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The impact of technology

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6 The impact of technology adoption on employment
Exploration from the perspective of the manufacturing industry in transitional China

Guangjie Ning

Introduction
Since executing economic reform and an open policy in the late 1970s, the Chinese economy maintains a high annual growth rate and technology innovation has also been improving. Technology adoption promoted economy growth, at the same time it exerted a great impact on employment quality and skill structure. Changes in employment quality and skill structure means a lot for China. We want to know if our future economic development demands more or less labour and more or less skilled labour. This will shed light on our educational development and the firms’ training programmes. If the technological change has some adverse impact on employment, how can we coordinate the dilemma of relative backward technology and a high unemployment rate during the economic development period? Further technological change coincided with institution innovation in China. During the transitional process many previously state-owned enterprises were reformed into shareholding enterprises, combined with foreign companies or have been privatized. Do different ownership enterprises perform differently in the process of technology adoption and exert different impacts on employment? Answering these questions needs us to conduct some empirical analyses. This chapter tries to investigate the impact of technology input expenditure on the employment quantity and skill structure from the perspective of the manufacturing industry.

In an advanced market economy technical progress and labour productivity growth generally will exert an effect on wages, for example, leading to wage increases and then influencing employment further (resulting in employment reduction). Exploring technology’s impact on wage and income inequality is an important channel and gains fruitful literature. However, if the wage’s market mechanism is unhealthy and the wage itself cannot be sensitive to technology or becomes sluggish, the technology’s impact on employment and skill structure should be considered seriously (Spitz-Oener 2006). Under the circumstance of imperfect labor market the direction and magnitude that technology influences employment will differ from that circumstance where wage adjusts to the technical change flexibly.
The wage-forming mechanism is not yet perfected in China, as the relationship between wages and productivity is not sufficiently strong, and the wage response to unemployment is lagged (Ning 2007). Under the circumstance that wages could not respond fully to technical change and labour productivity, directly investigating technology’s impact on employment quantity and skill structure becomes essential.

This chapter uses the panel data in China to evaluate how industrial employment is affected by the technology innovation at the industry level. First, it examines the impact of technology adoption on employment quantity and skill structure from the perspective of manufacturing industry, considering the special institutional characteristics in transitional China: the impact of ownership structure, imperfect competition and interaction of institutional structure and technology adoption. Second, examines technology’s effect on employment at the industry level, which will deepen our understanding of structural unemployment in China.

The plan of the chapter is as follows. The second section provides a literature review and establishes the analysis framework. The third section provides a theoretical foundation. The fourth section provides the econometric model and data description; the fifth section provides the results and discussion. Finally, we offer some conclusions and policy implications.

**The underlying mechanism of technology’s impact on employment**

Technologies are usually divided into two categories according to their adoption direction; one is process innovation and the other is product innovation. Process innovation is to reduce input cost and product price by means of productivity improvement in the manufacturing process. Product innovation aims to develop new kinds of final high-quality products to earn profit. There are no clear distinction between process innovation and product innovation in practice. At the enterprise level, product innovation is considered as output innovations to improve consumption by final consumers or the production processes of other firms. The firm who produces it often cannot use it. In parallel, process innovation will result from the use of new technology given by other firms. Therefore, one kind of technology innovation in one case acts as process innovation, while in other case it is product innovation. However, the different adoption direction is obvious even at the macro level and distinguishing these two technology categories in theory and empirical analysis is also necessary.

**Change of employment quantity**

In essence, the employment change at the industry level resulting from technology innovation is employment structure change from the perspective of the macro level, that is, employment’s industrial structure. Edquist et al. (2001)
states that process innovation exerts a greater shock on employment quantity, as process innovation relies mainly on increased labour productivity to reduce manufacturing cost and enlarge profit. The impact of process innovation in different industries varies, determined by the compensation mechanism. Technology progress can increase employment and compensate for the employment loss of replacing workers with machines by means of the enlarged investment or other mechanisms. Expanding industries’ demand increases greatly and the employment quantity will also grow faster. Vivarelli (1995) divides the compensation mechanism into eight different channels: (1) increase demand by reducing price; (2) increase employment through new investment; (3) increase employment through reduced wage; (4) increase employment through new machine manufacturing and links among industries; (5) increase employment through new product innovation; (6) increased income turns into consumption and investment; (7) increase investment through the Schumpeter effect;¹ (8) increase investment by reducing price through the Pigou effect.²

Product innovation includes new material products and new service products. Generally its impact on employment reduction is comparatively modest or weak. If the new product spurs demand, it can also promote an increase in employment. For instance, in the era of the information economy, employment-expanding capability improves through Internet externality. Information technology can reduce the transaction cost and realize the high level of employment equilibrium (Weel 2006). However, if the new product to some extent replaces some old one, then employment may not increase. If the new product is used for another product’s process innovation, it will also weaken the compensation mechanism.

In empirical fields, using the number of innovations a firm commercialized in a given year, Reenen (1997) investigated manufacturing firms in the UK and found that technology innovation has significantly positive effects on employment, even when one controls for fixed effects, dynamics and endogeneity. Yao and Xia (2005) analysed the impact of technology (the average of labour productivity and capital productivity) on employment using the provincial panel data from 2000 to 2002 in China and found that the coefficient is −0.434 and significant, suggesting that process innovation and capital deepening have adverse an effect on employment. Chen and Tang’s study (2006) also demonstrates that China’s industry tended toward heavy chemical industrialization during the periods 1991–95 and 1999–2003. In other words, process innovation dominates.

Change of skill structure

Technology adoption demands the adjustment of labour’s skill. Process innovation often requires the employee to improve skills or learn new skills, whereas product innovation often brings forth new occupations and leads to occupational structural change. We have to admit that the outcome of some
new products does not rely heavily on technology and R&D; therefore the skill structure will not be doomed to great change.

Braveman (1974) argued that the power of technology adoption is controlled by the capitalist and used as a tool for appropriating the maximum profit. Even though the technology is widely used in the US, for the majority of workers their skills were downgraded or they became deskillled and worked as simple operators. Only the minority who research the advanced technology and grasp it become the leader in the firm’s hierarchy and earn a high salary. Bauer and Bender (2004) analysed the effects of technology change on job and worker mobility from the perspective of micro firms in Germany. It promotes job creation and job destruction, increasing the hiring and firing activities. The results indicate that new information technology decreases both low-skilled and highly-skilled labour. Some management and technological employees are demoted to low-skilled occupations and the downgraded workers are more common than the upgraded ones. Most of the employment adjustment occurred outside of the firm and unemployment will arise.

Does technology adoption increase or decrease skill requirement? In fact, it depends on the direction of the technology process. Taking information technology as an example, what should be considered is whether it substitutes routine manual work or acts as a complements to analysis and interactive activity. If it is the latter, the skill requirement will grow. Spitz-Oener (2006) classified worker activities into five skill categories: non-routine analytical tasks, such as research, planning or evaluation activities; non-routine interactive tasks, such as selling or coordinating and delegating work; routine cognitive tasks, such as double-entry bookkeeping and calculating; routine manual tasks, such as machine feeding or running a machine; and non-routine manual tasks, such as housekeeping or restoring houses. His empirical results show that, as occupations have experienced a shift toward analytical and interactive activities and away from cognitive and manual routine tasks, occupations in western Germany require more complex skills today than in 1979 and that the changes in skill requirements have been most pronounced in rapidly computerizing occupations. Hence, we can learn that information technology acts as a complements to analysis and interactive activity. Garicono and Rossi-Hansberg (2006) suggest that if the technology reduces the cost of acquiring knowledge, the average worker’s skill improves; if it reduces the communication cost, the worker’s skill degrades.

Yao (2005) analysed the impact of technological progress on employment using the micro data from the manufacturing industry in the Zhejiang Province of China and found that technological progress makes the demand for skilled labour increase, and the proportion of skilled workers in both employment quantity and income share rises.
Change of management structure and firm organization

In relation to employment change, we should also consider the effects of technological innovation on management structure and firm organization. For instance, information technology reduces transaction and communication costs and reduces the administration layers; which, in turn, impacts on the number of management employees. There exists a double link between new technology and management structure. The adoption of new technology needs some management structure innovation, and, on the other hand, the management structure innovation makes it easy for the new technology to be adopted. In China it is often the case that enterprises promote the adoption of new technology by means of firm ownership reform. Ownership reform involves radical change of management structure; for instance, many traditional state-owned enterprises are transformed into shareholding enterprises or acquired by foreign firms and become joint ventures. Chen and Tang’s (2006) study shows that an industry with a high proportion of state-owned enterprises or a high degree of monopoly performs well in relation to technology change, but in relation to technology efficiency it is low and needs improving.

Furthermore, technological innovation and management structure are not two independent forces influencing employment; in fact, they often interact with each other and further affect employment quantity and structure. Wang et al. (2006) state that, information technology and organizational innovation complement each other and have great positive effects on production efficiency. He considers management structure from three perspectives: operational management, cooperation of manager and employee, and management of process innovation and product innovation.

Industry aggregate analysis

Rothwell and Zegveld (1979) analysed the impact of technical change on various industries in the UK. Impacts on the textile industry included: integration and rationality reducing demand for labour; the deskilling of labour; and the need for skilled workers to operate electrical machinery. Computer-aided design and control also changed management structure, such as outsourcing and hiring technical workers from outside of the firm. As the main technological advances since the Second World War are in the micro-electronic (ME) and information technology (IT) industries, they examine the impact of ME on industry employment. In the case of the textile industry, the impacts include reduced employment quantity and increased proportions of skilled and unskilled workers. As for the technical researcher, the proportion has decreased.

Schettkat and Russo (2001) analysed the relationship between labour productivity and employment in different industries and found that for the majority of countries, the relationship in manufacturing industries is negative,
while in transportation and communication industry the relationship is positive. Dobbs et al. (1987) considered the important role of market structure: as a result of the number of firms increasing and competition strengthening to expand labour demand elasticity, employment expands.

Most of the preceding study examined the impact of technology on employment in different industries. Our research centres on 38 manufacturing industries as a whole and investigates the average impact of technical change at the industry level on employment.

**Theory foundation**

We obtain insights from the new economic growth theory. The source of applied technology comes from the work of the R&D sector, and developing new technology needs both capital and research workers. In turn, it has the production function of technology as \( A = A(L, K_r) \), where \( A \) is the output of technology, \( L \), and \( K_r \) are the labour and capital input incurred in the research department, respectively. The chapter argues that technological progress is an endogenous variable in the overall economic system. For a developing country, even if it does not own the original technology and has to resort to imports from a foreign country, during the process of technical adoption research workers are still needed to analyse and assimilate the imported new technology.

Technology can be put into force and embodied by capital and labour. We argue that technology’s role depends fundamentally on skilled workers, which is consistent with human capital theory; in turn, we have \( Y = K^\alpha H^\beta A^\theta L_o^{1-\alpha-\beta-\theta} \), where \( Y, K, H, L_o \) is output, capital, human capital and ordinary labour, respectively. A skilled worker supplies both 1 unit of \( L \) and some amount of \( H \).

We can have a labour demand function such as below for our econometric analysis: \( \ln L = \gamma_1 \ln Y + \gamma_2 \ln K + \gamma_3 \ln A,^3 \) where \( L \) is the sum of human capital and all kinds of labour.

Under imperfect competition, the explanatory variable of number of firms in this industry should be added. Moreover, the institution factors also exert an effect on labour demand. We incorporate an important institutional variable to consider whether enterprise reform has a great effect on industry employment.

Industry employment fluctuation is also influenced by macroeconomic performance; the real business cycle school regards technology shock as the main driving force of the macroeconomic cycle. If it is the case, we will have a better understanding of the macro economy’s effect on employment when we explore the impact of technology on employment. However, we insist that macro price and inflation changes are separate forces from technological change. Studying employment change at the industry level should consider not only the technology at industry level but also the impact of macroeconomic shock.
Data and econometric models

The data for econometric analysis comes from the *China Statistical Yearbook on Science and Technology* from 1999 to 2005. The National Bureau of Statistics and the Ministry of Science and Technology prepare the yearbook jointly. It reports on the development of China’s science and technology activities. What we are concerned is the technological development condition and other economic indicators at the industry level. Only large and medium-sized industrial enterprises are included in the industrial data; that is to say, small firms’ data is not available. Because of the change of ownership classification, we have to divide the data into two groups: one for 1998–2002, comprising state-owned enterprises and joint ventures (Chinese and foreign); and one for 2003–04, including state-owned enterprises, limited liability corporations, shareholding enterprises and joint ventures. For every year, we have data on 38 two-digit industries (according to standard industrial classification (SICC) code) for two or four ownership categories. For the former group, the sample size is about $38 \times 2 \times 5$, for the latter it is $38 \times 4 \times 2$.

First, we use the equation below to analyse the impact of the adoption of technology on employment quantity:

$$
\ln L = \beta_0 + \beta_1 \ln TE + \beta_2 \ln LD + \beta_3 SZ + \beta_4 GY + \beta_5 GF \\
+ \beta_6 (\ln TE \ast SZ) + \beta_7 (\ln TE \ast GY) + \beta_8 (\ln TE \ast GF) \\
+ \beta_9 NF + \beta_{10} HY + \mu 
$$

(1)

$L$ stands for employment quantity at the end of a certain year in this two-digit industry. $TE$ is the technological input expenditure of this two-digit industry. The ratio of technology expenditure to output value is also useful, reflecting more accurately the direction of technology upgrading. We do not use R&D expenditure to represent technology, because it is the input occurring in the process of product experimentation, which cannot reflect accurately the condition of technology adoption.

Technical expenditure has the amount of capital stock (accumulating capital flow) and the amount of capital flow (expenditure occurred every year); as the change of ownership classification occurred since 2003 and the time longitude is relatively short, we only select the capital flow one and do not calculate the stock one. $LD$ represents the number of firms in this industry; if the coefficient is positive, it means that the strengthened market competition will result in employment expansion, otherwise it maybe that over-competition ruins employment growth or this industry should be a natural monopoly. $SZ$, $GY$ and $GF$ are the dummy variable to represent joint venture (if joint venture $SZ$ is defined as 1; for other firm categories, $SZ$ is 0), state-owned enterprise (if state-owned enterprise $GY$ is defined as 1; otherwise is 0) and shareholding enterprise (if shareholding enterprise $GF$ is defined as 1; otherwise is 0), respectively. The limited liability corporation is used for comparison. The next
three variables are the interactive term of enterprise ownership and technical expenditure. $NF$ is the dummy variable for 1998–99 (during 1998–2002 group, if 1998 and 1999, $NF$ is defined as 1; for other years, $NF$ is 0) or 2003 (during 2003–04 group, if 2003, $NF$ is defined as 1; for 2004, $NF$ is 0) to reflect effects of macroeconomic conditions. $HY$ is the dummy variable of industries. We classify the 38 two-digit industries into eight categories according to their characteristics. The mining industry is used for comparison, so we have seven industry dummy variables. $HY_1$ is food and drink manufacturing (if food and drink manufacturing, $HY_1$ is 1; for other industries, $HY_1$ is 0; the same applies to $HY_2$, $HY_3$, $HY_4$, $HY_5$, $HY_6$ and $HY_7$). $HY_2$ is the textile and clothing industry. $HY_3$ is the wood, paper and printing industry. $HY_4$ is oil products, chemical products and medical products. $HY_5$ is the metal product industry. $HY_6$ is transportation machinery, information facilities and computers. $HY_7$ is the production and supply of electrical power, gas and water. Note that as the appropriate data on capital is not available, unlike theory foundation, the variable of capital is not included in our estimate equation.

The following equation demonstrates the impact of different kinds of technology adoption on employment:

$$\ln L = \gamma_0 + \gamma_1 \ln(WD / SB) + \gamma_2 \ln(XCP / Y) + \gamma_3 \ln LD + \gamma_4 \ln SZ$$

$$+ \gamma_5 GY + \gamma_6 GF + \gamma_7 NF + \gamma_8 HY + \mu$$ (2)

where $WD / SB$ is the ratio of equipment controlled by micro-electronics to the original value of the equipment. It acts as an indicator of process innovation. $XCP / Y$ is the ratio of new product value to gross value of the output, which represents the development level of product innovation.

The equation for technology’s effect on employment structure is as follows:

$$\ln (LS / L) = \lambda_0 + \lambda_1 \ln TE + \lambda_2 \ln LD + \lambda_3 SZ + \lambda_4 GY$$

$$+ \lambda_5 GF + \lambda_6 (\ln TE \ast SZ) + \lambda_7 (\ln TE \ast GY)$$

$$+ \lambda_8 (\ln TE \ast GF) + \lambda_9 NF + \lambda_{10} HY + \mu$$ (3)

$LS / L$ denotes the ratio of technical engineering personnel quantity to total employee quantity, an indicator of the skill structure of labour. The measure of skill requirement can be the proportion of skilled workers or educated workers. The shortcoming of the latter lies in the fact that, if the educated worker does not possess the corresponding skill owing to educational failure or scarcity of on-the-job training, the proportion of educated workers cannot reflect the skill requirement accurately. If we have other data such as job type or management worker structure, we will test which one is a good indicator for skill structure and use it to conduct econometric analysis.

To assess the impact of different technology on employment structure, the function is similar to function (2); in turn, we have:
\[
\ln(\frac{LS}{L}) = \gamma_0 + \gamma_1 \ln(\frac{WD}{SB}) + \gamma_2 \ln(\frac{XCP}{Y}) + \gamma_3 \ln LD \\
+ \gamma_4 SZ + \gamma_5 GY + \gamma_6 GF + \gamma_7 NF + \gamma_8 HY + \mu
\] (4)

**Interpretation of econometric results and discussion**

**The impact of technical change on industry employment**

Based on equation (1), the econometric results are listed in Table 6.1. First, we conduct pool model analysis. Comparing column (1) with column (2), we see that the effect of technical expenditure on employment during 2003–04 is greater and the explanation power is stronger (as the adjusted \(R^2\) is higher). This reflects the characteristics of developing countries’ technology adoption: previous technology was backward. Upgrading technology can stimulate output expansion and have a positive impact on employment expansion.

It may also be that wages did not increase in relation to the technology adoption and labour productivity growth so that technical change could bring forth more employment. It is known that the bigger is the variable reflecting technological input–output efficiency, \(\frac{Y}{TE}\), the stronger is the compensation impact, and the more obvious is the employment creation effect. However, the unreported econometric result indicates that the impact of \(\frac{Y}{TE}\) on employment is negative, implying that technological development in China is still in the phase of relying on input increases to cope with the employment problem; the driving and spillover effect of technical change is not sufficient. Furthermore, with the number of firms in industry increasing and competition strengthening, the employment at industry level also rises. The ownership dummies show that employment in joint ventures is lower than in state-owned ventures during 1998–2002. During 2003–04, employment in shareholding enterprises is lower.

On the basis of column (1), we add the interactive term of technology expenditure and firm ownership to assess the effect of the interaction of technical change and management structure on employment. The results in column (3) show that the coefficient of interactive term is \(-0.167\), significant at the 1 per cent level. The common notion is that the reformed enterprises place more weight on technology adoption and also lay off redundant workers. Technology and ownership change correlated with and influenced employment change. The impact of interactive terms of technical expenditure and number of firms is also negative and significant, showing that the interaction of competition and technical change reduced employment at the industry level. However, the interactive term of technology expenditure and firm ownership during 2003–04 is not significant.

In columns (4) and (5), we add the impact of time and industry differences. It is clear that employment growth during 1998–99 is 0.178 per cent lower than that during 2000–02 and the growth rate during 2003 is 0.908 per cent higher than that in 2004. Considering the industry difference, we find that compared to the mining industry, other industries’ employment growth is slower,
Table 6.1  The impact of technical change on industrial employment

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<td>Constant</td>
<td>5.930***</td>
<td>5.713***</td>
<td>2.860***</td>
<td>6.253***</td>
<td>4.829***</td>
<td>5.076***</td>
<td>7.135***</td>
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<td>(0.200)</td>
<td>(0.203)</td>
<td>(0.556)</td>
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<tr>
<td>Log(TE)</td>
<td>0.219***</td>
<td>0.368***</td>
<td>0.523***</td>
<td>0.167***</td>
<td>0.351***</td>
<td>0.131***</td>
<td>0.189***</td>
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<td>(0.023)</td>
<td>(0.025)</td>
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<td>Log(TE(−1))</td>
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<td>(0.030)</td>
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<td>Log(LD)</td>
<td>0.752***</td>
<td>0.426***</td>
<td>1.290***</td>
<td>0.742***</td>
<td>0.673***</td>
<td>1.063***</td>
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<td>(0.039)</td>
<td>(0.032)</td>
<td>(0.106)</td>
<td>(0.044)</td>
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<td>(0.055)</td>
<td>(0.035)</td>
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<td>Log(TE)*log(LD)</td>
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<tr>
<td>SZ</td>
<td>−0.798***</td>
<td>−0.071</td>
<td>1.024**</td>
<td>−0.558***</td>
<td>−0.051</td>
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<td>(0.076)</td>
<td>(0.103)</td>
<td>(0.403)</td>
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<td>SZ*log(TE)</td>
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<td>−0.167***</td>
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<td>(0.036)</td>
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<td>GY</td>
<td>0.124</td>
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<td>GF</td>
<td>−0.212***</td>
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<td>(0.077)</td>
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<tr>
<td>NF(1998–99 or 2003)</td>
<td></td>
<td>−0.178**</td>
<td>0.908***</td>
<td>−0.178**</td>
<td>0.908***</td>
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<td>(0.080)</td>
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<td>−1.171***</td>
<td>−0.900***</td>
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<td>HY2</td>
<td>−0.494**</td>
<td>−0.287**</td>
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<td>HY3</td>
<td>−1.146***</td>
<td>−0.723**</td>
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<td>HY4</td>
<td>−1.141***</td>
<td>−0.993***</td>
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<td>HY5</td>
<td>−0.932***</td>
<td>−0.820**</td>
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<td>HY6</td>
<td>−1.252***</td>
<td>−1.090***</td>
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<tr>
<td>HY7</td>
<td>−0.977***</td>
<td>−0.628***</td>
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<td>Hausman test (Fixed or random effect)</td>
<td>16.292 Fixed effect</td>
<td>129.204 Fixed effect</td>
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<td>343</td>
<td>269</td>
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<td>343</td>
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<tr>
<td>AdjR²</td>
<td>0.841</td>
<td>0.841</td>
<td>0.855</td>
<td>0.874</td>
<td>0.921</td>
<td>0.984</td>
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</table>

Note: *, ** and *** indicate the variable is significant at the 10, 5 and 1% level, respectively.
especially in $HY_1$ (food and drink manufacturing), $HY_4$ (oil products, chemical products and medical products) and $HY_6$ (transportation machinery, information facilities and computers). To investigate the long-term impact of technology, in column (4) we add last year’s technology expenditure as an explanatory variable and find its coefficient positive (0.108) and significant, showing that technical change exerts long and lasting impact on employment.

Considering the concrete differences between industries and year to year, we applied fixed or random effect models. We discovered that a fixed effect model is suitable through the Hausman test, so we have columns (6) and (7). The basic conclusion does not change. The influencing coefficients of technology during 1998–2002 and 2003–04 are 0.131 and 0.189, respectively; the latter is higher. On average, the coefficient becomes smaller once we control every industry and every year’s difference.

Finally we consider the problem of a possible co-relationship between technical expenditure and employment, i.e. the employment quantity gives rise to the change in technology. We use R&D input expenditure and number of inventive patents owned as the instrument variables of technical expenditure in 2003–04. Applying two-stage least squares (an instrumental variables estimation technique), OLS methods and pool estimation, we find that the coefficient of technical expenditure hardly changed from that in OLS methods. Therefore the technical expenditure can be regarded as an exogenous variable in this case.

The impact of different technology on employment

In Table 6.2, applying equation (2), column (1) explains that process innovation has a positive impact on employment and the coefficient is 0.097. Contrary to the traditional theory and other empirical results, the process innovation is beneficial for employment growth, while the product innovation’s effect is significantly negative. Column (2) uses the 2003–04 data and derives a similar conclusion but the coefficients are not significant. This is partly because in this phase of a developing economy, cost competition and price competition dominate; it is process innovation that makes a firm obtain advantage over other competitors. On the other hand, it is difficult for new products to enter the market and win the consumer’s acknowledgement, so it has an adverse impact on employment. As before, the coefficients of number of firms and foreign ownership are significant.

Adding the dummy variables of industry and time, column (3) shows that the coefficient of process innovation is still positive. Compared to state-owned enterprises, the employment growth rate of joint ventures is lower by 0.703 per cent. Column (4) also illustrates that the growth rate of employment in 2003 is faster than that in 2004. Employment creation capability is lowest in joint ventures and highest in shareholding enterprises. This time, the effects of product innovation and process innovation are also not significant. This may be due to the relatively limited sample size during 2003–04.
Table 6.2  Different technology impact on employment quantity

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<td>7.485*** (0.282)</td>
<td>8.338*** (0.277)</td>
<td>9.291*** (0.366)</td>
<td>7.196*** (0.326)</td>
<td>6.218*** (0.250)</td>
<td>8.716*** (0.248)</td>
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<tr>
<td>Log(WD/SB)</td>
<td>0.097* (0.052)</td>
<td>0.068 (0.060)</td>
<td>0.201*** (0.047)</td>
<td>0.073 (0.046)</td>
<td>0.046* (0.024)</td>
<td>−0.039 (0.033)</td>
</tr>
<tr>
<td>Log(XCP/Y)</td>
<td>−0.102*** (0.031)</td>
<td>−0.052 (0.033)</td>
<td>−0.038 (0.042)</td>
<td>−0.040 (0.033)</td>
<td>−0.059*** (0.021)</td>
<td>0.036 (0.037)</td>
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<tr>
<td>Log(LD)</td>
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<td>0.685*** (0.034)</td>
<td>0.943*** (0.038)</td>
<td>0.945*** (0.034)</td>
<td>1.120*** (0.045)</td>
<td>0.600*** (0.041)</td>
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<tr>
<td>SZ</td>
<td>−0.811*** (0.091)</td>
<td>−0.251* (0.134)</td>
<td>−0.703*** (0.078)</td>
<td>−0.251** (0.098)</td>
<td>0.163* (0.093)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>GY</td>
<td>0.124 (0.129)</td>
<td>(0.134)</td>
<td>0.163* (0.078)</td>
<td>(0.098)</td>
<td>(0.093)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>GF</td>
<td>−0.052 (0.139)</td>
<td>(0.134)</td>
<td>0.279*** (0.038)</td>
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<td>(0.093)</td>
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</tr>
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<td>NF (1998–99 or 2003)</td>
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<td>1.162*** (0.093)</td>
<td>(0.093)</td>
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<tr>
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<td>Negative and</td>
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<td></td>
<td>1.116</td>
<td>Random effect</td>
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<tr>
<td>HY2</td>
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<td>Fixed effect</td>
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<tr>
<td>HY3</td>
<td>level.</td>
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<td>HY7</td>
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Hausman test (Fixed or random effect)  Observations  AdjR²

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<td>0.823</td>
<td>0.630</td>
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Note: *, ** and *** indicate the variable is significant at the 10, 5 and 1% level, respectively.
Columns (5) and (6) are the result of an optimal random effect model or a fixed effect model. As column (5) shows, process innovation contributes to employment growth, while product innovation leads to employment reduction. However, the impacts during 2003–04 still do not pass the significance test.

**Impact of technical change on employee skill structure**

The results of analysis applying equations (3) and (4) are shown in Table 6.3. In the first two columns, technical input expenditure is positively related to the proportion of technical workers, and the impact during 2003–04 is greater, which illustrates that the labour skill requirement is upgraded with technical progress in recent years. We also investigate the effects of number of firms, ownership, industry and time on the proportion of technical workers. The number of firms in both periods has a negative impact on the skill structure. In principle, with the number of firms increasing and competition strengthening, firms should pay more attention to technical competition and increased their number of technical workers. However, the analysis indicates the opposite result. The reasons may be that, first, technical competition does not occupy an important role in current China. Second, it may also reflect the fact that, with the removal of industry entry barriers, the new firms entering the market are relatively weak in establishing technical employee teams. The proportion of technical workers in different industries also varies. Compared to the mining industry, the skill structure in the textile and clothing industry ($HY_2$) is significantly lower, and in the production and supply of electric power, gas and water industry ($HY_7$) is significantly higher. Similarly, using the instrument variable method, it is shown that technical expenditure can act as the employee skill structure’s exogenous variable.

Columns (3) and (4) are the fixed effect models. Only during 1998–2002 does technical adoption have a positive effect on labour’s skill structure. Columns (5) and (6) evaluate the effects of different technology changes on employment skill structure: process innovation increases the demand for skilled worker in both periods; while product innovation does so only during 1998–2002. It is partly because product innovation in the current phase concentrates mostly on the simple design and packaging of new products without demanding high technical skills. It may also be because product innovation is only the task of researchers in the R&D sector and does not influence the skill requirement of ordinary worker as does process innovation; consequently, the proportion of technical workers does not increase. These results correspond with those obtained by Borghans and Weel (2006) indicating that technical adoption aiming to reduce production time (which is similar to process innovation in the context of our analysis) demands upgraded skills. This also implies that, if technical change centres on process innovation, the employment skill structure needs greater adjustment, otherwise structural unemployment will result from skill mismatch. In the fixed effect models of columns (7) and (8), only product
Table 6.3 Impact of technical change on employment structure

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<td>-1.710*** (0.213)</td>
<td>-2.007*** (0.182)</td>
<td>-1.832*** (0.267)</td>
<td>-2.568*** (0.249)</td>
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<td>Log(TE)</td>
<td>0.120*** (0.019)</td>
<td>0.146*** (0.016)</td>
<td>0.036* (0.021)</td>
<td>0.032</td>
<td>0.064** (0.027)</td>
<td>0.051* (0.029)</td>
<td>-0.024</td>
<td>-0.046</td>
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<tr>
<td>Log(WD/SB)</td>
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<tr>
<td>Log(XCP/Y)</td>
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<td></td>
<td>0.110*** (0.024)</td>
<td>-0.010 (0.022)</td>
<td>0.049**</td>
<td>-0.028</td>
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<tr>
<td>Log(LD)</td>
<td>-0.134*** (0.027)</td>
<td>-0.143*** (0.018)</td>
<td>-0.137** (0.054)</td>
<td>-0.061</td>
<td>0.016</td>
<td>-0.053*** (0.022)</td>
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<td>-0.103** (0.045)</td>
<td>-0.371*** (0.062)</td>
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<tr>
<td>SZ*log(TE)</td>
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<tr>
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<td></td>
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<td></td>
<td>0.084</td>
<td>(0.059)</td>
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<tr>
<td>GF</td>
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<td></td>
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<td>(0.064)</td>
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<td>0.256**</td>
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<tr>
<td>AdjR²</td>
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<td>0.585</td>
<td>0.791</td>
<td>0.472</td>
<td>0.516</td>
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Note: *, ** and *** indicate the variable is significant at the 10, 5 and 1% level, respectively.
innovation during 1998–2002 requires the skill structure to improve, which does not conform with the results in columns (5) and (6). This raises new concern about the technology category and skill structure.

As far as ownership is concerned, in most cases the proportion of technical workers in joint ventures is significantly lower than in other firm types, reflecting the fact that technological development in many joint ventures does not promote upgrading of skills. Moreover, in column (1), adding the interactive terms of ownership and technical expenditure, the coefficient during 1998–2002 is \(-0.051\) and significant; it is clear that the interaction degrades the skill structure. During 2003–04, the impact can be ignored. The reform of enterprise ownership and technical changes did not promote simultaneous skill structure upgrading. Considering the low quality of labour, on average, and the mobility barrier existing in the labour market, these results are understandable.

**Comparison of the relationship between technical change and employment in different types of firm**

Table 6.4 shows independent estimations for every firm ownership category and compares the coefficient differences in different types of firm ownership. All estimation functions are fixed or random effect models and the estimation functions with insignificant coefficients are omitted. For coefficient comparison, we list the related functions in one column. For example, in column (1) we have two separate functions for joint venture (SZ) and state-owned enterprise (GY) and compare the coefficients of log(TE) and log(LD), constant, observation and AdjR\(^2\) from top to bottom responding to these two functions. In column (2), we have three separate functions, for state-owned enterprises, shareholding enterprises and limited liability corporations; constant, observation and AdjR\(^2\) from top to bottom respond to these three functions. The same applies to other columns. From column (1), we can see that the coefficient of technical change in joint ventures is lower than that in state-owned enterprises, which may be attributed to the different direction of technical adoption in joint ventures. In column (2), apart from joint ventures, in the other three types of enterprise technical change has a positive impact on employment expansion. This further demonstrates the weak relationship between technical investment and employment growth in joint ventures. Columns (3) and (4) concern the impact of different types of technical change on employment quality. Column (3) illustrates that the process innovation of joint ventures has a positive impact on employment, while that of state-owned enterprises has a negative impact on employment, which is inconsistent with the anticipated outcome. In column (4), neither category of technology has a significant effect on employment in the four types of firm ownership, a finding that deserves attention.

Second, we examine the effect of technical change on employment skill structure. In column (5), only the technical change in joint ventures has
Table 6.4 Comparison of the relationship between technical change and employment in firms with different ownership

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Note: *, ** and *** indicate the variable is significant at the 10, 5 and 1% level, respectively; SZ stands for joint venture, GY is state-owned enterprise, GF is shareholding enterprise, YX is limited liability corporation.
an impact on skill structure. In column (6), technical change demands the improvement of skill structure in both joint ventures and state-owned enterprises. The coefficient in joint ventures is larger. Their technical changes match closely with the skill structure improvement inside the firm. These firms are relatively large scale and run formally, emphasizing labour quality improvement. It needs to be mentioned that, for a long period of time, some joint ventures relied on hiring temporary or part-time technical workers from outside; thus their employee skill structure did not respond to technical change and a low employee skill structure resulted. In 2004, the proportion of technical workers in shareholding and state-owned enterprises was 11.03 per cent and 11.12 per cent, respectively. The figure for limited liability corporations is 9.01 per cent, and for joint ventures is only 5.11 per cent.\(^8\) According to Yao and Zhang’s study (2001), the technology spillover effect in China works through labour mobility rather than imported technology, which also demonstrates the limitation of relying on imported technology for developing countries. Joint ventures played little role in improving labour quality. It is often the case that they seek out talented workers from other types of firm. In the era of new technology competition, however, they now have to place greater emphasis on their skill structures.

Finally, different types of technology have different impacts on labour skill structures. In column (7), the product innovation of state-owned enterprises demands labour skill improvement. In column (8), aside from the positive effect of product innovation, the process innovation of state-owned enterprises degrades the skill structure. For the limited liability corporation, product innovation lowers the skill structure. It seems that the impact of technology on the skill structure of different types of firm is heterogeneous and not confirmed.

**Summary**

Using the manufacturing industry’s panel data from 1998 to 2004 in transitional China, this chapter empirically analyses the impact of technology adoption on employment quantity and employment structure at the industry level. The econometric results indicate that, basically, technology adoption has a positive impact on employment quantities. This is mainly because, as a developing country, China’s technology adoption can improve competition power, expand product demand and increase employment. Technical change also demands the improvement of the labour skill structure. However, the impact of different types of technology varies. Contrary to the prediction of traditional theory, the impacts of process innovation on employment quantity are positive, whereas the impacts of product innovation on employment quantity are virtually negative or insignificant, which implies that our industries still rely on labour productivity improvement to win competition; product innovation is not performing well and cannot bring forth employment expansion.
During the transitional period, the technical adoption acted together with enterprise ownership reform and market structure (competition) and will in future generate negative shocks on employment. The performances of different ownership enterprises also vary. The coefficient of the impact of technology on employment quantity in joint ventures is low or insignificant. Regarding the coefficient of the impact of technology on employment skill structure, for state-owned enterprises it is lower. When the joint venture works as a dummy variable, the impacts on both employment quantity and skill structure are often negative, showing the limited ability of joint ventures to create employment. It should be mentioned that we take a conservative attitude toward our results owing to the relatively small sample size.

The chapter places great emphasis on the role of employment in economic development. Its policy implication is that strengthening the manufacturing industry’s technology processes and upgrading international competition power can effect employment expansion. Apart from persisting in developing process innovation, we should carry out meaningful product innovation in order to expand employment. Technology adoption raises the demand for skilled workers, though in some technology categories the impact is not obvious and definite. This challenges the education system and enterprise training programme. If graduate students and employees cannot make an adjustment to the skill requirement, skill mismatch and structural unemployment will occur. In the transitional period, technological progress and institutional structural adjustment are concomitants, which places greater pressure on employment. Therefore we should consider this problem seriously. The policy for joint ventures should also be adjusted accordingly so that the spillover and employment creation effects of technology can be undertaken smoothly.

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Notes

1 The ‘Schumpeter effect’ refers to the positive impact on employment resulting from the entry of new firms and higher levels of entrepreneurship.
2 The ‘Pigou effect’ means that a large fall in prices would stimulate an economy and create the ‘wealth effect’ that will generate full employment.
3 Technology here refers to the technological input expense in the real manufacturing process; it is rarely influenced by employment quantity or structure, and hence can be regarded as an exogenous variable when considering its impact on employment. We will test its validity by using a method of instrument variable later.
4 Even though we know fixed or random effect models should be established after the $F$ and $LM$ tests, as our pool model design (ownership and industry dummy vari-
ables) will shed some new insights we retain them and compare them with fixed or random effect models.

5 Given a model and data in which fixed effects estimation would be appropriate, a Hausman test tests whether random effects estimation would be almost as good. In a fixed-effects case, the Hausman test is a test of $H_0$: that random effects would be consistent and efficient, versus $H_1$: that random effects would be inconsistent. (Note that fixed effects would certainly be consistent.) The result of the test is a vector of dimension $k$ ($\text{dim}(k)$), which will be distributed chi-square ($k$). So, if the Hausman test statistic is large, one must use FE. If the statistic is small, one may get away with RE.

6 The employment quantity constraint can lead to technological adoption in manufacturing, in turn increasing technology expenditure. However, it will not inevitably lead to a rise in R&D input expenditure and patent quantity.

7 There is an absence of strong multicollinearity between product innovation ($x_{cp/ly}$) and process innovation ($wdlsb$).


References


7 Evaluating job training in two Chinese cities

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Introduction

Over the past decade, traditional job guarantees and economic security provided by urban state-owned enterprises (SOEs) in China have been reduced as part of a nationwide economic reform effort. To help workers transition to the free labour market, China instituted what was called the xiagang system. Xiagang were redundant workers who remained attached to the SOE and to whom the SOE provided subsistence income payments along with contributions to public health insurance and pension funds, and often times housing. While the aim was to smooth labour adjustment, many redundant workers have experienced significant income losses and difficulty finding new jobs. The xiagang system has been dismantled, and much restructuring has already occurred. Still, even the most optimistic observers recognize that China faces more labour adjustment challenges, especially with reforms called for by China’s accession to the World Trade Organization (WTO). China – like virtually all countries and especially transition countries – is increasingly facing difficult policy questions about how to address the problem of laid-off workers, in order to provide effective social protection and maintain social stability.

How well can publicly provided training works influence policy decisions in a range of programmes, including social security, unemployment insurance and public employment services designed to help workers find new jobs and restore their incomes? These latter interventions are collectively known as ‘active labour market programmes’ (ALMPs) and include retraining programmes, employment services (e.g. labour exchange, counselling, etc.), job creation through loans or subsidies, public service employment, public works and self-employment assistance. ALMPs such as these have been used extensively in developed and transition economies for many years. They represent an attractive policy approach because they are intended to provide jobless workers with a ‘trampoline’ for getting back into productive employment, as opposed to simply providing them with a financial ‘safety net’.

However, as international experience has clearly demonstrated, implementing an effective active labour market policy poses many challenges. The
immediate challenge is to design and implement retraining and other ALMPs that actually benefit participants in a cost-effective manner. Indeed, it is apparent from many studies in developed and transition countries that this is very often not the case. For this reason, there is growing emphasis on scientifically evaluating the effects and cost-efficiency of these programmes and basing future programme expenditures on such results.

In turn, this has led to a surge in the academic literature on impact evaluation of training programmes. While a large literature has now been established for developed countries, the evidence for developing and transition economies is scarce. For China, in particular, no evidence is presently available. Given the extent of recent decades’ economic reforms in China and associated massive lay-offs and accompanying public retraining programmes, this is paradoxical, as these events virtually cry out for rigorous evaluation of the impact of job training.

This study evaluates retraining programmes for laid-off workers in the Chinese cities of Shenyang and Wuhan, using a carefully designed comparison group methodology. To our knowledge, this is the first evaluation of its kind in China. The results suggest that retraining helped workers find jobs in Wuhan, but had little effect in Shenyang. The study raises questions about the overall effectiveness of retraining expenditures and offers some directions for policy-makers about future interventions to help laid-off workers. The structure of the chapter is as follows. The next section presents the institutional context and labour market context of training for laid-off workers in China, focusing on the experiences of workers in Shenyang and Wuhan. The third section discusses the methodology underlying the analyses in this chapter, while the fourth section presents the data. Results follow in the fifth section, while the sixth concludes and provides suggestions for future research on the possible impact of active labour market programmes in China.

**The institutional and labour market context of training**

To understand the potential for job training, it is important to know the institutional framework and labour market context of training for laid-off workers in China. We first discuss national government policies promoting re-employment of laid-off workers, and then review the economic conditions at the national and provincial levels. This is followed by a brief examination of the economic conditions in the cities of Shenyang and Wuhan around the time retraining programmes there were evaluated.

In May 1998, the Central Party Committee and the State Council jointly organized a conference on safeguarding the Basic Living Standards of Laid-off Workers in SOEs and their Re-employment. After the conference, the Central Party Committee and the State Council jointly issued an outline of various policy measures adopted. These included setting up re-employment service centres (RSCs) and establishment of programmes to promote the
re-employment of laid-off workers. Registration with an RSC established an institutional membership for the jobless distinct from being either xiagang or openly unemployed.

Beginning in 2001, programmes for laid-off workers started to change in Liaoning province, of which Shenyang is the capital city, and in some other provinces piloting social security reform. Wuhan, capital of Hubei province, was not among the cities where social security reforms were tried. In the pilot cities, including Shenyang, no additional RSCs were created starting in 2001, and newly laid-off workers unable to find new jobs joined the ranks of the unemployed as soon as they were separated from their prior employer. Current RSC registrants retained their institutional affiliation during the pilot test period. In Wuhan, newly laid-off workers were required to register with an RSC between 2001 and 2003, right up until the final closure of all RSCs in 2003. By 2003, all workers who were registered with RSCs terminated their membership and became unemployed unless they had found new jobs.

When RSCs were closed, a range of new active labour market policies (e.g. training, job information, job referrals, career information, etc.) was adopted to strengthen labour market development. These were available at public labour bureaus not requiring compulsory registration by the jobless. For example, in both Shenyang and Wuhan, the government required that the labour bureau offer at least three opportunities for employment for laid-off workers who demonstrated a great need. Special services in Wuhan were also targeted to households in which both husband and wife were laid-off and unemployed. Arrangements for publicly funded job training were handled differently.

Other policy measures included development of tertiary industries, particularly community services; encouraging the development of small and medium enterprises; facilitating self-employment including credit support; and expediting social security reform particularly in the areas of pensions, health care and unemployment insurance. The contribution rate for unemployment insurance was increased to 3 per cent from 1 per cent beginning in the latter half of 1999, with the 2 percentage point increase shared equally between employers and employees.

In Wuhan, 40,000 laid-off workers were employed in community services by the end of June 1998. By May 2001, in Shenyang there were over 600 grass-roots level organizations providing employment to about 90,800 laid-off workers. During the same period, the Shenyang municipal government set up various markets employing over 170,000 workers. Additional local efforts were also undertaken to encourage workers to set up businesses. These included tax reductions and exemptions, a temporary reduction in municipal administrative fees, and credit support.

China’s GDP growth rates over the past few years have been enviable, but employment growth rates were more modest. Urban employment has been growing, albeit at a slower rate in recent years, while rural employment has
declined significantly. However, provinces differ from the national averages in GDP and employment growth rates, unemployment rates and the number of xiagang. Unemployment rates in both Liaoning and Hubei provinces have been higher than the national average since 1996, even though their provincial GDP growth rates have exceeded the national average since 1997. Despite the relatively high output growth, employment has been falling in Liaoning and Hubei, with even larger reductions in their urban areas in 1998 and 1999.

Nationwide, SOEs continued to be the dominant employer in 1999, with a 55 per cent share of all urban employment in 1999, with another 11 per cent of the workforce employed in collectively-owned enterprises. By 1999, the private sector share of all urban employment nationwide had risen to 22 per cent. In the provinces of Liaoning and Hubei, a somewhat larger share of total employment was in the private sector.

Regions vary in the share of the workforce who is xiagang, with the magnitude dependent on the extent of the SOE reform and the industrial composition of employment. By the end of 1999, laid-off workers in Liaoning, Heilongjiang, Hubei and Hunan constituted 41 per cent of all lay-offs nationwide, with Liaoning and Hubei accounting for 13 and 7 per cent, respectively. As shares of the total employed nationwide, Liaoning and Hubei account for 3 and 4 per cent, respectively, so that these two provinces have disproportionately high shares of the nation’s laid-off workers. In Liaoning and Hubei provinces, 57 and 59 per cent, respectively, of xiagang were from SOEs, while 38 and 29 per cent, respectively, were from the urban collectively-owned enterprises. Nationally, 70 per cent of xiagang workers were from the SOEs and 28 per cent from collectively-owned enterprises.

Job lay-offs are also concentrated in certain industries. Textiles, coal mining, armaments and machinery are the harder hit industries. Data on the industrial distribution of laid-off workers in SOEs in 1998 and 1999 reveal that the industrial classification is broad – and shows that over half the laid-off workers are from the manufacturing industry in Wuhan. Supplemental information indicates that the manufacturing sectors impacted greatest by lay-offs were textiles and general machinery manufacturing. In certain categories of manufacturing, for example, cultural, educational and sports products, leather, fur and rubber manufacturing, the ratio of laid-off workers to total workers was between 40 and 50 per cent. Evidence for Shenyang identifies four sectors with relatively high redundancies – light industry, textiles, petroleum and chemical and agricultural machinery.

When we examine employment growth rates across sectors, we find that between 1996 and 1999, while employment in the manufacturing and mining/quarrying sectors declined significantly, in the financial services, estate agency activities and social services rose. Employment in the wholesale and retail trades grew between 1996 and 1998, but contracted between 1998 and 1999.

Among laid-off workers registered with RSCs in 1999, about 47 per cent were female in both Wuhan and Shenyang, while the proportion of female in the urban labour force was only 28 and 29 per cent, respectively, in Hubei and
Liaoning provinces. The vast majority of workers were less than 46 years old and among the less educated, with most having attained no higher than a junior middle school level.

Turning to benefits, laid-off workers in the Hubei RSCs are much more likely to be paid all basic living expenses (88 per cent) than those in Liaoning (59 per cent). Nearly 16 per cent of Liaoning workers in the RSCs do not receive any basic living expenses, while only 4 per cent in Hubei go without basic support. About half of the laid-off workers in Hubei belonged to an RSC for less than a year, with none staying more than two years. In Liaoning, about 37 per cent of the laid-off stayed with an RSC for less than a year, while 12 per cent stayed for over two years.

Were economic conditions in Shenyang and Wuhan different? Wuhan had a more dynamic economy than Shenyang. GDP per capita in 2000 in both cities was about the same – 16,111 yuan in Wuhan and 16,333 yuan in Shenyang. GDP growth rates have exceeded 10 per cent annually in both cities over the period 1996–2000, though growth rates in Wuhan have been higher. Wuhan’s growth exceeded that in Shenyang by 5–6 per cent between 1996–97 and 1–2 per cent between 1998–2000. Higher growth rates provide greater opportunities for creating jobs. But, did the jobs actually materialize? Employment elasticities show the responsiveness of employment to economic growth, and are calculated by dividing the net new job growth rate by the economic growth rate. The employment elasticity was higher in Wuhan than in Shenyang. Between 1996 and 2000, Shenyang’s employment elasticity was −0.001, while Wuhan’s employment elasticity was 0.069. Thus, despite growth rates exceeding 10 per cent annually over this period, Shenyang did not experience net new job creation. Over this five-year period, while growth rates were high in both cities, Wuhan succeeded in creating significantly more jobs than Shenyang.

The employment structure across primary, secondary and tertiary industries in both cities was similar in 1999, with about 36 per cent employed in the secondary industry, around 41 per cent in the tertiary sector and the remainder in the primary sector. However, the pattern of employment growth differed by city over the period 1996–2000. From 1996 to 2000, the growth rate of employment in the primary industry was negative in Wuhan, while it was positive (5.7 per cent) in Shenyang. In both Shenyang and Wuhan, employment in the secondary industry declined; it declined by an average of 0.27 per cent annually in Wuhan between 1996 and 2000, while in Shenyang the decline was more substantial (4.1 per cent annually). The tertiary industry was the engine of employment growth in both cities, with employment growth in Wuhan over the 1996–2000 period averaging 3.03 per cent annually, while it was 2.07 per cent in Shenyang. The higher growth rate in the tertiary industry provided better employment opportunities in Wuhan.

Wuhan also enjoys better connections to the rest of China; with better-developed rail and communications systems, there are better opportunities for developing trade and commerce. The tourism sector is also better developed.
in Wuhan, providing an important impetus for the development of self-employment. Wuhan has also invested significantly more than Shenyang in fixed assets. In 2000, Wuhan spent 46.2 billion yuan (or 6,166 yuan per capita) on investments in fixed assets, compared to 26.2 billion yuan (or 3,824 yuan per capita) in Shenyang. Foreign investment in 2000 in Wuhan (1.3 billion US dollars) also exceeded that in Shenyang (1.04 billion US dollars).

The average annual disposable income of urban residents in 2000 in Wuhan was 6,763 yuan, while it was only 5,850 yuan in Shenyang. However, despite lower incomes, Shenyang residents saved more in the aggregate than Wuhan residents. The differences in saving rates indicate either a scarcity of investment opportunities or reduced consumer confidence leading to lower spending. These savings represent a resource that could help create jobs given the right incentives. Individually owned businesses saw strong growth in both Wuhan and Shenyang over this period, though overall development was stronger in Wuhan.

Methodology

This section presents our methodology. First, we discuss the economic theory underlying the analyses, and then we discuss the empirical strategy.

The theoretical framework for this chapter is standard human capital theory, according to which an individual builds up knowledge and skills through education, experience and training (formal and/or on-the-job) and subsequently gets rewarded in the labour market in terms of wages (Becker 1964; Mincer 1974). This leads to the following simple model:

\[ Y_i = Y(S_i, E_i, T_i, O_i) \]

where \( Y \) is the employment outcome for individual \( i \), \( S \) is schooling, \( E \) is experience, \( T \) is training and \( O \) is other individual characteristics, for example gender, for individual \( i \). Schooling and experience are thought to affect employment prospects positively, since these factors positively affect the marginal product of an individual’s labour services. Training may or may not affect employment prospects positively. This depends on, for example, whether the training in question is perceived by prospective employers to affect workers’ productivity positively. If the training is thought to be of low quality or to be given to workers of low quality, thereby acting as a negative ‘signal’ to prospective employers (Spence 1973), training might have no effect on employment and may even stigmatize trainees.

Rigorous evaluations of social programmes, such as training, are needed to learn if a programme achieves its intended objectives. The central design issue in the evaluation is constructing a proper counterfactual. That is, what would have happened in the absence of the programme? In the case of a training programme, the evaluation must attempt to assess the employment outcomes of participants against what would have been the outcomes if they had not
participated in the programme. The counterfactual is approximated by the experiences of a ‘comparison group’ of workers, who are similar in all respects except programme participation. Programmes that are evaluated on the basis of techniques that do not use a comparison group, relying only on statistics of programme participants alone (e.g. employment rates of graduates), are of little use in measuring whether programmes are generating positive net benefits.

Lacking a field experiment involving random assignment, our approach is based on a quasi-experimental design, whereby participant and comparison groups are selected after the programme has commenced (how this is done in practice is discussed in detail in the next section). Because of non-random selection into participation, one cannot simply compare means on outcomes between participants and non-participants. Adjustments must be made in the estimation process to account for the differences in the characteristics of the participant and comparison groups.

To examine more closely whether results are robust to the choice of estimator, our approach here is to use several techniques to adjust for differences in observable characteristics of workers from the participant and treatment groups when estimating the empirical counterpart of equation (1). First, we estimate the effect of training as simply the coefficient for \( \beta_1 \) in the regression:

\[
y_i = \beta_0 + \beta_1 T_i + \text{other controls} + \varepsilon_i, \tag{2}
\]

where \( y_i \) is the employment outcome for individual \( i \), one if employed, zero otherwise, \( T_i \) is a binary indicator for whether individual \( i \) received training or not, ‘other controls’ include additional controls – such as age (to proxy potential general experience), gender and education – to ensure that the impact estimate (i.e. the estimate of \( \beta_1 \)) is valid, and \( \varepsilon_i \) is an error term that takes into account measurement error on the dependent variable \( y_i \) and other (unobserved) factors that may affect the dependent variable \( y_i \). Equation (2), therefore, effectively is the empirical counterpart of equation (1). We estimate (2) as a probit model outcome. Additionally, to provide a robust alternative to the probit estimation, we also estimate the employment regression by OLS, thereby effectively estimating (2) as a linear probability model.

As yet another alternative, we apply propensity score matching methods. The intuition behind this method is to compare the mean values of outcomes across the participant and comparison groups. The comparison group is constructed in this case by a two-stage approach, where participants and non-participants first are pooled and a regression of the determinants of participation is performed. Based on this, the individuals are ranked across to their predicted probability of participation in the programme, i.e. their (predicted) ‘propensity score’. When a participant and a non-participant are ‘close’ in terms of their propensity score, we have a match. This procedure is carried out for the entire sample and the impact estimate – which corresponds to the estimate of \( \beta_1 \) in (2) from the regression case – is then calculated as the
difference in means on employment outcomes between matched participants and non-participants. There are several different ways to do the matching, for example ‘nearest neighbour’, where the match is based on only the closest non-participant; ‘k-nearest neighbours’ matching, where the match is based on a weighted average of the k-nearest matches of non-participants in terms of their propensity scores; as well as kernel based and other methods (for details on propensity score matching, see Dehejia and Wahba 1999, 2002; Heckman et al. 1997, 1998; Rosenbaum and Rubin 1983, 1984, 1985).

Another widely used estimation method is to use instrumental variable (IV) techniques or two-stage least squares. However, since we do not have any instruments in our dataset which affect selection into programmes without at the same time affecting the outcome(s) of interest (here, employment), we cannot apply these methods. Consequently we must treat all observables, including assignment to training, as predetermined.

Data

This section discusses the data and survey methodology, and also provides descriptive statistics on the samples for analysis. Tests for homogeneity in observable characteristics between the participant and comparison groups are presented. Additionally, the nature of training is discussed.

The survey was designed and implemented by the Chinese Institute of Labour Studies and the World Bank. Respondents for the survey were selected from lists of laid-off workers who had received training (the treatment group) and laid-off workers who had not received training (the control group) from lists provided by the Shenyang and Wuhan Labour Bureaux, as well as local training institutions (for details on the sampling procedure, see Bidani et al. 2004, 2005). The World Bank team prepared a draft questionnaire, which was revised by counterparts in the Chinese Institute of Labour Studies (the text of the final questionnaire is provided in Annex 4 of Bidani et al. 2004). The team from the Institute of Labour Studies then carried out the data collection. Fielding of the survey began towards the end of May 2000, and was completed the following month. Successful interview rates were highest for the Shenyang participant group (61 per cent) and lowest for the Shenyang comparison group (48 per cent). Wuhan’s response rates were 51 per cent for the participant group and 55 per cent for the comparison group. The survey teams indicated that inaccurate contact information was the primary cause of non-response. The address on the identity card of workers differed from their actual residence in many cases.

Two anomalies related to this dataset were discovered by and discussed in Betcherman et al. (2002). First, a substantial fraction of workers report working in July 1998, when they were assumed to have been xiagang. This is addressed by deleting these workers to yield a ‘true’ xiagang-only sample. Second, the dataset contain ‘late xiagangers’, that is, individuals reporting having become xiagang after July 1998. These persons therefore were
employed immediately prior to the intervention, and were still in their old firms. This second group was also deleted from the sample for analysis since they too were not ‘true’ xiagang. Another contamination issue was that some individuals in the comparison group reported having received training. Since these more appropriately belong in the participant group, they were reassigned (see Bidani et al. 2004 for details).

We find significant (statistically and substantively) differences between the comparison and participant groups in terms of the demographic variables occupation, industry and other separating firm characteristics (firm type, firm size) in samples from both cities (see the Appendix). The differences are more pronounced in Shenyang than in Wuhan. Training participants in both cities were more likely to be female and younger. Participants in Shenyang were less likely to be married but more likely to have a high educational attainment than the comparison group members. Such differences were not observed to the same extent in the Wuhan sample. The occupational structure of the participant and comparison groups was more similar in Wuhan. In Shenyang, occupational structure differed more significantly, with a higher share of the participant group in the professional, clerical and services categories, and a lower percentage in the craft and machine operator categories. Thus, it would be misleading to use unadjusted means to compute impacts of the training programme. We will therefore adopt methodologies that allow us to control for observable differences when computing the programme impacts.

In 1998, there were 113 schools to train skilled workers and 199 enterprise-based training units in Shenyang. The municipal government launched an ambitious training plan that year which provided free training to all laid-off workers, and a budget of 10 million yuan was allocated for this purpose. The city’s re-employment training centre administered the programme, which was implemented by training organizations under the district labour bureaus. In Shenyang, the allocation of funding prior to training had recently been replaced by an after-training expense reimbursement contingent on training results. For training programmes with attendance rates of over 80 per cent, a passing rate of over 90 per cent and a re-employment rate of over 70 per cent, training expenses were reimbursed in full. When the re-employment rate fell below the required level, a 10 per cent deduction was made in the reimbursement for every 10 per cent difference. Training institutions could be disqualified if they did not meet the performance standards set.

In Wuhan, the government’s role in retraining of laid-off workers was less active. In 1998, there were 32 job skills schools and employment training centres within the labour system. The city’s labour bureau administered the city’s re-employment training programme for laid-off workers and unemployed persons. The training was conducted by the labour bureau training organizations (such as the city employment training centre and district employment training centres). Other organizations that satisfied the qualification requirements also undertook this training, for which they were compensated to cover part of their expenses.
Training programmes in Shenyang were conducted on a significantly larger scale (Bidani et al. 2004, 2005). Between 1998 and 2000, 279,000 workers were trained in contrast to around 64,000 workers in Wuhan. Shenyang offered its workers a larger menu of training courses; 59 courses in 1999 compared to 34 different courses in Wuhan. The gross re-employment rates, according to administrative data, were in the 60–70 per cent range for both cities, increasing steadily in Wuhan over the three-year period.

Nearly all training in Shenyang was of one-month’s duration, with 132 hours of study. In Wuhan, training lasted between one and six months, with the usual duration being two to three months of full-time study. Between July and December 1998, the average number of course hours was 255, of which 55 per cent were practical. In Shenyang, training courses with a minimum duration of one month were eligible for the government subsidy of 100 yuan per trainee. Laid-off workers did not contribute to the training courses. However, in Wuhan, only courses of two to three months were eligible for the government subsidy, and government policy was to provide 50–100 yuan from the re-employment fund for every laid-off worker trained and 300–400 yuan for every unemployed worker trained. Trainees in Wuhan were charged part of the training costs – they were exempt from paying the training fees but were expected to purchase textbooks and practice materials. Most trainees contributed about 200 yuan to the cost of their training.

Despite the more ambitious xiagang training programme by the Shenyang government, the quality of programmes varied widely across training institutions. Training institutions differed greatly in capacity, space, classroom set-up, workshop facilities, and laboratory and mechanical equipment. A number of training institutions only provided theoretical instruction without any practical training in their vocational courses. Some of the training courses did not provide skills demanded in the local labour market, and there were not even minimal standards governing the content of curricula and the qualifications of instructors.

The survey also asked about the nature of training. Information on the training provider, the duration of training, the type of training and whether individuals paid for training are shown in Table 7.1. Training was different across the two cities. As indicated, we restricted our list to three district training schools run by the labour bureau in Shenyang. So, the training there was almost exclusively provided by the labour bureau. In contrast, training in Wuhan was more varied. The Labour Bureau provided about three-quarters, with the rest provided by other organizations. The training in Shenyang was substantially shorter than that in Wuhan, averaging about one month, while the average duration of training in Wuhan was two to three months. Only about 3 per cent of the participants in Shenyang paid all or part of the costs of training, whereas about 21 per cent of participants paid at least part of the cost in Wuhan. The training organizations in Wuhan included colleges, universities and secondary technical schools, with presumably better ability to deliver quality training.
There were also variations in the type of courses that the participants attended. In Shenyang, about 37 per cent of the sample took computer courses, 29 per cent cooking, 19 per cent beauty, massage and hair cutting, and another 17 per cent sewing and toy making. In Wuhan, about 33 per cent took computer courses, 28 per cent took management courses, 9 per cent cooking, 9 per cent repairs and 11 per cent driving. There is some evidence that the types of training courses conducted in Wuhan, especially those run by the private sector, were selected by the organizers to accommodate the labour market demand for certain skills.

**Results**

Our analyses focus on one key outcome, namely, current employment. We use various estimators in this study to examine impacts of training on re-employment among xiagang workers. Additionally, we also examine more closely the determinants of training and briefly discuss determinants of re-employment beyond training.

Table 7.2 presents impact estimates for training computed by several different estimators: OLS/linear probability model, probit, and four different propensity score matching estimators. Training has a significantly positive impact on the likelihood of finding employment in Wuhan, but no significant effect on employment in Shenyang. Specifically, the numerical estimate for Shenyang is nil, but an employment rate gain of 9 to 12 percentage points was estimated for training in Wuhan by OLS and probit, respectively. The impact estimates are robust across the different estimators in both cities.

One potential problem with the propensity score matching methods is that they use markedly fewer observations than the regression approaches (see the
This reflects the fact that the overlapping area between the distributions of participants and comparison group observations, the so-called ‘region of common support’, is limited. This problem enhances the appeal of the more traditional regression-based methods (OLS and probit), where all observations are retained in the calculation of the training impact estimates. Since the impact estimates are similar across the different estimators, and OLS more completely use our sample information, OLS is therefore also our preferred estimator.

While the impact estimates and their magnitudes clearly are of interest to policy-makers, there are other aspects of the programmes that would potentially be relevant for policy regarding the design of future training programmes in China, as well. In particular, it would be interesting to examine a bit more closely who actually participates in the training, in other words, ‘who actually picks up the training offered to prospective participants’? This amounts to examining the results from the ‘first stage’ of the propensity score matching estimations.
Among the main findings are that training programme participants are predominantly younger females who have visited an employment service centre at some point. Also, workers in industries other than manufacturing (the reference category) are more likely to participate in training. For workers’ occupation prior to becoming xiagang, there are no strong results. However, workers who previously worked in SOEs (the reference category) are less likely to have participated in training. Workers who currently receive unemployment benefits are more likely to participate in training than are workers who do not receive unemployment benefits. In Shenyang, workers from households with more employed workers are more likely to receive training than other workers. For all samples except the employment sample for Wuhan, workers who were working in July 1998 are less likely to have participated in training than those who did not work in July 1998.

Based on the previous discussion, there appears to be mixed evidence on the targeting of the training programmes in Shenyang and Wuhan. On one hand, workers who were working in July 1998, that is, immediately prior to the intervention, are less likely to participate in training, while workers collecting unemployment benefits (and, therefore, presumably are unemployed) are more likely to participate in training, indicating effective targeting of the training programmes in Shenyang and Wuhan in terms of labour market status (presumably it would also be difficult to both work and participate in the programme, anyway). On the other hand, at least in Shenyang, workers from households with more working household members are more likely to participate in the training programme, which seems to indicate poor targeting, at least as measured by the presence of other earners in the household. Indeed, in a sense the targeting is worsened the better off the individual is in terms of the presence of other earners in the household.

It will also be interesting to shed additional light on determinants of employment other than training. In the evaluation of the effectiveness of the programme – which is the primary objective of this chapter – explanatory variables other than the training (participant) indicator were included mainly to reduce the overall variance of the estimator and increase the reliability of the inferences from estimated coefficients. In particular, to the extent that impacts from other factors are confounded within the training indicator variable, those factors should be controlled for in the estimation. For example it is possible that the participation in the programme is related to gender, education or other factors. However, even if the primary role of explanatory variables other than the training (participant) variable are to serve as controls, the results for the estimated parameters of these variables are interesting in their own right. In particular, it will be instructive for policy to know how other factors, such as gender, education, previous occupation, and so on affect the labour market prospects of laid-off workers in China. After having completed a review of the core evaluation results, we therefore now examine results on the secondary variables.

First, females and disabled workers are consistently much less likely to be
employed in both Wuhan and Shenyang. This should be an issue of concern for policy-makers, particularly if equity is considered important but also since these two groups could potentially contribute significantly to their households’ livelihoods. Second, there are strong positive education effects from tertiary education in Wuhan. Since job training works for those more prepared to benefit from it, more effort should focus on identifying ways to help those with less formal education prepare for success in the job market.

In Shenyang, workers from households with more employed household members are also more likely to be employed themselves, which might be due to spill-over effects or social networks. In Wuhan, the time since becoming xiagang has a negative impact on being employed, that is, the longer one is unemployed, the less likely that person is to find employment.

Conclusion

This chapter presents results of an evaluation of retraining programmes for laid-off workers in Shenyang and Wuhan. To our knowledge, this is the first evaluation of its kind in China. Training programmes were estimated to have markedly different impacts in the two cities. In Shenyang, workers who had taken training in 1998 were no more likely to be employed in mid-2000 than workers who had not participated in training programmes. In Wuhan, however, participation in training was estimated to have raised the probability of employment relative to the comparison group. These results are robust across alternative estimation methods.

Analyses of training determinants indicate mixed evidence on the targeting of the training programmes in Shenyang and Wuhan. On one hand, workers who were working in July 1998, that is, immediately prior to the intervention, were less likely to participate in training, while workers collecting unemployment benefits (and, therefore, presumably are unemployed) were more likely to participate in training, indicating effective targeting of the training programmes in terms of labour market status (presumably it would be difficult to both work and participate in the programme). On the other hand, at least in Shenyang, workers from households with more working household members are more likely to participate in the training programme, which suggests poor targeting, at least as measured by the presence of other earners in the household.

While this evaluation must be supported by further research, it does raise a number of issues regarding training policies for laid-off workers. Most obviously, the study suggests that policy-makers must adopt a critical approach to retraining and recognize that expectations should be moderate. Unless training programmes are carefully designed and targeted, there are no guarantees that impacts will be positive. This finding is consistent with the international experience.

The different results for the two cities should be of interest for policy-makers. Why did this occur? It may be due to factors that have nothing to do
with training – for example, the stronger economy in Wuhan may explain the more positive outcomes for employment in that city. However, the different results may well be due to differences in the retraining offered in the two cities. The quality and the relevance of the training programmes being offered probably contributed to the different outcomes. Training that is more responsive to market conditions and equips workers for jobs that are being created has a greater likelihood of creating a positive impact. Compared to Shenyang, Wuhan’s training programmes had certain features that may explain the more positive training outcomes. These include longer programmes with more practical content, and stronger supporting employment services (as indicated by the much higher proportion of workers going through Re-employment Service Centres).

This evaluation, in combination with the international literature, therefore suggests the following lessons for retraining policy. First, moderate expectations about the capacity of retraining programmes to reintegrate laid-off workers back into the labour market are in order. Second, diversification of the sources of training appears fruitful; public, non-profit and commercial providers may have comparative advantages in providing different types of training. Third, the focus should be on providing training that is responsive to labour demand. The best way of doing this is to involve employers in planning training. Fourth, the most important supporting services are job search, counselling and good labour market information. These not only can increase the returns to training but they tend to be the most cost-efficient of all active labour market programmes. For some workers, particularly those who are job-ready, these employment services should be the priority. Fifth, programmes should be carefully targeted to groups that are most likely to have a net positive benefit. Lastly, it seems fruitful to experiment with different financing schemes, including those that require some financial contribution from trainees.

These results should be compared to findings from future evaluations. The experience of other countries with long experience in labour adjustment programmes can help inform Chinese training strategies. But national characteristics do matter a great deal. Programme evaluation should become an intrinsic part of the active labour market strategy in China. Such evaluations need to be carried out in a range of municipalities with varying characteristics and on diverse programme designs. They must also take into account the costs of programmes, something that has not been analysed in this study. Only through such rigorous evaluations can policy-makers determine what works and for whom in supporting laid-off workers. In addition, it is important to compare training to other active labour market alternatives (such as employment services) and to highlight the costs and benefits of alternate interventions to support laid-off workers. It would also be useful to complement the quantitative survey information with qualitative information on the quality and relevance of training programmes from trainees, training institutes and employers. This would enrich the understanding of which training programmes work and why.
Acknowledgements

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Notes

1. See Heckman et al. (1999) for a comprehensive review of impact evaluations in OECD countries; Dar and Gill (1998) for a review of 11 studies covering the US, Sweden, Australia, Canada and France; Galasso et al. (2001) for a study on the Argentinian Proemplo experiment; Jimenez and Kugler (1987) for a study on Columbia’s national in-service training systems; Revenga et al. (1994) for an evaluation of the Mexican Probecat programme; Fretwell et al. (1999) for an evaluation of training programmes in Hungary, Poland and the Czech Republic; and NEI (2001) for an evaluation of training programmes in Bulgaria.

2. This section draws heavily on Bidani et al. (2004, 2005), where all the tables with the background statistics discussed here may also be found.

3. In 1999, laid-off workers in textile enterprises directly affiliated to the central government numbered 600,000; there were 400,000 in coal mining, 200,000 in armaments and 200,000 in machinery enterprises. These figures are taken from the presentation, ‘Situation of laid-off workers in state enterprise and policies on securing their basic living standards and promoting their re-employment’ given by the Labour Bureau at the Labour Market Policies Seminar in Beijing in May 1999.


6. In an earlier version of this chapter, we also examined the effect of training on wages (Bidani et al. 2005). Based on the comments and suggestions of a referee, however, we exclude the training–wage analysis here and, hence, focus exclusively on the employment analysis.

7. To conserve space, the results discussed here and in the remainder of this section are not reported here; they are available upon request.

8. To impose common support, the propensity score methods exclude extreme (in terms of their propensity score) observations. See the notes to Table 7.2 for details.

References


Reduction and Economic Management Unit, East Asia and Pacific Region, World Bank, Washington, DC.


Appendix: Sample means for training: participant and comparison groups

<table>
<thead>
<tr>
<th>Variable</th>
<th>Shenyang</th>
<th></th>
<th></th>
<th>Wuhan</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treatment</td>
<td>control</td>
<td>difference</td>
<td>Treatment</td>
<td>control</td>
<td>difference</td>
</tr>
<tr>
<td>Outcome variable</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed</td>
<td>0.457</td>
<td>0.560</td>
<td>−0.103***</td>
<td>0.447</td>
<td>0.410</td>
<td>0.037*</td>
</tr>
<tr>
<td>Control variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>36.76</td>
<td>40.05</td>
<td>−3.29***</td>
<td>36.98</td>
<td>38.28</td>
<td>−1.30***</td>
</tr>
<tr>
<td>Female</td>
<td>0.780</td>
<td>0.473</td>
<td>0.307***</td>
<td>0.620</td>
<td>0.422</td>
<td>0.198***</td>
</tr>
<tr>
<td>Disabled</td>
<td>0.048</td>
<td>0.051</td>
<td>−0.003</td>
<td>0.043</td>
<td>0.045</td>
<td>−0.002</td>
</tr>
<tr>
<td>Married</td>
<td>0.834</td>
<td>0.888</td>
<td>−0.054***</td>
<td>0.855</td>
<td>0.867</td>
<td>−0.012</td>
</tr>
<tr>
<td>Time since becoming xiag.</td>
<td>4.465</td>
<td>4.815</td>
<td>−0.350***</td>
<td>5.741</td>
<td>5.057</td>
<td>0.684***</td>
</tr>
<tr>
<td>Ever visitedempl. centre</td>
<td>0.387</td>
<td>0.138</td>
<td>0.249***</td>
<td>0.440</td>
<td>0.291</td>
<td>0.149***</td>
</tr>
<tr>
<td>Primary education</td>
<td>0.015</td>
<td>0.015</td>
<td>0.000</td>
<td>0.005</td>
<td>0.016</td>
<td>−0.011***</td>
</tr>
<tr>
<td>Junior education</td>
<td>0.443</td>
<td>0.662</td>
<td>−0.219***</td>
<td>0.342</td>
<td>0.347</td>
<td>−0.005</td>
</tr>
<tr>
<td>Senior education</td>
<td>0.272</td>
<td>0.160</td>
<td>0.112***</td>
<td>0.455</td>
<td>0.421</td>
<td>0.034</td>
</tr>
<tr>
<td>Vocational education</td>
<td>0.125</td>
<td>0.098</td>
<td>0.027**</td>
<td>0.135</td>
<td>0.123</td>
<td>0.012</td>
</tr>
<tr>
<td>Tertiary education</td>
<td>0.145</td>
<td>0.065</td>
<td>0.080***</td>
<td>0.064</td>
<td>0.093</td>
<td>−0.029**</td>
</tr>
<tr>
<td>Industry, low-skilled</td>
<td>0.100</td>
<td>0.036</td>
<td>0.064***</td>
<td>0.150</td>
<td>0.134</td>
<td>0.016</td>
</tr>
<tr>
<td>Industry, manufacturing</td>
<td>0.766</td>
<td>0.942</td>
<td>−0.176***</td>
<td>0.758</td>
<td>0.808</td>
<td>−0.050**</td>
</tr>
<tr>
<td>Industry, services</td>
<td>0.083</td>
<td>0.015</td>
<td>0.068***</td>
<td>0.069</td>
<td>0.038</td>
<td>0.031***</td>
</tr>
<tr>
<td>Industry, pub. adm/education</td>
<td>0.049</td>
<td>0.006</td>
<td>0.043***</td>
<td>0.023</td>
<td>0.019</td>
<td>0.004</td>
</tr>
<tr>
<td>Occupation, manager</td>
<td>0.044</td>
<td>0.043</td>
<td>0.001</td>
<td>0.046</td>
<td>0.056</td>
<td>−0.010</td>
</tr>
<tr>
<td>Occupation, professional</td>
<td>0.062</td>
<td>0.035</td>
<td>0.027***</td>
<td>0.031</td>
<td>0.027</td>
<td>0.004</td>
</tr>
<tr>
<td>Occupation, technician</td>
<td>0.132</td>
<td>0.095</td>
<td>0.037***</td>
<td>0.096</td>
<td>0.136</td>
<td>−0.040***</td>
</tr>
<tr>
<td>Occupation, clerk</td>
<td>0.124</td>
<td>0.076</td>
<td>0.048***</td>
<td>0.138</td>
<td>0.117</td>
<td>0.021</td>
</tr>
<tr>
<td>Occupation, service worker</td>
<td>0.088</td>
<td>0.042</td>
<td>0.046***</td>
<td>0.067</td>
<td>0.051</td>
<td>0.016</td>
</tr>
<tr>
<td>Occupation, agric./fishery</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.003</td>
<td>0.008</td>
<td>−0.005</td>
</tr>
<tr>
<td>----------------------------</td>
<td>-------</td>
<td>-------</td>
<td>-------</td>
<td>-------</td>
<td>-------</td>
<td>--------</td>
</tr>
<tr>
<td>Occupation, craft worker</td>
<td>0.185</td>
<td>0.263</td>
<td>−0.078***</td>
<td>0.165</td>
<td>0.200</td>
<td>−0.035*</td>
</tr>
<tr>
<td>Occupation, machine op.</td>
<td>0.278</td>
<td>0.337</td>
<td>−0.059***</td>
<td>0.395</td>
<td>0.333</td>
<td>0.062**</td>
</tr>
<tr>
<td>Occupation, unskilled labour</td>
<td>0.087</td>
<td>0.111</td>
<td>−0.024**</td>
<td>0.058</td>
<td>0.072</td>
<td>−0.014</td>
</tr>
<tr>
<td>Tenure as xiagang (mths)</td>
<td>134.47</td>
<td>165.62</td>
<td>−31.15***</td>
<td>140.48</td>
<td>156.22</td>
<td>−15.74***</td>
</tr>
<tr>
<td>Usual earnings, xiagang</td>
<td>297.99</td>
<td>306.64</td>
<td>−8.65*</td>
<td>263.04</td>
<td>283.94</td>
<td>−20.90***</td>
</tr>
<tr>
<td>Firm type, state enterprise</td>
<td>0.680</td>
<td>0.881</td>
<td>−0.201***</td>
<td>0.876</td>
<td>0.966</td>
<td>−0.090***</td>
</tr>
<tr>
<td>Firm type, collective ent.</td>
<td>0.262</td>
<td>0.112</td>
<td>0.150***</td>
<td>0.116</td>
<td>0.032</td>
<td>0.084***</td>
</tr>
<tr>
<td>Firm-type, private enterprise</td>
<td>0.024</td>
<td>0.003</td>
<td>0.021***</td>
<td>0.003</td>
<td>0.000</td>
<td>0.003*</td>
</tr>
<tr>
<td>Firm-type, joint venture</td>
<td>0.024</td>
<td>0.002</td>
<td>0.022***</td>
<td>0.003</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>Firm-type, other</td>
<td>0.010</td>
<td>0.002</td>
<td>0.008***</td>
<td>0.002</td>
<td>0.000</td>
<td>0.002</td>
</tr>
<tr>
<td>Benefits, medical</td>
<td>0.380</td>
<td>0.446</td>
<td>−0.066***</td>
<td>0.646</td>
<td>0.707</td>
<td>−0.061***</td>
</tr>
<tr>
<td>Benefits, pension</td>
<td>0.398</td>
<td>0.423</td>
<td>−0.025***</td>
<td>0.619</td>
<td>0.624</td>
<td>−0.005</td>
</tr>
<tr>
<td>Receives unemp. benefits</td>
<td>0.057</td>
<td>0.010</td>
<td>0.047***</td>
<td>0.089</td>
<td>0.034</td>
<td>0.055***</td>
</tr>
<tr>
<td>Working in July 1998</td>
<td>0.365</td>
<td>0.557</td>
<td>−0.192***</td>
<td>0.369</td>
<td>0.381</td>
<td>−0.012</td>
</tr>
<tr>
<td>House owned by individual</td>
<td>0.287</td>
<td>0.296</td>
<td>−0.009</td>
<td>0.175</td>
<td>0.186</td>
<td>−0.011</td>
</tr>
<tr>
<td>House owned by enterprise</td>
<td>0.102</td>
<td>0.163</td>
<td>−0.061***</td>
<td>0.168</td>
<td>0.277</td>
<td>−0.109***</td>
</tr>
<tr>
<td>House owned by parents</td>
<td>0.523</td>
<td>0.444</td>
<td>0.079***</td>
<td>0.418</td>
<td>0.357</td>
<td>0.061**</td>
</tr>
<tr>
<td>House owned by other</td>
<td>0.088</td>
<td>0.097</td>
<td>−0.009</td>
<td>0.239</td>
<td>0.181</td>
<td>0.058***</td>
</tr>
<tr>
<td>Household size</td>
<td>3.201</td>
<td>3.184</td>
<td>0.017</td>
<td>3.351</td>
<td>3.286</td>
<td>0.065</td>
</tr>
<tr>
<td>Number of employed in HH</td>
<td>0.703</td>
<td>0.536</td>
<td>0.167***</td>
<td>0.495</td>
<td>0.486</td>
<td>0.009</td>
</tr>
<tr>
<td>Children age 6 or older</td>
<td>0.652</td>
<td>0.855</td>
<td>−0.203***</td>
<td>0.732</td>
<td>0.736</td>
<td>−0.004</td>
</tr>
<tr>
<td>Children below age 6</td>
<td>0.102</td>
<td>0.043</td>
<td>0.059***</td>
<td>0.098</td>
<td>0.094</td>
<td>0.004</td>
</tr>
</tbody>
</table>

N  882  939  653  625

*Notes*: *T*-tests are one-sided and allow the error variance for treatment and control groups to differ, using the Satterthwaite (1946) correction; *statistically significant at 10%, **statistically significant at 5%, ***statistically significant at 1%.
8 Job search with non-participation

Teng Ge

Introduction

In this chapter, we add flow into and out of the labour market to the standard search-and-matching model to endogenize the aggregate labour force flows across different market states. In our framework, workers are heterogeneous with respect to home productivity, which will drive some of them out of the labour market. Furthermore, labour market conditions are stochastic, in that during good times the expected payoff of searching is higher relative to the value of home production, while in bad times the reverse is true. Therefore, agents in this model have to optimize the usage of time among the trade-off between employment, job search and home production. The stochastic nature of the model, with heterogeneous agents, can drive the flow of the labour force in and out of the market, thus generating additional variability of labour force participation and unemployment in the standard model. Qualitatively, we show that these flows into and out of labour markets are increasing in market-dependent state premiums (the capital gains (losses) from the switch of the aggregate state from bad to good (from good to bad); that is, the extra amount of payoffs to the agents whose market status is not changed. Specifically, functions (14) and (15) define its value), like wage payments, net searching income, but decreasing in non-market-dependent state premiums, say home productivity. We also show that, even under the assumption of risk neutral workers prefer persistent participation decisions when the shocks are transient, and flows in and out of the market are smaller than the case of persistent shocks. A quantitatively calibrated model shows that we can increase the standard deviations in variables such as participation, employment and unemployment and generate well-behaved time series to replicate the stylized facts in the labour market. This occurs because in addition to the standard variability of employment and unemployment there is now variability in the size of the market. In the set-up of this chapter, in comparing with the benchmark model calibrated by Shimer (2005), these in and out of market labour force flows account for more than 90 per cent of all variability in unemployment.

The benchmark model of the labour market developed by Mortensen and
Pissarides (1994) studies worker flows between employment and unemployment. Despite its success in many aspects of the labour market, recent research has shown that with a fixed size of labour market, the standard model seriously neglects many major labour force flows in the market. A genuine model that describes the dynamics of the labour market is required so as to explain and understand the following six different flows:

- Flows from employment to unemployment ($E-U$ flows), for example quitting jobs or layoffs.
- Flows from unemployment to employment ($U-E$ flows), for example successful job matching.
- Flows from unemployment to inactivity ($U-N$ flows), for example withdrawal from the labour market.
- Flows from inactivity to unemployment ($N-U$ flows), for example first entry or back to the labour market.
- Flows from inactivity to employment ($N-E$ flows), for example a very fast job search or return from a short leave.
- Flows from employment to inactivity ($E-N$ flows), for example withdrawal from the labour market.

Flows in and out of the labour market are sizeable and systematical, as has been shown in many empirical studies. Blanchard and Diamond (1989, 1990), Fallick and Fleischman (2004) and Jones and Riddell (1999) show that the average flows from non-participation to employment are as large as the flows from unemployment to employment. Furthermore, there are fundamental differences in the cyclical behaviours of these flows through the different phases of business cycles, as can be seen in Figure 8.1. The dashed lines in the upper and lower panels plot rate of unemployment, whilst those in the middle represent the rate of employment. Flows like $E-U$, $U-E$ and $N-U$ show strong counter-cyclical movements, and flows like $N-E$ and $E-N$ represent pro-cyclical behaviors and are relatively weak. Pries and Rogerson (2004) emphasized that cross-country differences in labour market participation are often larger than differences in unemployment rate. The same holds true for the cross-demographic groups within a given country. Thus, they argue that non-participation is a necessary element for a precise picture of the labour market.

The labour force participation in the standard model only concerns the static trade-off between market production and home production. The implication of this view is that any factor that will increase returns on home production – e.g. positive shocks to productivity of home production – or any factor that will decrease returns on market production – e.g. lower wage payments, higher searching costs – will lead to lower participation. Although these static trade-offs play an important role in workers’ participation decisions, the dynamic considerations also have a significant influence on workers’ behaviour. For example, the empirical findings from...
Figure 8.1 US labour market flows and business cycles, 1970–98.
Abowd and Zellner (1985) and Poterba and Summers (1986) suggest that ‘groups which have lower participation rates tend to have larger flows between participation and non-participation’.4

The model in this chapter is an extension of Mortensen and Pissirides’ standard searching and matching model. We assume that the economy is subject to a series of shocks to firms’ vacancy costs. In good times, the cost is low and in bad times it is high. Hence firms close existing vacancies or slow job creation in the down phase of the cycle, and re-open unfilled vacancies or accelerate job creation in up-turns of the cycle. Accordingly, a market boom will heighten job seekers’ hazard rates and shorten their searching spells. Given that any active job seeker will bear certain strictly positive searching costs during a job search, only a tight market will be attractive to those who greatly value leisure, as an opportunity cost of participation. The model predicts a pro-cyclical behaviour of labour force flows in and out of the labour market and counter-cyclical flows in the labour market. These predictions meet with most of the empirical findings in Blanchard and Diamond (1989, 1990), Bleakley et al. (1999) and Fallick and Fleischman (2004).

The model

The set-up in this section is an extension of Mortensen and Pissarides’ (1999a, 1999b) standard searching and matching model. It follows the same participation principle as in Pissarides (2000) and Garibaldi and Wasmer (2005), and a comparison with these is given in a later section.

The basic set-up

Time $t$ is infinite and continuous. There is a continuum of workers with a measure normalized to one. Each worker is characterized by his home productivity (value of leisure) $h$ uniformly distributed on $[0,1]$. The worker may be in one of two states: employed or unemployed, where $U_t$ denotes the measure of workers unemployed at time $t$. There is also a continuum of vacancies with measure $V_t$ which will be determined endogenously via a standard free-entry condition.

A matching function characterizes job-worker matching in a frictional labour market. The total number of matches at any point in time is a function of job vacancies $V_t$ and unemployment $U_t$, such as $M(V_t, U_t)$. The matching function is increasing in both arguments, decreasing marginal products to each input and constants return to scale, such that $M(0, U_t) = M(V_t, 0) = 0$ and assumes $M_t(U_t, 0) = \infty$ for $U_t > 0$.

The vacancy–unemployment ratio $\theta_t = \frac{V_t}{U_t}$ measures the market tightness at time $t$. Each unemployed worker applying for a vacant job follows a Poisson process, with a rate of $\frac{M(V_t, U_t)}{U_t}$. Constant returns to scale in $M(.)$ imply
workers apply for vacancies according to a Poisson process with a parameter \( f(\theta_t) = M(\theta_t, 1) \) is worker’s job-finding rate. Further \( f(.) \) is strictly increasing and concave in \( \theta \), and \( f(0) = 0, f'(0) = \infty \). A vacancy contacts the unemployed, according to the same arguments, and also following a Poisson process with a parameter \( \frac{f(\theta_t)}{\theta_t} \). We denote vacancy’s matching probability by \( q(\theta_t) = \frac{f(\theta_t)}{\theta_t} \).

The economy has two states: good (G) and bad (B). A firm’s vacancy cost is lower in a good state than in a bad state, and it is publicly observed. Each active firm comes to the market with a vacant job and searches for an unemployed worker to fill it. Firms attempt to create vacancies by paying a strictly positive cost, \( k_t dt \), where \( k_t \in \{ k^G, k^B \} \), for each time period \( dt \). The market is subject to a series of aggregate shocks that switch vacancy costs. Suppose, further, that the vacancy cost shock is independent and identically distributed (i.i.d.) with an arrival rate of \( \pi \in (0,1) \). Hence, the state of the market follows a two-state Markov process.

Labour is the only input. A good market is competitive, and market price is normalized to unity. A filled job generates flow revenue \( p > 0 \). A firm obtains net profit \( (p - w) dt \) per period \( dt \). Instead of the benchmark Nash bargaining solution, wage \( w \) is a somewhat loosely determined fixed wage. There are job separation shocks; each filled job is destroyed according to an independent Poisson process with parameter \( \delta > 0 \). Separation shocks terminate current matches, a firm makes no further profit and a worker becomes unemployed. Free entry determines the number of unfilled jobs in equilibrium such that expected payoff to a vacancy equals zero.

For simplicity, all agents are risk-neutral and have the same discount rate \( r \). Workers derive linear utility from home production (leisure) and from market activity. At each point in time, the worker is either employed or unemployed. Unemployed workers are free to choose job search or home production (non-participant). Employed individuals are paid \( w \) until separation. Unemployed workers gain a payoff; \( b - c < w \); \( b \) is unemployment insurance benefit and \( c \) is searching cost. They meet job offers according to a Poisson process with parameter \( f(\theta_t) \). A non-participating worker gains \( h \in [0,1] \) only.

**Search equilibrium of the labour market**

**Firms’ searching problem**

Let \( J^F_t \) denote the present-discounted value of expected profit from a filled job, and \( J^V_t \) the present-discounted value of expected profit from a vacant job, in state \( i \in \{ G, B \} \). In general, both \( J^F_t \) and \( J^V_t \) depend on state variable \( \theta_t \). The Bellman equation for payoff in equilibrium is as follows:
\begin{equation}
 rJ^i_V (\theta_i) = -k^i + q(\theta_i)[J^i_V (\theta_i) - J^i_V (\theta_i)] + \pi[J^i_V (\theta_i) - J^i_V (\theta_i)] \tag{1}
\end{equation}

Equation (1) dictates that the present-discounted value of expected profit from a vacant job is a sum of three parts: first, the current vacancy cost; second, capital gains from job matching; and third, the capital gains (or loss) from state switching. For the purposes of distinction, we call the payoff gains from matching ‘capital gains’, and the payoff gains from state switching ‘state premium’.

Following a similar principle, we can write down the rest of Bellman equations for a filled job in both a good and bad state, and a vacant job in a bad state:

\begin{equation}
 rJ^i_F (\theta_i) = (p - w) - \delta[J^i_F (\theta_i) - J^i_F (\theta_i)] + \pi[J^i_F (\theta_i) - J^i_F (\theta_i)] \tag{2}
\end{equation}

While the instantaneous cost of a vacant job will be influenced by aggregate shock, the wage and productivity are constant through the cycle. Under free entry $J^i_V = J^i_V = 0$, the payoff to a filled job can be solved from (2):

$$J^i_F = J^i_F = \frac{p - w}{r + s}$$

Then, from (1), the equilibrium job creation conditions, which will underpin market tightness, are given by:

$$q(\theta_i) = \frac{k^i (\delta + r)}{p - w}, \quad \text{where} \quad i \in \{G, B\} \tag{3}$$

As the free entry implies, $\theta_i$ will jump immediately to meet the job creation condition (3), and it is uniquely defined by constants such as $k^G$, $k^B$, $r$ and $s$. Hence, $\theta_i$ is a two-state Markov process that follows (3). Further, since $k^G < k^B$, it is not hard to show that $q(\theta^G) < q(\theta^B)$, which implies at a given level of unemployment firms post more vacancies in good times than in bad times. We have the following proposition.

**Proposition 1** Market tightness is a Markov process, and in each state, it is uniquely defined by job creation condition. More vacancies will be created in good times when the vacancy cost is low than in bad times when the cost is high. For each particular state of the economy, vacancy rate increases in the firm’s net payoffs $p - w$, and decreases in separation rate $s$ and discount rate $r$.

**Workers’ searching problem**

Similarly, workers’ searching payoffs are given by recursive Bellman equations. An employed worker’s payoff is denoted by $W^i (h)$ if she is payed at $w$,
her value of leisure is \( h \), and state is \( i \); and \( Z^i(h) \) denotes the payoff to the same worker when she is unemployed. Hence, an employed worker’s payoff in state \( i \) is defined by:

\[
 rW^i(h) = w + \delta[Z^i(h) - W^i(h)] + \pi[W^j(h) - W^i(h)] \quad \text{where } i \neq j \in \{G, B\}
\]

After a separation shock \( \delta \), the worker becomes unemployed and is free to choose her job search decision \( s \in \{0,1\} \) so as to maximize her payoff set down as the following:

\[
 rZ^i(h) = \begin{cases} 
 (b - c) + f(\theta^i)[W^i(h) - Z^i(h)] + \pi[Z^j(h) - Z^i(h)] & \text{if } s = 1; \\
 h + \pi[Z^j(h) - Z^i(h)] & \text{if } s = 0 
\end{cases} (4)
\]

Unemployed workers choose to search \( (s = 1) \) or not \( (s = 0) \). A searching unemployed person enjoys unemployment benefits \( b \), incurring searching cost \( c \), and forgoing home production \( h \). Accordingly, the worker’s optimal searching strategy implies there exists a \( \bar{h} = (b - c) + f(\theta^i)[W^i(h) - Z^i(h)] \) such that workers will choose \( s = 1 \) if, and only if, \( h \leq \bar{h} \). More specifically we have the following hypothesis.

**Hypothesis 1** With a given distribution of home productivity, there exists \( \bar{h} \) and \( \bar{h}^G \), such that \( \bar{h} < \bar{h}^G \). An unemployed worker’s optimal searching strategy satisfies the following:

- **Strategy 1** – search in both states if \( h \leq \bar{h} \).
- **Strategy 2** – search only in good state if \( \bar{h} < h \leq \bar{h}^G \).
- **Strategy 3** – never search if \( h > \bar{h}^G \).

The following steps are necessary to prove a candidate strategy we presume is optimal: first, we need to solve the model for \( \bar{h} \) and \( \bar{h}^G \). Then, with these two critical thresholds and value functions for each candidate strategy, to show that it cannot be improved upon. With sufficient conditions for dynamic optimality, we can conclude that candidate strategies in hypothesis are optimal.

In order to solve the model, we need to define these payoffs to each strategy conditional on the state of the economy:

- **Strategy 1** (search, search)

\[
\begin{align*}
 rW_i^G &= w - \delta(W_i^G - Z_i^G) - \pi(W_i^G - W_i^B) \\
 rZ_i^G &= b - c + f(\theta^G)(W_i^G - Z_i^G) - \pi(Z_i^G - Z_i^B) \\
 rW_i^B &= w - \delta(W_i^B - Z_i^B) - \pi(W_i^B - W_i^G) \\
 rZ_i^B &= b - c + f(\theta^B)(W_i^B - Z_i^B) - \pi(Z_i^B - Z_i^G)
\end{align*}
\]
• Strategy 2 (search, quit)

\[
\begin{align*}
  rW^G_2 &= w - \delta(W^G_2 - Z^G_2) - \pi(W^G_2 - W^B_2) \\
  rZ^G_2 &= b - c + f(\theta^G)(W^G_2 - Z^G_2) - \pi(Z^G_2 - H^B_2) \\
  rW^B_2 &= w - \delta(W^B_2 - H^B_2) - \pi(W^B_2 - W^G_2) \\
  rH^B_2 &= h_2 + \pi(Z^G_2 - H^B_2)
\end{align*}
\] (9-12)

• Strategy 3 (quit, quit)

\[
H_3 = \frac{h_3}{r}
\] (13)

where \(H_i\) denotes the payoff to home production, since we want to explicitly differentiate the states of searching unemployment and home production.

Notice that if we subtract (7) from (5) we get the expression of the state premium for an employed worker:

\[
W^G_1 - W^B_1 = \delta[(W^B_1 - Z^B_1) - (W^G_1 - Z^G_1)]
\]

Equation (14) states that the state premium of an employed worker is a proportion of the capital gains from job separation in two states. Similarly, the state premium of an unemployed worker can be found by subtracting (8) from (6):

\[
Z^G_1 - Z^B_1 = \frac{f(\theta^G)}{r + 2\pi} (W^G_1 - Z^G_1) - \frac{f(\theta^B)}{r + 2\pi} (W^B_1 - Z^B_1)
\] (15)

Let \(\Psi_1 = W^G_1 - W^B_1\) and \(\Phi_1 = Z^G_1 - Z^B_1\), and lemma 1 shows that these two state premiums are both positive constants.

**Lemma 1** Given the job creation condition by (3), the value of the state premium by choosing strategy one defined in (14) and (15) is positive constant, and uniquely defined in steady-state.

**Proof.** See Appendix.

Further, to simplify equations (5) to (8) and solve the payoffs of each labour market state:

\[
W^G_1 = \frac{w[r + f(\theta^G)] + (b - c)\delta - [\pi \Psi_1 (r + f(\theta^G)) + \pi_3 \Phi_1]}{r[r + \delta + f(\theta^G)]}
\]
A similar principle is also applicable to the workers who choose strategy 2. Through several steps of algebra, we have:

\[
W^B_2 - W^B_2 = \frac{s[(W^B_2 - H^B_2) - (W^G_2 - Z^G_2)]}{r + 2\pi} \tag{17}
\]

\[
Z^G_2 - H^B_2 = \frac{(b - c) - h_2 + f(\theta^G)(W^G_2 - Z^G_2)}{r + 2\pi} \tag{18}
\]

Notice that the state premiums incurred by choosing strategy 2 are agent-dependent because the agent’s outside option \(H^B_2\) is increasing the agent’s non-market productivity \(h_2\). However, since for each agent his value of home production is a constant, his state premiums of \(W^G_2 - W^B_2\) and \(Z^G_2 - H^B_2\) are constant. Let us denote these values \(\Psi_2 = W^G_2 - W^B_2\) and \(Y_2 = Z^G_2 - H^B_2\) and solve equations (9) to (12):

\[
W^G_2 = \frac{w[r + f(\theta^G)] + (b - c)(s + r) - [\pi \Psi_2 f(\theta^G) + \pi s Y_2]}{r[r + s + f(\theta^G)]}
\]

\[
Z^G_2 = \frac{w f(\theta^G) + (b - c)(s + r) - [\pi \Psi_2 f(\theta^G) + \pi s Y_2]}{r[r + s + f(\theta^G)]}
\]

\[
W^B_2 = \frac{w r + h_2 \delta + [\pi \Psi_2 r + \pi s Y_2]}{r(r + s)} \tag{19}
\]

\[
H^B_2 = \frac{h_2 + \pi Y_2}{r}
\]

From the above group of equations, we have the following lemma characterizing the properties of these value functions.

**Lemma 2** The value functions \(W^G_2, Z^G_2, W^B_2,\) and \(H^B_2\) are monotonically increasing in \(h_2\); \(H^B_2\) is increasing faster. There exist unique cutoff points between \(H^B_2\) and the other three.

The proof of lemma 2 can be ascertained from Garibaldi and Wasmer (2005: Appendix). Lemma 2 implies that there is a trade-off between choosing
strategies 1, 2 or 3. For some groups of workers, as their non-market productivity is low, payoffs from strategy 2 are lower than from strategy 1; for others, with a higher level of \( h \), their optimal strategy is to adopt strategy 2. The rest of the workers, with extremely high levels of \( h \), never participate in the market, hence they choose strategy 3. In equilibrium, there must be two cutoff agents who are indifferent between choosing between strategies 1 or 2, and choose strategy 2 or 3. Since the agents who choose strategy 2 will stop searching and quit the market in bad times, these two workers at the participation margin hence pin down the equilibrium rate of participation in bad state and good states. Additionally, combined with lemma 1, the marginal worker only participates in good times; his home production value must be no lower than the worker who is indifferent between searching and quitting in bad times, since the the state premium is non-negative.

To solve the model by setting \( N_B^2 = Z_B^1 \) for the lower bound of the participation margin, \( h_B \), and \( H_3 = Z_G^2 \) for the upper bound, \( h_G \), respectively:

\[
\begin{align*}
\bar{h}_B &= \frac{wf(\theta_B) + (b - c)(\delta + r) + f(\theta_B)\pi \Psi_1 + \pi \Phi_1 (\delta + r)}{\delta + r + f(\theta_B)} - \pi Y_2 \tag{20} \\
\bar{h}_G &= \frac{wf(\theta_G) + (b - c)(\delta + r) - [\pi \Psi_2 f(\theta_G) + \pi Y_2 (\delta + r)]}{\delta + r + f(\theta_G)} \tag{21}
\end{align*}
\]

By solving the participation margin \([\bar{h}_B, \bar{h}_G]\) one can characterize the size of different types of workers. \([0, \bar{h}_B]\) are active job-seekers, \([\bar{h}_B, \bar{h}_G]\) are marginal attached workers and \([\bar{h}_G, 1]\) are discouraged workers.

Equations (20) and (21) imply that the size of the labour force is increasing in wage \( w \), net searching income \((z - c)\); but other parameters have opposite effects on active job-seekers and marginal attached workers. First, \( \bar{h}_B \) is increasing in \( \Psi_1, \Phi_1 \) but decreasing in \( Y_2 \) and \( \bar{h}_G \) is decreasing in \( Y_2, \Psi_2 \). This result implies that the participation rate is decreasing with home productivity. From (14) and (15), \( \Psi_1 \) and \( \Phi_1 \) are independent of home productivity \( h \); they stand for pure premium from market income. However, from (17) and (18) and lemma 2, both \( \Psi_2 \) and \( Y_2 \) are increasing the value of home production. The higher \( \Psi_2 \) and \( Y_2 \) represent a higher opportunity cost of participation, and hence a lower participation rate. Second, \( \bar{h}_B \) is increasing with \( \pi \) but \( \bar{h}_G \) is decreasing with \( \pi \). Our result implies that as \( \pi \) increases, the state of the market will be switching back and forth frequently. In this case, more workers at the lower margin will adopt strategy 1 and less will choose strategy 2; and more workers at the higher margin will adopt strategy 3 over strategy 2. On the one hand, transitory shocks increase the number of active job-seekers, who are more willing to labour; on the other hand, they also increase the number of workers who quit the market permanently but who are willing to look for a job during economic booms – even the workers are risk neutral. A summary of workers’ labour supply behaviour is shown in proposition 2.
Proposition 2 The equilibrium rate of participation in the labour force is increasing in market wage $w$, net searching income $b - c$, and market dependent state premium $\Psi_1$ and $\Phi_1$; it is decreasing in the non-market production state premium $\Psi_2$ and $\Phi_2$. The number of marginal attached workers is increasing in the persistency of shock, $\pi$, but the active job-seekers are decreasing in $\pi$.

Finally, we shall prove that, in relation to the above solution, given workers’ home production $l$, the strategy we proposed in the above hypothesis cannot be improved upon by one-step deviation.

Lemma 3 The strategies proposed in hypothesis 1 cannot be improved upon.

Proof. See Appendix.

Sufficient conditions for an optimal strategy in a dynamic programming problem (see Kreps 1990) require, first, that a candidate strategy cannot be improved upon; and second, that the flow of payoffs is bounded below. The following proposal concludes our proof.

Proposition 3 Strategies in hypothesis 1 are optimal.

Proof. The first condition has been approved in lemma 3, and the second is obviously met given $b - c > 0$, and $h \in [0,1]$. Hence we have proved that searching strategies in hypothesis are optimal.

Q.E.D

Labour market flows

The search equilibrium of the labour market described in the last section pins down the equilibrium rate of participation in good times and in bad times: $\bar{h}^G$ and $\bar{h}^B$, respectively. We show that those flows into and out of the market, located in the range $(h^B, h^G)$, are marginally attached to the market. These flows are an equilibrium phenomena of the labour market since they reflect an optimum of switching between market production and home production for those who rationally choose strategy 2. We can thus transcribe the changes in unemployment with the following equation:

$$u_t = (1 - u_t) \delta - u_t f(\theta_t) + n_t$$  \hspace{1cm} (22)

where $n_t$ notes the effective factor of labour flows in and out of the labour market. It is a proportion of the marginally attached workers across the market, and may be either positive (flows in), negative (flows out), or zero (constant), depending on the nature of the state. Specifically, it is calculated as below:
where $u_M^i$ is the unemployment rate of marginal attached workers, which equals $u^G$ in steady state since active job-seekers and marginal attached workers are equally likely to be unemployed; $h_t \in [h^B, h^G]$ is thus a transition participation rate.

Given a current state, a steady state is achieved when inflows to equal outflows from unemployment, for example $\dot{u}_t = 0$. Hence a conditional steady-state unemployment rate is:

$$u^G = \frac{\delta}{\delta + f(\theta^G)}$$

$$u^B = \frac{\delta}{\delta + f(\theta^B)}$$

Equations (20), (21) and (24) characterize two conditional steady-state equilibriums of the market when it is in a good and a bad state. Obviously, we have $u^G < u^B$.

The out of (conditional) steady-state adjustments of market tightness, unemployment rate and vacancy rate are shown in Figure 8.2. Suppose the initial condition of the economy is point $A$. $BC^B$ and $JC^B$ represent the Beveridge curve and job creation condition in a bad state. A favourable shock shifts the state from bad to good, and forward-thinking firms will adjust their vacancies. Since investment in opening of new vacancies is less

\[ n_t = \begin{cases} 
- (1 - u^M_S) & \text{if state switches from good to bad} \\
- (\bar{h}_t - h^B) & \text{if state is bad and } h_t > h^B \\
\frac{h^G - h_t}{h^G} & \text{if state switches from bad to good} \\
0 & \text{otherwise} 
\end{cases} \]  

(23)
costly in good times, and current unemployment is high, it is relatively profit-
able for firms to open new vacancies and recruit employees. This implies that
there will be a jump in the job vacancy rate and hence in market tightness $\theta$.
In the meantime, it induces inflows of new entrants into the market. Such
an increase in the aggregate size of the labour market shifts the Beveridge
curve to $BC^G$, and the economy jumps to point B, which is a combination of
a higher rate of vacancies and a higher rate of unemployment. After the
participation rate jumps to its new equilibrium rate and the unemployment
starts to converge with the conditional steady state, the adjustment will follow
the $JC^G$ from point $B$ to point $C$. During this process, unemployment is
decreasing, together with the matching probability for a new vacancy. Firms
find it less easy to recruit, while holding market tightness constant, and they
then start to close vacancies. As long as the vacancy rate is still above its
steady-state level, unemployment will continue to decrease. At point $C$, the
intersection of $BC^G$ and $JC^G$, both job vacancies and unemployment
adjust to their new steady-state level. To summarize, when the labour market
shifts from a bad to a good state, participation rates and job vacancies jump
to their steady-state level; job vacancies will then overshoot the steady-state
level and gradually converge. Unemployment initially increases, then
decreases until it reaches the steady-state level; unemployment and job
vacancy rates are characterized by a counter-clockwise loop to redistribute
the labour force.

By a similar logic, a negative shock rotates the job creation curve from $JC^G$
to $JC^B$, and the economy jumps from point $C$ to point $E$ – an overshoot of the
job vacancy rate. However, the unemployment rate will gradually increase to
its new steady-state level by converging from the left. Further outflows from
the labour force will continue until it shrinks to its steady-state level $H^B$;
during this process, the Beveridge curve keeps on moving towards the origin.
Further adjustment will not rotate the curve of the job creation condition; the
economy moves to its steady state on the saddle path from $E$ to $A$. In this
process, the job vacancy rate first overshoots its steady-state level, while
adjustments of the unemployment and job vacancy rates are not monotonic,
and the relationship between job vacancy rate and unemployment shows a
counter-clockwise loop.

Furthermore, this model could be employed to analyse the business cycle
behaviour of an economy by introducing a series of shocks. The dynamics of
business cycle analysis are similar to those discussed in the previous section.
The adjustment path shown in Figure 8.3, considers a simple case whereby
the economy is hit by a favourable shock followed by a negative shock. The
unemployment rate, following the same economics, adjusts by first diverging
during the period of shock, and then gradually converging. The same prin-
ciple applies to the job vacancy rate, as depicted in Figure 8.3. Based on
equations (22) and (23), our analytical discussions of dynamic adjustment
in labour market provides an intuitive explanation of the market flows and
cyclical behaviour of the labour market.
Figure 8.3 Adjustment path to steady state after a series of shocks.
A numerical exercise

The preceding sections provide analytical descriptions of the steady-state equilibrium and out of steady-state dynamics of labour market flows. These arguments are intuitive. To test the model’s quantitative performance, we need to calibrate the model. In this section, we shall run a numerical experiment to compare the model’s performance with the actual US data.

Simulation exercise

The calibration exercise takes three steps. The first is to pin down the value of steady-state equilibrium characterized by \( \bar{h}^G, \bar{h}^B, u^G \) and \( u^B \). The second is to simulate a series of random market state variables: unemployment rate, employment rate and participation rate. The last step is to compare the time series properties of these artificial series with actual data.

We start by specifying parameter values and the functional form of matching functions. For simplicity, but without losing generality, we assume that the matching function is Cobb–Douglas,

\[
f(\theta) = \theta q(\theta) = \mu \theta^{1/2}
\]

where \( \mu \) is the matching efficiency. The separation rate is equal to 0.04 for a quarterly level, which is the same as in Shimer (2005). Discount rate is set to be 0.012, the quarterly rate equivalent to an annual discount factor of 0.953. Unemployment insurance equals 0.4. According to Shimer, it lies below the upper-end of the income replacement rate range in the US, if interpreted entirely as an unemployment benefit. The vacancy cost is set to be 7.2 in good times and 10.8 for bad times. All other parameters are left to be calibrated in the model, since they are unobservable in a real economy. Table 8.1 provides all the parameter values employed in the calibration and simulation exercises.

The first step was to determine the value of market tightness. We collected the data for the unemployment rate and vacancies from BLS (Bureau of Labor Statistics). The sample covers December 2000 to February 2006.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good state</th>
<th>Bad state</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount rate ( r )</td>
<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
<td>Separation rate ( s )</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>Unemployment insurance ( z )</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Matching technology</td>
<td>0.6 ( \theta^{1/2} )</td>
<td>0.6 ( \theta^{1/2} )</td>
</tr>
<tr>
<td>Vacancy cost ( k )</td>
<td>7.2</td>
<td>10.8</td>
</tr>
<tr>
<td>Searching cost ( c )</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Wage ( w )</td>
<td>0.56</td>
<td>0.56</td>
</tr>
</tbody>
</table>

Table 8.1 Calibrated values of parameter

Teng Ge
the mean value of the vacancy unemployment ratio is about 0.46. Next, we calculated the artificial value of market tightness with different values of shocks. By solving the free entry, one can pin down the value of market tightness. We picked the value of parameters, including the value of shocks, vacancy costs and wages, which gave the best estimation of the mean value of market tightness. We employed the simulated method of moments model, following the structural model – see the Appendix. The model generates a mean value of market tightness at 0.46, which minimized the distance from the empirical level. Following equation (24), the model gives equilibrium rates of unemployment for a good state and a bad state at 0.069 and 0.107, respectively. With these known parameter values, one can solve the extensive margin, which represents the locations of two marginal workers. Using a similar simulation method, we find that the payoffs for each state correspond to all searching strategies. The model generates the equilibrium participation rates for good and bad times as 0.552 and 0.515, respectively.

In the second step, we generated time series of unemployment, employment and participation. These series are given by a random series of aggregate states, according to the functions of equations (22) to (23), and we can locate those of unemployment and employment rates. We repeated this process 2,880 times to replicate 20 different samples, and then picked the sample which gave the best estimation of average unemployment.

The business cycle simulation result is depicted in Figure 8.4. The first panel of the first column is the index of state; ‘1’ represents the good state and ‘2’ the bad. The second panel is the adjustment path of the unemployment rate of active searching workers. As predicted in our theory, the unemployment rate of active searching workers is higher in bad times than in good times. The third panel represents the adjustment path of the participation rate; in good times it is high, and in bad times it is low. However, the adjustment to the steady-state level is not monotonic, as can be seen. There is initially a sharp decrease, followed by a gradual convergence to the new steady state, because the number of unmatched marginal attached workers shrinks if a negative shock is persistent.

The adjustment path of marginal attached workers is depicted in the first panel of the second column of Figure 8.4. The simulation result shows that in bad times, the unemployment rate of marginal attached workers is zero; while, as the state switches from bad to good, the unemployment rate first starts to increase sharply in response to a favourable shock, than gradually converges to its steady state. The second panel of the second column describes the adjustment of aggregate unemployment rate. Overshooting the aggregate unemployment rate is also captured in the figure as both periods show change. Correspondingly, the cyclical behaviour of the employment rate is described in the last panel of the second column. One can see the overshootings in this figure, too. Notice that the similarity in the adjustment path of the unemployment rate in Figures 8.5 and 8.4 offers evidence of the solid approximation of our model.
Figure 8.4 Simulation path.
Furthermore, we can also generate the time series of six labour force flows from the model, and compare their cyclical behaviours with actual time series. They are plotted in Figure 8.5. We can see that the model’s prediction about labour force flows meets most of the facts from the actual data. In comparison with Figure 8.1, our simulation generates four out of six flows which are consistent with their corresponding empirical movements. The only counter-factual flows are $E-U$ flows and $N-U$ flows. In Figure 8.1, the actual data shows that these two are counter cyclical flows; however, in our model they are pro-cyclical. A pro-cyclical $E-U$ flow comes from a constant separation rate; throughout the cycles aggregate employment is pro-cyclical, hence the $E-U$ flow. However, the counter-factual feature of the $N-U$ flow in this model is unexplained.

We also wanted to know the descriptive statistic characteristics of this model. Hence we compared the corresponding first and second moments of the rates of employment, participation and unemployment. Results are given in Table 8.2. The first part represents the corresponding statistics from artificial data generated by the model, whilst the second part represents the actual data from CPS. Compared with the actual data, the quantitative performance of the model is good. We measured the volatility of the time series by their standard deviations. From Table 8.2, it is clear that the model generates very close standard deviations in terms of the rate of unemployment and employment, but it over-estimates the volatility of the participation rate. The model predicts that the most volatile variable is unemployment rate, followed by employment, whereas participation is the most stable of these three indicators; this prediction is consistent with the observations from actual data. However, the model under-estimated persistency, as measured by auto-correlation (AC), both in unemployment and employment; it matched persistency in participation rate very well. The model predicts a positive correlation between the rate of employment and participation, negative correlations between rates of unemployment with participation and employment, which is consistent with the actual data.

In comparison to Shimer’s (2005) calibration, the model solves the problem inherited from the benchmark model. Shimer argued that the equilibrium rate of unemployment generated in Mortensen and Pissarides’ model explains only about 10 per cent of the response in the vacancy–unemployment ratio, and only 5 per cent in unemployment rate. However, in this chapter it has been found that extending the standard model with the third state, labour force, could reasonably improve performance of the searching and matching model. The volatility predicted in this chapter addresses almost every criticism from actual data, with certain sacrifices in persistency.

Veracierto (2004) tested the performance of the real business cycle (RBC) model with home production. The author replaced the single state of non-employment in the standard RBC model by search and non-participation, and found that the RBC model generates highly counterfactual labour market dynamics, such as unemployment being weakly pro-cyclical, and participation
Figure 8.5 Simulated labour force flows.
being more volatile than employment. However, we have seen that these problems can be solved by introducing the non-participation state into the matching model with the explicit searching cost.

In particular, there are two issues that need to be pointed out. The first is that the rates of unemployment and participation adjust in opposite directions. If the in and out of market flows dominate the inner market flow, we observe a pro-cyclical movement of unemployment. Therefore, this requires cross-market adjustment, or the number of marginal attached workers cannot be greater than unemployment in the bad state.

Second, the aggregate shock in this model could only generate flows in one direction. However, we observe from the real world that these flows may happen in both directions. We believe this is because the economy is experiencing multiple shocks. For example, if the economy in this chapter experienced two shocks – one in investment cost, increased from low to high, and the other a preferences shock related to individuals’ domestic productivity – then we could observe labour force flows in both directions.

<table>
<thead>
<tr>
<th></th>
<th>P</th>
<th>E</th>
<th>U</th>
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<tr>
<td>Statistics of simulated time series with 144 observers</td>
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<tr>
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<td>0.915</td>
<td>0.085</td>
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<td>0.013</td>
<td>0.133</td>
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<tr>
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<td>0.66</td>
</tr>
<tr>
<td>AC(2)</td>
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<td>0.26</td>
<td>0.34</td>
</tr>
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<td>Cross-correlation</td>
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<td>0.227</td>
<td>−0.279</td>
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<tr>
<td>Summary of US labour market, 1970 Q1 to 2005 Q4</td>
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<tr>
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</tr>
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<td>AC(2)</td>
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<td>U</td>
<td>−0.60</td>
<td>−0.98</td>
<td>1</td>
</tr>
</tbody>
</table>
Conclusion

In this chapter, we build a searching and matching model with heterogeneous workers. Workers are assumed to be free to adjust their participation decisions, facing a trade-off between market production and home production. We modeled workers’ optimal searching strategies and characterized equilibrium in the labour market and steady-state unemployment and participation. Comparative statistical analysis with equilibrium solutions argue that greater worker participation in the market can be obtained with the higher wage, net searching income, and market dependent state premiums. However, workers’ domestic productivity will genuinely discourage worker participation as it stands for the opportunity cost of searching. The comparative dynamic analysis describes cyclical behaviours of market flows. Qualitatively, the model’s predictions are consistent with empirical findings.

Numerically, we calibrated the model, simulated its business cycle behaviours and generated six labour force flows across these cycles. We find the adjustment paths of the participation rate, unemployment rate and employment rate, and find that they are consistent with our analytical predictions. Descriptive statistics argue that, by comparing relative moments of time series properties generated by the model with the actual data from CPS, together with the additional market state and domestic production, the extended model genuinely avoids the problem of lack of unemployment volatility in the benchmark searching and matching model, and counter-factual cyclical facts of market indicators in the RBC model.

Notes
1 See also Mortensen and Pissarides (1999a, 1999b) and Pissarides (2000).
2 According to the conventional definition of labour market states, for example CPS (2001), there are six flows across different market states (see Figure 8.1). For convenience of analysis, I omitted the job search, or E–E, flows in this chapter; the effect on cross-market flows is trivial.
3 This data was constructed by Bleakley et al. (1999) based on CPS. For additional details, please see this text.
4 Quoted from Pries and Rogerson (2004).
5 For empirical evidences on properties of the matching function, see Blanchard and Diamond (1989) and Pissarides (2000).
6 Because of the adverse selection in workers’ type, a wage determined by a Nash bargaining solution becomes problematic, and can become even more complex in out-of-equilibrium cases. Wage is assumed to be determined by the Nash demand game, or auction. It adopted Hall’s (2005a) ‘metaphor’. Employer and worker simultaneously make an offer. If the worker’s offer $w_w$ is no greater than the employer’s offer $w_E$, the match is made and the contracted wage is agreed at $w = \gamma w_w + (1 - \gamma) w_E$, where $\gamma$ is represented by the worker’s bargaining power. In equilibrium, the wage must be such that $w = w_w = w_E$. Given that there is no productivity shock to filled jobs, as far as both sides of the matching are ‘happy’ with the current wage, they do not renegotiate over the splitting rule. Hence, $w$ is a constant? For details on this Nash demand wage, see Hall (2005a) and Muthoo (1999).
7 In equation (20), the last term shows a decreasing relation in $\pi$, since we imposed
the condition $Z_B^B = H_B^B$ for this particular worker at the lower bound of the participation margin to pin down the value of $h^B$. By assuming that workers will take strategy 1 over strategy 2 in cases of indifference, then $Y_2 = 0$ and $h^B$ is strictly increasing in $\pi$. 

8 This number is larger than other authors’ estimations. However, these values are only used to pin down the participation rates and hence will not fundamentally influence the whole system’s quantitative behaviour.

9 We only obtained the data for vacancy rates for 2000 onwards.

10 Notice that we missed the $N-E$ flow in our continuous model. However, we can conveniently ‘create’ this flow in a discrete version. A solution to our model in a discrete version can be supplied on request.

11 Hagedorn and Manovskii (2005) claim that Shimer’s calibration failed to fully incorporate the opportunity cost of work. But their work has been proved to be true only in very extreme cases in which workers receive only 3 per cent profit from their work compared with large profits from home production. Mortensen and Nagypal (2005) claim that, even with investment cost and on the job search, however, Shimer’s finding is still a robust consequence of the standard model.

References


Appendix

Proof of lemma 1

Subtracting equation (5) from (6), and (8) from (7) results in:

\[
W^G_i - Z^G_i = \frac{w - (b - c)}{r + f(\theta_i^G) + s + \pi} + \frac{\pi}{r + f(\theta_i^G) + \delta + \pi} (W^B_i - Z^B_i)
\]

\[
W^B_i - Z^B_i = \frac{w - (b - c)}{r + f(\theta_i^B) + s + \pi} + \frac{\pi}{r + f(\theta_i^B) + \delta + \pi} (W^G_i - Z^G_i)
\]

(26)

then we compare the difference between:

\[
(W^G_i - Z^G_i) - (W^B_i - Z^B_i) = \frac{w - (b - c)}{r + f(\theta_i^G) + s + \pi} + \frac{\pi}{r + f(\theta_i^G) + \delta + \pi} (W^B_i - Z^B_i)
\]

\[- \frac{w - (b - c)}{r + f(\theta_i^B) + \delta + \pi} - \frac{\pi}{r + f(\theta_i^B) + \delta + \pi} (W^G_i - Z^G_i)
\]

(27)

From (3) we know that \(f(\theta_i^G) > f(\theta_i^B)\), and if \((W^G_i - Z^G_i) > (W^B_i - Z^B_i)\) the left-hand side of (27) is positive. However, the right-hand side of the equation is negative, since the sign of the following expression follows:

\[
\frac{w - (b - c)}{r + f(\theta_i^G) + s + \pi} - \frac{w - (b - c)}{r + f(\theta_i^B) + \delta + \pi}
\]
\[
\frac{\pi}{r + f(\theta^{G}) + \delta + \pi} (W_{1}^{B} - Z_{1}^{B}) - \frac{\pi}{r + f(\theta^{B}) + \delta + \pi} (W_{i}^{G} - Z_{i}^{G})
\]

(28)

given that \(w > z - c\). It is contradictory. Similarly, one can prove that the equality does not hold here either. Hence it must be the case that \((W_{i}^{G} - Z_{i}^{G}) < (W_{i}^{B} - Z_{i}^{B})\). Therefore, from (14) \(\Psi_{1} = W_{i}^{G} - W_{i}^{B} > 0\). Therefore it is not hard to prove that:

\((W_{i}^{G} - Z_{i}^{G}) - (W_{i}^{B} - Z_{i}^{B}) < 0 \Rightarrow 0 < W_{i}^{G} - W_{i}^{B} < Z_{i}^{G} - Z_{i}^{B}\)

Hence we have proved that \(\Psi_{1} > 0\) and \(\Phi_{1} > 0\).

The second part of the lemma can be proved by a contraction mapping theorem. The preceding argument also proved the property of monotonicity of \([W_{i}^{G} - Z_{i}^{G}) - (W_{i}^{B} - Z_{i}^{B})\]. Since \(\frac{\pi}{r + f(\theta^{G}) + \delta + \pi} < 1\) and \(\frac{\pi}{r + f(\theta^{B}) + \delta + \pi} < 1\), hence equation (27) also satisfies the property of discounting. Hence \([W_{i}^{G} - Z_{i}^{G}) - (W_{i}^{B} - Z_{i}^{B})\] satisfies the Blackwell sufficient conditions for a contraction. The contraction mapping theorem ensures there exists a unique value (fixed point) of \([W_{i}^{G} - Z_{i}^{G}) - (W_{i}^{B} - Z_{i}^{B})\] that satisfies (27). Further, given the job creation condition (3), the value of \([W_{i}^{G} - Z_{i}^{G}) - (W_{i}^{B} - Z_{i}^{B})\] itself is a constant since it is recursively defined by constant parameters like \(w, f(\theta^{G}), f(\theta^{B}), r, s\). Insert the value of \([W_{i}^{G} - Z_{i}^{G}) - (W_{i}^{B} - Z_{i}^{B})\] into (14) and (15) then one proved the lemma 1. QED.

**Proof of lemma 3**

We prove that the strategy cannot be improved upon with a so-called single-step deviation. Candidate strategies are labeled with asterisks, as in the following equations:

\[
Z'(h^*) = \begin{cases} 
(b - c) + f(\theta^i)[W'(h^*) - Z'(h^*)] + \pi[Z'(h^*) - Z'(h^*]) & \text{if } h \leq \overline{h}^i \\
\overline{h} + \pi[Z'(h^*) - Z'(h^*)] & \text{if } h > \overline{h}^i 
\end{cases}
\]

Now, suppose a worker with a domestic productivity such that \(h \leq \overline{h}^i\) chooses to deviate from the candidate strategy by arbitrary period \(\Delta\). In other words, rather than searching for a job, he opts for home production in period \(\Delta\). At the end of \(\Delta\), he returns to the candidate strategy of job searching. A strategy that cannot be improved upon requires such a single-step deviation which cannot improve his payoff. By choosing deviation in period \(\Delta\), his payoff will be

\[
D(h) = h\Delta + \frac{1 - \pi \Delta}{1 + r\Delta} Z'(h^*) + \frac{\pi \Delta}{1 + r\Delta} Z'(h^*)
\]

(29)
On the other hand, the payoff to the same worker gained by following the candidate strategy is:

\[ Z_i(h^*) = (b - c) \Delta + \frac{1 - \pi \Delta}{1 + r \Delta} \left\{ f(\theta^i) \Delta W^i(h^*) + [1 - f(\theta^i) \Delta] Z^i(h^*) \right\} \]

\[ + \frac{\pi \Delta}{1 + r \Delta} \left\{ f(\theta^i) \Delta W^i(h^*) + [1 - f(\theta^i) \Delta] Z^i(h^*) \right\} \]

\[ = (b - c) \Delta + \frac{1 - \pi \Delta}{1 + r \Delta} f(\theta^i) \Delta [W^i(h^*) - Z^i(h^*)] \]

\[ + \frac{\pi \Delta}{1 + r \Delta} f(\theta^i) \Delta [W^i(h^*) - Z^i(h^*)] \]

\[ + \frac{1 - \pi \Delta}{1 + r \Delta} Z^i(h^*) + \frac{\pi \Delta}{1 + r \Delta} Z^i(h^*) \]

by comparing (29) and (30), since \( \Delta h \leq \Delta \tilde{h} \). Further, knowing that \( \tilde{h} \) is solved by (21) and (22) satisfies:

\[ \Delta \tilde{h} = (b - c) \Delta + \frac{1 - \pi \Delta}{1 + r \Delta} f(\theta^i) \Delta [W^i(h^*) - Z^i(h^*)] \]

\[ + \frac{\pi \Delta}{1 + r \Delta} f(\theta^i) \Delta [W^i(h^*) - Z^i(h^*)] \]

Therefore, it is straightforward to show that \( D^i(h) \leq Z^i(h^*) \). Hence any finite deviation from candidate strategy \( Z^i(h^*) \) cannot improve his utility given that \( h \leq \tilde{h} \). On the other hand, following the same logic one can show that agents with domestic productivity such that \( h > \tilde{h} \) will be strictly worse off if they deviate from the candidate strategy. Hence we proved that the strategy could not be improved upon.
9 Youth unemployment in urban China

Zhongmin Wu

Introduction

Although China has sustained high economic growth for a quarter of a century, unemployment has become a big problem in recent years. The unemployment rate in China is called the urban registered unemployment rate. The term ‘registered unemployed persons’ only refers to the persons who are registered as permanent residents in the urban areas engaged in non-agricultural activities. The rural labour force is outside the purview of unemployment statistics. The number of registered unemployed was only 5.95 million (3.1 per cent of the urban labour force) at the end of 2000 (NBS and MoL 2001: 67). To reduce a potentially explosive political situation, several new categories of joblessness were created, in addition to the registered unemployed. Thus, there are xiagang (laid-off workers) – employees who have been laid off but still have some link with their previous place of employment – the enterprise. Official sources put the number of laid-off workers at 9.11 million at the end of 2000 (NBS and MoL 2001: 402). The laid-off workers are not counted as unemployed as they still maintain a close link with and obtain a minimum payment from their enterprises. Such workers are not required to register for unemployment in order to obtain some benefits from the state or their firms (Gu 1999). Hence, the majority of officially recognized unemployed people are school-leavers in the cities. Over the last 20 years, 70 per cent of the total urban unemployed comprised youths, aged between 16 and 25. Youth unemployment data are more reliable than adult unemployment data in China, as youth unemployment data are not distorted by the exclusion of significant numbers of adult laid-off workers from the more familiar unemployment statistics.

Before the economic reform, it had not been admitted that unemployment existed in China. The logic is that socialism guarantees everybody food, housing and a job. Therefore, China had full employment. If some people did not have a job and wanted one, they were classified as ‘waiting for employment’. Since the economic reform, the reality of unemployment has gradually been accepted. In 1994, China began to use the word ‘unemployed’. In 1949, at the establishment of the People’s Republic of China, there were 4.742 million
unemployed and the unemployment rate was 23.6 per cent. The high unemployment rate was due to the war against Japan and the civil war. The economy of the Kuomintang had almost collapsed. In 1952, the number of unemployed fell to 3.766 million and the unemployment rate was 13.2 per cent. After China completed the transformation to socialism, 2.004 million were unemployed and in 1957 the unemployment rate was 5.9 per cent. The disaster began from the ‘great leap forward’ in 1958. China tried to realize the economic revolution in order to overtake Britain. From 1959 to 1963, the situation was very difficult for China, both economically and politically. After the economic recovery in 1965, ‘the cultural revolution’ began. The slump in the economy could not afford school-leavers to be employed. So from 1966 to 1977, about 17 million urban youth (the Red Guard) went to the rural areas to be re-educated by the peasants in response to Chairman Mao’s call. Some of them did not even finish junior middle school and they spent most school time on ‘revolution’ rather than study. After the economic reform of 1978, youths gradually returned to the urban areas. They had been recruited through the government’s intervention, although some of them were not qualified and poorly educated. They now form the majority of laid-off workers in contemporary China. From 1978 onwards, open unemployment changed to hidden unemployment and under-employment.

Chinese young people occupy an important position in the economic construction and social life of China. Since China adopted its policy of economic reform and opening up to the outside world, youths have been more conscious of social participation. At the start of the new century, youth employment problems continue to pervade China, with a disproportionately large number of young women and men exposed to long-term unemployment or else limited to precarious or short-term work. As a result, many drop out of the workforce or fail to enter it successfully in the first place and become inactive. Socially disadvantaged youth are particularly affected, thereby perpetuating a vicious cycle of poverty and social exclusion. In China, where very few can afford to be openly unemployed, the employment problem is more one of under-employment and low pay and low quality jobs in the typically large informal sector.

After the reform of the job-assignment system in Chinese universities, jobs are no longer guaranteed to the graduates. Some of these young elite find they do not have the right skills to match demands in the job market and become another part of the unemployed or under-employed army. The reason for this problem lies in the static university education system in China. As the country becomes more open to the global economy, the demand and supply in its employment market has undergone great changes in the past few years but educational reform has not kept up with it. Because there is usually a time lag between students choose their major subject and when they enter the job market, they might become victims of structural changes in the economy.

China is facing serious labour over-supply, with the number of people coming into the labour market reaching an unprecedented peak. College
graduates who were formerly guaranteed jobs in the centrally controlled economy now must compete for work in an economy rife with laid-off workers caused by industrial reforms. The existence of large numbers of unemployed will exert severe pressures on the social security system, and will cause social instability. Many employers are reluctant to hire first-time job seekers with no work experience and unprepared for the challenges of work, particularly in a recession. Young people are disadvantaged because they lack experience, and when corporations are laying off staff they are not going to hire inexperienced youths.

Using simulation results, Zhai and Wang (2002) argue that if China adopts a policy of gradually relaxing its rural–urban migration control in conjunction with its labour market reform, it not only prevents a dramatic worsening of the urban unemployment problem, but also permits enough labour market flexibility to create more employment opportunities for rural unskilled labour shifted out of the farming sector. Econometric evidence from the US clearly does not support commonly expressed fears that undocumented immigration has caused a substantial increase in unemployment (Winegarden and Khor 1991). Evidence from the UK (Gregg 2001) suggests that those hit by youth unemployment, from any background, carry persistent effects from their past until at least age 33. Efforts to raise human capital once people become unemployed have rarely been successful in the past (Robinson 2000).

Youth unemployment is generally viewed as an important policy issue for many economies, regardless of their stage of development. The main purpose of this chapter is to analyse how rural–urban income inequality has affected urban youth unemployment. The underlying hypothesis is that the higher the rural–urban income gap, the more incentives rural people will have to migrate to the cities. Rural–urban migration will increase the pressure on job seeking, reducing the chances for urban school-leavers to find employment. The empirical work follows Okun’s law and uses a panel data set of 29 provinces over a ten-year period from 1988–98. The results show strong evidence to support our hypothesis and validate Okun’s law in the Chinese context. The rest of this chapter is organized as follows: the second section presents some stylized facts on youth unemployment in China, the third section discusses data and regression results, and the fourth section 4 draws conclusions.

**Stylized facts on youth unemployment in China**

Youth unemployment forms the majority of total unemployment stock. Since the laid-off workers are not counted as unemployed, the majority of measured unemployed comprises school-leavers. Over the last 20 years, 70 per cent of total urban unemployed has been youths, aged between 16 and 25 (see Figure 9.1). Hence, the majority of officially recognized unemployed people are school-leavers in the cities. Youth unemployment data are more reliable compared to adult unemployment data in China, as youth unemployment data are not distorted by the exclusion of significant numbers of adult laid-off
workers from the more familiar unemployment statistics. As shown in Table 9.1, in 1998, of 5.71 million urban unemployed, 54.7 per cent are 16–25 years of age. Meanwhile, of total employees (both urban and rural), only 20.1 per cent are 16–25 years of age. The majority of adult jobless are the laid-off workers. The laid-off workers are not counted as unemployed, because they are still affiliated to their enterprise.

Lassibille et al. (2001) find that in Spain young workers are more likely to be under-utilized compared to their adult colleagues. Their results indicate that people with higher education have, all else being equal, a lower probability of being overeducated and a shorter length of unemployment. The labour market in China is very rigid and inflexible. The most important reason for rigidity is the political constraints both for official dismissals and the closure of loss-making state enterprises. The employee protection regulations in China mainly safeguard adults. Even though youths have been laid-off, they still do not count as unemployed. So only a few of the unemployed have had previous employment. Meanwhile, most unemployment outflow is to employment, not to leave the labour force.

The youth unemployment rate is much higher than the total unemployment rate. In urban China, as the majority of adult jobless people are laid-off workers who are not considered as being unemployed, the youth unemployment rate is more than three times that of the aggregate unemployment rate.

### Table 9.1  The age level of urban unemployed in 1998 (millions)

<table>
<thead>
<tr>
<th>Grouped by age</th>
<th>Unemployed</th>
<th>Total employees</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number</td>
<td>5.71</td>
<td>699.57</td>
</tr>
<tr>
<td>16–25 years old</td>
<td>54.7%</td>
<td>20.1%</td>
</tr>
<tr>
<td>26 years old and above</td>
<td>45.3%</td>
<td>79.9%</td>
</tr>
</tbody>
</table>


![Figure 9.1](image.png)

*Figure 9.1* Youth unemployment as a proportion of total unemployment.
In addition, urban youth unemployment fluctuates more than aggregate unemployment over time. In times of recession, when aggregate demand falls, unemployment rates tend to grow. However, it has been demonstrated that under these circumstances the increase in the youth unemployment rate is often more substantial than the increase in the adult rate, implying that young workers are likely to suffer more than their adult counterparts. Gustman and Steinmeier (1981) use the local youth unemployment rate as a measure of job availability, which seems to influence youth labour supply and have the strongest effect on the labour supply for non-white males.

In 1979, there was a big increase in new urban employees; it lasted three years in an attempt to solve the problem of returning youths. Because of the returned youth, the new school-leavers got fewer opportunities than before. So youth unemployment (covering those aged between 16–25 years) increased rapidly in 1980 and 1981 (Figure 9.2). The decrease in new urban employment in 1989 led to the rise of both overall unemployment and youth unemployment. This was because, in 1989, GDP annual growth rates were only about 4 per cent (China has experienced an average 10 per cent annual growth rate in the last 25 years). The slump in the economy caused a decrease in labour demand, and new hiring decreased.

The provincial youth unemployment rate in the West has been much higher than that in the East. In 1996, the People’s Republic of China comprises 30 provinces, municipalities and autonomous regions, 12 of which are in the eastern coastal region, nine in the middle region and a further nine in the western region. Tibet has been omitted from the empirical analysis, as unemployment data for Tibet is not available. The data set includes the remaining 29 provinces, municipalities and autonomous regions for the period 1988 to 1998. The top six provinces with the highest average provincial youth unemployment rates are Ningxia, Gansu, Qinghai, Guizhou, Inner Mongolia and Sichuan. They are all in the interior regions. Five of them are in the western region and only

![Figure 9.2](image)

*Figure 9.2* Youth unemployment rate and total unemployment rate.
one is in the middle region. The bottom six provinces with the lowest average provincial youth unemployment rates are Beijing, Shanghai, Shanxi, Tianjin, Guangdong and Fujian. Five of them are in the eastern coastal region and only one of them is in the middle region. None of them is in the western region. Figure 9.3 shows that the provincial youth unemployment rates are much higher in the western than in the eastern region. All the higher unemployment rates occurred in the western region and they are much higher than those of the eastern coastal and middle regions. Lower unemployment rates only occurred in the eastern coastal and the middle regions (Wu 2004).

Youth unemployment is persistent. The provincial youth unemployment rates in 1988 and 1997 are presented in a scatter graph (Figure 9.4). The

![Figure 9.3 Provincial youth unemployment rate panel data for 1988–98 in 29 provinces.](image1)

![Figure 9.4 Youth unemployment rate in 1988 and 1997.](image2)
ranking of provinces according to their youth unemployment rate has remained remarkably stable over the nine-year period. Table 9.2 shows a cross-correlation matrix for regional patterns of provincial unemployment rates. If the correlation below 0.7 is taken as indicating substantial change, it suggests that the regional pattern of youth unemployment altered in 1994 and 1998. Compared with OECD countries (OECD 1989), regional youth unemployment in China is more persistent than that in Australia and the US, less persistent than that in the UK and Italy, and is similar to that in Canada, West Germany and France (Wu 2003).

Youth unemployment is less persistent than total unemployment. Blanchard and Summers (1986) estimated an AR (1) process for the UK and USA, using the degree of first-order serial correlation to represent unemployment persistence. To measure unemployment persistence in China, their model is developed to:

\[
\text{Time series } U_t = \alpha + \beta U_{t-1} + \varepsilon_t \\
\text{Panel data } U_{it} = \alpha + \beta U_{it-1} + \varepsilon_{it}
\]

The empirical results are provided in Table 9.3. The persistence of youth unemployment is always smaller than the persistence of total unemployment. Youth unemployed mainly comprises school-leavers. They are actively searching for their first job. Adult unemployed mainly failed to keep their jobs. They find it difficult to maintain their skill and they have a disadvantage in learning new skills compared with youths. Just like physical capital, human capital is likely to depreciate in the absence of regular maintenance. Moreover, long-term unemployment may have a demoralizing effect on search behaviour, contributing to a less efficient matching process (Roed 1997).

It is necessary to run a unit root test for unemployment analysis. The augmented Dickey–Fuller (ADF) test is used to run regressions:

<table>
<thead>
<tr>
<th></th>
<th>98</th>
<th>97</th>
<th>96</th>
<th>95</th>
<th>94</th>
<th>93</th>
<th>92</th>
<th>91</th>
<th>90</th>
<th>89</th>
</tr>
</thead>
<tbody>
<tr>
<td>97</td>
<td></td>
<td>0.67</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>96</td>
<td></td>
<td>0.73</td>
<td>0.93</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>95</td>
<td></td>
<td>0.77</td>
<td>0.74</td>
<td>0.83</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>94</td>
<td></td>
<td>0.74</td>
<td>0.70</td>
<td>0.77</td>
<td>0.93</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>93</td>
<td></td>
<td>0.68</td>
<td>0.84</td>
<td>0.88</td>
<td>0.89</td>
<td>0.87</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>92</td>
<td></td>
<td>0.64</td>
<td>0.76</td>
<td>0.85</td>
<td>0.86</td>
<td>0.82</td>
<td>0.92</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>91</td>
<td></td>
<td>0.64</td>
<td>0.81</td>
<td>0.88</td>
<td>0.85</td>
<td>0.78</td>
<td>0.89</td>
<td>0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td>90</td>
<td></td>
<td>0.55</td>
<td>0.75</td>
<td>0.83</td>
<td>0.81</td>
<td>0.73</td>
<td>0.83</td>
<td>0.79</td>
<td>0.94</td>
<td></td>
</tr>
<tr>
<td>89</td>
<td></td>
<td>0.58</td>
<td>0.76</td>
<td>0.84</td>
<td>0.80</td>
<td>0.72</td>
<td>0.76</td>
<td>0.75</td>
<td>0.89</td>
<td>0.96</td>
</tr>
<tr>
<td>88</td>
<td></td>
<td>0.56</td>
<td>0.75</td>
<td>0.80</td>
<td>0.77</td>
<td>0.69</td>
<td>0.73</td>
<td>0.70</td>
<td>0.87</td>
<td>0.93</td>
</tr>
</tbody>
</table>

*Table 9.2 Correlation matrix of provincial youth unemployment rates*
\[ \Delta U_{it} = a_i + \gamma_i \text{Time} + \delta_i U_{it-1} + \Sigma \theta_i \Delta U_{i,t-1} + \epsilon_{it} \]

where \( \Delta U_{i,t} = U_{i,t} - U_{i,t-1} \). The ADF test evaluates the null hypothesis \( H_0: \delta_i = 0 \). Levin and Lin (1992, 1993) develop a unit root test for panel data, by performing the following regression:

\[ \bar{e}_{i,t} = \delta \bar{v}_{i,t-1} + \mu_{it} \]

where

\[ \bar{e}_{i,t} = \Delta U_{i,t} - \bar{a}_{iit} - \bar{\gamma}_{i1i} \text{Time} - \Sigma \bar{\theta}_{i1i} \Delta U_{i,t-1} \]
\[ \bar{v}_{i,t-1} = U_{i,t-1} - \bar{a}_{2i} - \bar{\gamma}_{2mi} \text{Time} - \Sigma \bar{\theta}_{2mi} \Delta U_{i,t-1} \]

The null hypothesis for the panel unit root test is \( H_0: \delta = 0 \), which is to say that \( \beta = 1 \), or unit root. Here, the Levin–Lin test is used for panel data of both youth unemployment and total unemployment.

When \( T = 10 \) and \( N = 25 \), the 1 per cent critical statistics computed by Levin and Lin are \(-2.78\). The computed \( t \) value is \(-6.20\) for youth unemployment, which is smaller than the 1 per cent critical values. So the null hypothesis can be rejected at the 1 per cent critical level. That is, unit root does not exist in provincial youth unemployment in China.

Many experts have applied the Levin–Lin test. Maddala and Wu (1999) compare the Levin–Lin test, its extension by Im et al. (1997) and a simple alternative Fisher test. The Levin–Lin test gives us enough power to reject the unit root for regional youth unemployment in China. Unit root in unemployment normally has been termed as ‘hysteresis’. The hysteresis is rejected but ‘persistence’ is accepted, which is in-between the hysteresis theory and the natural rate theory, NAIRU.

### Table 9.3 Persistence of unemployment

<table>
<thead>
<tr>
<th>Persistence of</th>
<th>Youth</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>National unemployment rate</td>
<td>0.732***</td>
<td>0.812***</td>
</tr>
<tr>
<td>(4.76)</td>
<td>(10.5)</td>
<td></td>
</tr>
<tr>
<td>log(national unemployment rate)</td>
<td>0.758***</td>
<td>0.828***</td>
</tr>
<tr>
<td>(5.24)</td>
<td>(9.46)</td>
<td></td>
</tr>
<tr>
<td>Without year dummy provincial unemployment rate</td>
<td>0.793***</td>
<td>0.820***</td>
</tr>
<tr>
<td>(19.9)</td>
<td>(15.3)</td>
<td></td>
</tr>
<tr>
<td>log(provincial unemployment rate)</td>
<td>0.829***</td>
<td>0.870***</td>
</tr>
<tr>
<td>(14.7)</td>
<td>(28.6)</td>
<td></td>
</tr>
<tr>
<td>With year dummy provincial unemployment rate</td>
<td>0.808***</td>
<td>0.842***</td>
</tr>
<tr>
<td>(21.8)</td>
<td>(17.4)</td>
<td></td>
</tr>
<tr>
<td>log(provincial unemployment rate)</td>
<td>0.844***</td>
<td>0.891***</td>
</tr>
<tr>
<td>(15.7)</td>
<td>(32.7)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Numbers in parentheses are \( t \)-ratios; * \( p < 0.10 \); ** \( p < 0.05 \); *** \( p < 0.01 \).
Methodology and empirical findings

In recent years, rural people have been allowed to work in the cities. The primary motivation of rural–urban migration is huge rural–urban income inequality. Harris and Todaro’s (1970) pioneering study on rural–urban migration in Africa suggests that rural-to-urban migration is driven by expected income. Migrants flow from the countryside of the poor regions to the more prosperous cities in the hope of earning higher incomes. The recent economic reforms in China have exaggerated the rural–urban income gap, providing strong incentives for the exodus of rural people into the cities. This has inevitably led to employment pressure, particularly on urban youth. Figure 9.5 shows a relationship between the provincial youth unemployment rate and the rural–urban per capita consumption ratio, which is an important measurement of rural–urban income inequality. It is obvious that there exists a positive relationship between the rural–urban income gap and the urban youth unemployment rate. The bigger the income gap between urban and rural areas, the higher the provincial youth unemployment rate.

Okun’s law is an empirical law that relates short-run changes in output to changes in unemployment, and examines the sources of output changes that go along with changes in unemployment. When unemployment falls, more people tend to come onto the labour market to find work. For these reasons, reductions in unemployment and increases in output occur together. The empirical law that Okun discovered is that, in the short run, a 1 per cent change in the unemployment rate tends to accompany a 3 per cent reduction in the GNP gap. Figure 9.6 confirms that Okun’s law fits in China. It also shows that the Okun curve is non-linear (Viren 2001).

Based on Okun’s law and Edwards and Edwards (2000) methodology, the following regression equation is derived for China:

![Figure 9.5 The relation between unemployment and the income gap.](image-url)
The data are drawn from 29 provinces of China, over the period 1989–98. The consumption data are measured in constant prices, using provincial level and urban/rural deflators. The summary statistics and explanations of the dependent and independent variables are provided in Table 9.4. The explanatory variables are instrumented to avoid the problem of endogeneity. The instruments are the lagged values of the corresponding variables. The results for the simple linear form are given in Table 9.5, and those in double-log form in Table 9.6. The plain OLS, the random effect model, and the fixed effect model are estimated. Using Hausman’s test, LM het. test, R-square and t ratios, we find that the random effect model without a year dummy is acceptable. It also performs better.

In both regressions, the results are quite consistent. There is strong empirical evidence of the rural–urban income inequality gap impacting on urban youth unemployment. A reduction in the rural–urban income gap will help reduce urban youth unemployment pressure. The results support our
Table 9.5 Regression results: dependent variable = youth unemployment rate

<table>
<thead>
<tr>
<th>Variable</th>
<th>OLS</th>
<th>FE</th>
<th>RE</th>
<th>OLS</th>
<th>FE</th>
<th>RE</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Youth unemployment rate)_{t-1}</td>
<td>0.764***</td>
<td>0.390***</td>
<td>0.664***</td>
<td>0.777***</td>
<td>0.337**</td>
<td>0.634***</td>
</tr>
<tr>
<td></td>
<td>(17.4)</td>
<td>(2.77)</td>
<td>(16.7)</td>
<td>(17.7)</td>
<td>(2.41)</td>
<td>(14.9)</td>
</tr>
<tr>
<td>(Consumption ratio of nonpeasants/peasants)_{t-1}</td>
<td>0.487</td>
<td>0.258</td>
<td>0.689**</td>
<td>0.527*</td>
<td>1.525**</td>
<td>1.047***</td>
</tr>
<tr>
<td></td>
<td>(1.47)</td>
<td>(0.52)</td>
<td>(2.24)</td>
<td>(1.88)</td>
<td>(2.34)</td>
<td>(2.90)</td>
</tr>
<tr>
<td>Growth rate of real per capital GDP</td>
<td>−6.554***</td>
<td>−5.306***</td>
<td>−6.670***</td>
<td>−2.310</td>
<td>−1.270</td>
<td>−2.476</td>
</tr>
<tr>
<td></td>
<td>(−3.86)</td>
<td>(−3.43)</td>
<td>(−3.61)</td>
<td>(−0.79)</td>
<td>(−0.55)</td>
<td>(−1.02)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.732</td>
<td>0.789</td>
<td>0.730</td>
<td>0.768</td>
<td>0.825</td>
<td>0.762</td>
</tr>
<tr>
<td>LM het. Test</td>
<td>6.87</td>
<td>12.5</td>
<td>7.51</td>
<td>4.19</td>
<td>8.92</td>
<td>4.46</td>
</tr>
<tr>
<td>Haussman Test</td>
<td>7.29</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5.47</td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Numbers in parentheses are $t$-ratios; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. 
Table 9.6 Regression results: dependent variable = log(youth unemployment rate)

<table>
<thead>
<tr>
<th>Variable</th>
<th>OLS</th>
<th>FE</th>
<th>RE</th>
<th>OLS</th>
<th>FE</th>
<th>RE</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(youth unemployment rate)$_{-1}$</td>
<td>0.864***</td>
<td>0.466***</td>
<td>0.757***</td>
<td>0.879***</td>
<td>0.444***</td>
<td>0.759***</td>
</tr>
<tr>
<td></td>
<td>(22.7)</td>
<td>(4.61)</td>
<td>(21.1)</td>
<td>(24.2)</td>
<td>(4.25)</td>
<td>(20.3)</td>
</tr>
<tr>
<td>log(consumption ratio of nonpeasants/peasants)$_{-1}$</td>
<td>0.087</td>
<td>0.041</td>
<td>0.168*</td>
<td>0.080</td>
<td>0.305**</td>
<td>0.223**</td>
</tr>
<tr>
<td></td>
<td>(0.96)</td>
<td>(0.37)</td>
<td>(1.93)</td>
<td>(0.95)</td>
<td>(2.05)</td>
<td>(2.25)</td>
</tr>
<tr>
<td>Log(growth rate of real per capital GDP)</td>
<td>−0.760***</td>
<td>−0.695***</td>
<td>−0.825***</td>
<td>−0.052</td>
<td>−0.151</td>
<td>−0.150</td>
</tr>
<tr>
<td></td>
<td>(−3.93)</td>
<td>(−3.35)</td>
<td>(−3.91)</td>
<td>(−0.17)</td>
<td>(−0.55)</td>
<td>(−0.53)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.820</td>
<td>0.863</td>
<td>0.818</td>
<td>0.848</td>
<td>0.887</td>
<td>0.845</td>
</tr>
<tr>
<td>LM het. Test</td>
<td>3.68</td>
<td>2.21</td>
<td>12.9</td>
<td>2.90</td>
<td>2.25</td>
<td>12.1</td>
</tr>
<tr>
<td>Haussman Test</td>
<td>17.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Numbers in parentheses are t-ratios; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. 
proposed hypothesis in this chapter. That is, the greater the rural–urban income gap, the more incentive rural people will have to move to the cities and look for jobs. This in turn will increase the pressure on job seeking in the cities, reducing the chances of employment for urban young people, particularly school-leavers.

A recent study by Roberts (2001) provides similar evidence. Roberts’ study in Shanghai concludes that it is very hard for urban unemployed workers to compete with migrant workers who are willing to accept low wages and work long hours. The internal labour migration pressure has been constantly growing since China initiated its open door policy in the early 1980s. It is highly possible that this river will become an uncontrollable flood. The unequal distribution of foreign investment between the coastal and inland areas is one of the most important reasons leading to large-scale labour movement from the inland areas to the more prosperous coastal cities. These rural migrants are a more favoured choice for foreign-funded firms in the labour intensive manufacturing sector than the urban workers since they are cheaper, harder working and more willing to work overtime. Though a large number of laid-off workers live in the cities, the foreign-funded firms in the textile, electronic and other labour intensive industries in the suburban area are crowded with young migrant workers. This migration of rural labour has become a threat to the resolution of the urban employment problem.

It is also interesting to note that economic growth has a significant and negative effect on youth unemployment if there is no year dummy in the model. In other words, output growth will reduce youth unemployment. This means that Okun’s law is validated in the Chinese context. If the year dummy is included in the empirical model, output growth is no longer significant in the model, although it still has a negative effect, as economic growth varies by year but not really by province.

Conclusion

The problem of urban unemployment has become a major concern of policy makers and academic researchers in China. This chapter aims to understand the principal causes of urban youth unemployment. Following Okun’s law, and using a panel data set, an empirical model is established to test an important hypothesis, that is, rising rural–urban income inequality can lead to higher urban youth unemployment. The results have important policy implications. They suggest that the reduction of urban youth unemployment could be brought about through rural economic development. Hence, government policies should emphasize how to raise rural income and reduce rural–urban inequality. Such policies may be expected to produce simultaneous win–win results for both the rural and the urban populations.
References


