planning', Beijing was designated as the National Innovation Center, with Zhong Guan Cun Science Park as the National Independent Innovation Pilot Base. Such incentives will further shape Beijing's regional innovation system and its related skill requirements.

On the quantity side, the characteristics above may entail technological innovations in Beijing with positive employment effect. While on the quality side, such characteristics may induce the innovations biasing towards high-level tacit knowledge and professional skills, which are more fluid, transferable and couldn't be commanded after short-term specialized vocational trainings, such as strong learning skills, creative skills, cognitive skills and interactive skills (Howells, 2003), instead of the engineering skills, motor competences and manual skills much required by the scale intensive industries. This may cause increasing proportions of R&D staff, technical professionals and employees with high level general educations. The author will test this hypothesis empirically in the following section.

4 Empirical Evidences

4.1 About the questionnaires

Empirical researches is conducted based on questionnaires responded by 235 enterprises in Beijing. The questionnaires were designed according to the questionnaires used in famous Community Innovation Survey (CIS) in Europe, with specific questions about innovation, and added more employment related questions by the author. The investigation period was the beginning of 2008 to the end of 2010. The innovation related questions include whether the firm conducted product innovation or process innovation, whether the innovation is primal, imitation or by adoption and assimilation, how much are the R&D expenditures, numbers of patents approved and which are the major innovation hampers, etc.; employment related questions include the increasing rate of total employment, R&D staff, technological professional, non-operative staff (white collar workers), technicians and senior technicians, employees with master and doctoral degrees, etc. and average wage of each category.

Among the 235 observations, 44.62% belong to the manufacturing sector and 55.38% belong to the service sector. 53.95% belong to the hi-tech industries which involves intensive use of ICT and highly skilled workers, which far surpasses the national average level; respectively, they are cultural and art (12.31%), computer and software (10.77%), electric and electronics equipment (10.07%), transportation equipment (8.35%), pharmaceutical and bio-medical (7.90%), and financial and insurance (4.62%).

Such a structure coincides with the pattern of science-based firms and specialist suppliers mentioned above.

4.2 Empirical evidences on the quantity side

According to Zimmerman (2008) and Verspagen (2004), the labor demand L of enterprise i can be expressed as the function of technology level T, product quality Q and a set of control variables, X. The following function can be got by differentiation of the logarithmic form:

$$\Delta InL_i = \varepsilon_T \Delta InT_i + \varepsilon_Q \Delta InQ_i + \varepsilon_X \Delta InX_i$$

ΔInL_i stands for the increasing rate of logarithmic employment amount of enterprise i from 2008 to 2010. Technology change corresponds to improvement of labor productivity, with process innovation (PC) as the proxy. If the enterprise has conducted process innovation during the period, $PC = 1$, or else $PC = 0$. Changes of the product quality can be indicated by the proxy product innovation (PD), If the enterprise has conducted process innovation during the period, $PD = 1$, or else $PD = 0$.

In order to detect the employment effect of different types of product and process innovations, the author conducts a second phase regression analysis to all the enterprises which have ever conducted product or process innovations. $PCP = 1$ means at least one of the process innovations is primal innovation, while $PCP = 0$ means all of the process innovation are imitation innovation or re-innovation after adaptation and improvement. Similarly, $PDP = 1$ means at least one of the product innovations is primal innovation, while $PDP = 0$ means all of the product innovations are imitation innovation or re-innovation after adaptation and improvement.

Control variables include labor cost, indicated by the increasing rate of logarithmic average wage (WG) of the enterprise from 2008 to 2010, logarithmic employment amount of the enterprise at the end of 2008 ($L08$), and whether the enterprise has ever conducted organizational innovation, ORG (ORG=1 if the answer is yes).

Henceforth, the regression equation of phase 1 and phase 2 are as follows, respectively (for simplicity, the subscript i is omitted):

$$LGR = \alpha + \beta_1 PC + \beta_2 PD + \beta_3 WG + \beta_4 L08 + \beta_5 ORG + u ,$$

$$LGR' = \alpha' + \beta_1' PCP + \beta_2' PDP + \beta_3' WG + \beta_4' L08 + \beta_5' ORG + u' .$$

In order to eliminate the co-linearity among the variables, the author uses forward directional stepwise regression method to estimate the equation, with the stopping rule that p value equals 0.5, and technological innovation variables (PC, PD, PCP, PDP) always included. The estimation results of phase 1 and phase 2 are displayed in Table 1 and Table 2.

Table 1　Estimation Results for Equations of Employment Quantity and Innovations (Phase 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PC	0.058672	0.089622	1.654663	0.1139
PD	0.126601	0.093257	3.357546	0.0770*
ORG	0.486817	0.100390	4.849258	0.0000***
L08	-0.083604	0.018545	-4.508250	0.0000***

Table 2　Estimation Results for Equations of Employment Quantity and Innovations (Phase 2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PCP	-0.067974	0.127531	-0.533002	0.5953
PDP	0.219148	0.110081	1.082366	0.0820*
ORG	0.562082	0.136031	4.132017	0.0001***
L08	-0.089765	0.023769	-3.776509	0.0003***

*: significant at 90% level, **: significant at 95% level, ***: significant at 99% level

From Table 1, we see that both product and process innovation are positively correlated with the employment amount, while compared with process innovation, product innovation contributes more to employment increase and the correlation is more significant. This result is consistent with the findings of most existed literature. Table 2 further shows that primal product innovation makes no more contribution to employment increase than general product innovation, which means imitation innovations or re-innovations after adoption and improvement can cause even more employment than primal innovations. Such paradox reflects one of the major challenges faced by Beijing regional innovation system: public organizations (such as universities, research institutes and state-owned labs)

instead of enterprises undertake lion's share of technology innovation activities, without tight collaboration with enterprises in the innovation processes. Such shortage of market orientation makes these primal innovations couldn't create as much demand as that made by innovations imitating or adopting existed novelties which have proved successful in the market.

In both phases, organization innovations and employment amount in 2008 are control variables which have significant correlation with employment increase (much more significant than technological innovation variables). It's not surprising that organization innovations are strongly positively correlated with employment increase, since Beijing is so rich in contemporary service industries, for which organization innovations play significant role in enterprise growth. Employment amount in 2008 is slightly negatively correlated with employment increase, which is also reasonable since the bigger the company, the slower the company will grow. Average wage was kicked out by the stopping rule for its correlation with employment increase is far from significant. That's not because average wage is really not correlated with employment increase, but because it has strong co-linearity with other variables: employees in companies which are big or good at innovations tend to have higher wages.

4.3 Empirical evidences on the quality side

In order to explore the correlation between technological innovation and skill composition, the author makes linear regression between each employment variable and each innovation variable, with employment variable as the explained variable and innovation variable as the explanatory variable. Employment variables include growth rate of proportion of R&D staff (*RD*), technological professionals (*TP*), white collar workers (*WC*), technicians and senior technicians (*TN*), employees with master and doctoral degrees (*MD*), respectively. Innovation variables include whether the firm has conducted product innovation (*PD*), whether the firm has conducted process innovation (*PC*) and whether the innovations are primal (*PR*).

Inspired by Piva and Vivarelli (2002), each employment variable is defined as the function of an innovation variable, sales growth rate (SA) and growth rate of average wage of the corresponding employment category, which are named as *WRD*, *WTP*, *WWC*, *WTN*, and *WMD*, respectively. Hence the regression equations between each employment variable and *PD* will be like follows:

$$RD = \alpha_0 + \alpha_1 PD + \alpha_2 SA + \alpha_3 WRD + \mu_1$$

$$TP = \beta_0 + \beta_1 PD + \beta_2 SA + \beta_3 WTP + \mu_2$$

$$WC = \delta_0 + \delta_1 PD + \delta_2 SA + \delta_3 WWC + \mu_3$$

$$TN = \theta_0 + \theta_1 PD + \theta_2 SA + \theta_3 WTN + \mu_4$$

$$MD = \xi_0 + \xi_1 PD + \xi_2 SA + \xi_3 WMD + \mu_5$$

The equations for other innovation variable (*PC*, *PR*) will take the same form. As analyzed in section 3, technological innovations in Beijing is expected to bias towards high-level tacit knowledge and professional skills, which may cause growing proportion of R&D staff, white collar workers, employees with masters and doctoral degrees and probably technological professionals, so we expect α_i, δ_i, ξ_i and probably β_i ($i \neq 0$) to be positive. However, we couldn't expect whether θ_i ($i \neq 0$) is positive or negative, for the expected skills composition and the technicians' manual skills can either be complementary or substitutive. Such expectation goes for not only *PD*, but also *PC* and *PR*; nevertheless the values of their coefficients are probably different, since their contributions to the skill composition are different.

The same regression method is used for the quality side, still with the stopping rule that p vale equals 0.5 and innovation variables always included. The results are shown in Table 3.

Table 3   Estimation Results for Equations of Employment Quality and Innovations

	RD	TP	WC	TN	MD
PD	0.092 (0.000)***	0.145 (0.001)***	0.212 (0.005)***	0.032 (0.087)*	0.219 (0.000)***
PC	0.071 (0.001)***	0.216 (0.003)***	0.128 (0.001)***	0.068 (0.056)*	0.153 (0.000)***
PR	0.103 (0.000)***	0.256 (0.000)***	0.142 (0.001)***	0.079 (0.048)**	0.194 (0.000)***

*: significant at 90% level, **: significant at 95% level, ***: significant at 99% level

In each cell there's filled the value of corresponding coefficient, *p* value in the bracket and stars standing for the significance level. To concentrate our attention onto the correlations between employment variables and innovation variables, the author omitted the estimation results for the coefficients of *SA* and wage variables. In fact, for a majority of the 15 equations (12 out of 15 for *SA* and

10 out of 15 for wage variables), *SA* and wage variables have been kicked out under the stopping rule for their correlations with the explained variables are too insignificant. Just as the quantity side, this isn't because their correlations are too weak in reality, but because *SA*, wage variables and innovation variables are so strongly correlated, so that they are kicked out in the process of step-wise regression. The true story is: innovation activities significant promote the sale growth, improve each employment category's productivity and hence the average wage.

As expected, all the coefficients are positive and significant, showing a strong skill biased nature. What should be noticed is that not only our expected coefficients, but also coefficients of *TN* are positive, which means our expected skill composition is complementary with the technician's manual skills: more products or processes embodied with higher technology especially tacit knowledge require more highly skilled manual workers. Since the proportions of all the mentioned employment categories proportions increase, then which employment category's proportion decreases? The answer is those unskilled manual workers, such as apprentices, junior level workers, intermediate level workers and rural migrant workers without adequate vocational trainings.

It's interesting to dive into the differences among the coefficient values. On one hand, product innovation, especially primal innovation leads to more proportion growth of the listed employment categories. It's reasonable, since in-house R&D require not only more R&D staff, but also more technology professionals, white collar workers, highly educated employees and even manual technicians with supporting tacit professional knowledge and skills (in accordance with the theory of defensive skill biased innovation). On the other hand, *TP*, *WC* and *MD* take on more proportion growth, which also matches our expectation made in section 3.

In summary, the empirical results are reasonable and have tested the author's hypothesis, for both quantity and quality aspect.

5 Conclusion

Beijing has always been one of the top regions in technological innovation capability of China. Compared to other top innovative regions, Beijing has obvious characteristics including abundant supply of human capital and R&D facilities, intensive trade flow of hi-tech products and hence higher risk of knowledge spillovers, concentrated hi-tech industrial clusters and strong policy incentives for skill biased innovations. According to relevant theories on innovation-employment relationships, such characteristics may lead to positive employment increase and bias towards tacit professional knowledge and skills, such as creative skills, cognitive skills and interactive skills, which requires more white-collar workers, technological professionals and highly educated employees.

Such hypothesis is tested by the empirical research. Based on the questionnaires collected from 235 enterprises in Beijing, the author made linear regression between employment quantity/quality variables and innovation variables, respectively. The results show that for quantity aspect, both product and process innovations are positively correlated with employment increase, but primal innovations make no more contribution to employment increase than innovations based on imitation or adoption; for quality aspect, there exist significant positive correlation between technological innovation and expected skill compositions, indicated by the proportion of R&D staff, white collar workers, technological professionals, employees with master and doctoral degrees and skilled manual technicians. Product innovation, especially primal innovation makes more contribution to the proportion increases of the mentioned skill composition.

The local government could take proactive measures to better explore the positive employment effect of innovations and hence alleviate structural unemployment pressure brought by technology change. Firstly, keep on promoting the development of productive service industries with higher elasticity of employment. XU (2011) had ever estimated top 10 industries with highest elasticity of employment in China, among which ICT, leasing and business service, healthcare and social security, environment and public utilities administration, scientific research and technology service, financing and insurance are all productive service industries encouraged by national policies, as well as sectors in which Beijing has comparative advantages.

Secondly, improve the sensitivity of college and vocational education to the demand of labor market. Structural unemployment will be mitigated unless the massive graduates meet the skill requirements of the rapidly developing hi-tech industries. By adjusting the curriculum setting and cultivation mode of college graduates escorted by intensive communication between colleges and enterprises, the local government could better match the human capital supply with the demand of labor

market. As important complements, vocational education should be developed vigorously to provide enough talents with suitable vocational skills.

Thirdly, encourage the enterprises to take on the major part of technological innovations. The local government could leverage enough policy incentives to help enterprises, especially small and medium enterprises play the major role in technological innovations, including strengthen collaboration between universities, public R&D institutes and enterprises in innovation activities. Such measure is necessary to enhance the innovations' market orientation, and further effects of employment promotion.

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