The Wage Structure in China, Late 1990s to 2000s: A Young Labour Market in A Transforming Economy

By

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Declaration

1. I declare that this thesis has been composed solely by myself and that it has not been submitted, in whole or in part, in any previous application for a degree. Except where states otherwise by reference or acknowledgment, the work presented is entirely my own.

2. I confirm that this thesis presented for the degree of [degree sought], has

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Date: July 21, 2016

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Abstract

This thesis discusses the changes and corresponding causes of the wage distribution in China from the late 1990s to the 2000s. According to various data sources, real wage inequality in China has been increasing over time. People have become increasingly concerned about such a phenomenon, which can potentially cause economic instability and further social unrest.

From the analysis of household survey data, a significant part of the the increase in wage dispersion in China can be attributed to changes in the institutional changes. Having gone through the institutional reform of state-owned enterprises in the late 1990s, many Chinese firms have become more privatized and smaller in size. That is to say, the Chinese labour market becomes less affected by the government intervention (through public enterprises). Changes in the supply side of the labour market have also been examined. The increase in the number of university graduates slows down the growing wage dispersion.

A comparison between the household survey data and the industrial enterprises data tells a slightly different story about Chinas wage structure. As the firm-level data omits within-firm wage inequalities and excludes data of primary sectors, the service sectors, and the small businesses, a decrease in the logarithm of the wage variation has been found. The inconsistency between the changes of real wage dispersion and the dispersion of log wages has been discussed in depth in the thesis.

Nonetheless, since China set the new minimum wage in 2004, the wage distribution in the countrys industrial sector has been reshaped, which is not obviously shown in the household data. The impact of increasing the national minimum wage has been evaluated under a set of relatively conservative assumptions.

Further analysis has been conducted to quantify the effect of trade liberalization on wage dispersion. It turns out that starting to export on the part of the firms has a significant positive effect on firm-level wages and employments, but the impact of an increasing export exposure remains debatable.

Lay Summary

This thesis studied the effect of individual attributes, firms' characters and institutional changes on the Chinese wage structure. It is the first, to my knowledge, to study the effect of redistribution of independent factors on restructuring wage distribution in China. It is also the first, to my knowledge, to make elaborate comparison between the samples of China Health and Nutrition Survey, Chinese Industrial Enterprises data and China Statistical Yearbook.

To summarise, I found that higher education expansion in China has helped to reduce its wage inequality to a significant extend. However, the privatization and downsizing of firms, as a result of public sector reform, contributed to increase the wage dispersion. The increase and better enforcement of the minimum wage policy has made the wage in industrial sector more condensed, which is consistent under various assumptions. Though export exposure does not have strong effect on redistributing workers to different kinds of firms, it shows a significant influence on the wage premiums. With the least strict assumptions and firm-level controls, exposure exposure shows a positive effect on the wage.

Chapter 1

Introduction

Being famous for its three decades of rapid growth and continuous reform, China's economic performance has been the subject of increasing attention worldwide. Many studies have considered China's economy as an exogenous factor on economies elsewhere. This thesis, on the other hand, takes the opposite stand point and intends to study the effects of China's development on Chinese individuals, especially labourers.

The main questions that this thesis seeks to answer are: have Chinese people benefited from the economic growth and reform? Have they benefited equally? More specifically, have Chinese workers enjoyed an equal return from economic and institutional changes in the form of wages? These are important questions because changes in wage distribution can shed light on Chinese labour market dynamics, which can affect Chinese production, which in turn will affect global trade and investment. The answers to these questions can also help to enhance the understanding of the changes experienced by the Chinese people. In addition, growing wage inequality may, to some extent, bring social instability to communities. It is, therefore, important for policymakers to understand how institutional reforms can affect the wage dispersion if they want to reduce wage inequality.

The Chinese labour market in the early twenty-first century is particularly interesting because it is young and evolving. After its "birth" in 1995[1], the Chinese labour market has experienced an institutional reform of the state-owned enterprises (SOEs) in 1998, expansion in enrolment to higher education in 1999, an aging work-force, significant labour migration under segmental residence registration control (the Chinese *hukou* system[2]), joining the World Trade Organisation

[1]Before 1995, matching of firms and labour are substantially planned by government. More details of changes in 1995 will be discussed in Section 1.2

[2]*Hukou* system is a unique residence management system that monitors and restricts people's migration. It will be discussed in more details in section two.

(WTO) in 2001 and a rise in the minimum wage in 2004. All of these are potentially very important political, social and economic features affecting the Chinese economy in the early twenty-first century.

Variation in wages can also be called wage dispersion, which can measure how unequal workers are paid in a labour market. Previous studies about wage dispersion in China have mostly focused on explaining the difference in wage premiums individual attributes, e.g. gender (Meng, 1998; Gustafsson and Li, 2000; Liu et al., 2000; Rozelle et al., 2002; Hughes and Maurer-Fazio, 2002; Chen and Hamori, 2008), education (Fleisher and Chen, 1997; DÉmurger, 2001; Chen and Feng, 2000; Zhao, 1997), rural-urban ID and migration [3] (Hertel and Zhai, 2006). Some other studies have examined industrial wage differentials between non-agricultural and agricultural jobs in China (Knight and Song, 1997; Meng, 2000; Michelson et al., 2000; Sicular and Zhao, 2004). There has also been debate about whether exports have an effect on wage inequality in China (Wang and Si, 2011; Yang and Jiang, 2012; Chen and He, 2013). In addition, some studies have discussed the effect of policies on employment and unemployment. For example, Ma et al. (2012) discussed the disemployment and spillover effect of the minimum wage on Chinese labour market.

The empirical studies of Chinese wage dispersion have used different variations of Oaxaca's (1973) decomposition, which focuses on explaining the conditional elasticity of various factors on real wages and employment, but not their effects on the wage distribution as a whole. This study, on the other hand, seeks to determine how policy changes in China in the early 21^{st} Century have altered the overall wage structure, taking into account both wage and employment effects.

Chapter 2 studies the effect of the expansion of higher education, aging, reform of SOEs, and *hukou* system on wage density in China. The effect of changes in minimum wage policy between 2000 and 2004 is discussed in Chapter 3, and the impact of trade on wages in China is explored in Chapter 4. Finally, in Chapter 5, a general conclusion will summarize the results and limitations of the thesis.

Chapters 2 and 3 employ a same semi-parametric model from DiNardo et al. (1996). These two chapters focus on employment share changes given the fact that relative wages changed little in a short period of time. Parametric panel data models are tested and compared in the Chapter 4 due to the relative long timespan and significant changes in wages.

Different datasets are used in this thesis. There is no comprehensive data on both employees' attributes and employers' characteristics. To study the effects

[3] Rural-urban ID is part of the *hukou* system.

of different policies, therefore, two datasets were mainly used – household survey data in Chapter 2 and firm-level data in Chapters 3 and 4. A detailed comparison of these two datasets is provided in Chapter 3.

The main findings and contributions of this thesis are:

- that it is the first attempt to quantify the counterfactual effect of relative policies on Chinese wage density;
- that it has found that demographic diversification have brought significant variation in wages;
- that it has found that reform in the public sector has brought more wage dispersion;
- that it identifies that demographic-biased demand shifts can be very important for the wage dispersion issue and is left to be done;
- that it reveals that minimum wage plays a significant role in reducing wage inequality even under most conservative assumptions;
- that it has found export can increase wage dispersion under firm-specific trends;
- that it provides evidences for the "lock-in" effect of international trade on the Chinese labour market;

Before the analysis of wage dispersion in later chapters, some key facts about the relative changes in China will be presented in the next sections. Section 1 summarizes basic facts about the Chinese labour market. Section 2 introduces key institutional changes in China. Section 3 provides a brief summary of this introduction.

1.1 Data and Statistical Facts about Wages

A detailed national labour profile, wherein the workers' wages and individual attributes are matched with their employers' characteristics has long been absent in China.[4] There are, however, several datasets that contain wage information

[4]The "Chinese employer-employee matching data survey" project started in 2011 by the School of Labour and Human Resources, Renmin University of China. The project was set up for tracking employer-employee matched observations nationwide from 2011 onwards. For studying the transition periods before 2011, e.g. the "Open-up" in 1978, the "Joining WTO" in 2001, etc., researchers still have to rely on unmatched, one-sided datasets, however.

for China. Three of these are used in this thesis – China Labour Statistical Yearbook (Labour Yearbook)[5], China Health and Nutrition Survey (CHNS)[6][7] and Chinese Industrial Enterprises Data (CIE).[8] Chinese Household Income Project (CHIP)[9] data was considered, but not used. The reason for not using CHIP data is discussed later in Chapter 2.

According to the Labour Yearbook, the CHNS and the CIE datasets, the average real hourly wage rate in China has increased since 1996 (Figure 1.1). This suggests that workers in China have benefited from the country's high growth rate through their wages. Nevertheless, average wage fluctuations are not always procyclical, especially before the current financial crisis (Figure 1.2). Other institutional factors, e.g. higher education, SOEs reform and minimum wage policies, can have played an important role in changing the pre-financial-crisis Chinese labour market.

There are some differences in wages between the datasets, which can be attributed to their sampling differences.

The Labour Yearbook contains the most comprehensive data about the labour market at the provincial and industrial level. Its sample, however, is limited to the employees of urban firms and institutions and therefore cannot generate detailed wage distributions. Moreover, employers' profiles and employees' profiles are not matched, which makes it difficult to distinguish demand-side effects from supply-side ones. In later chapters, therefore, the Labour Yearbook is not used in empirical estimations, but is contrasted with other datasets as a form of sample biasness check.

CHNS data is used to study the effect of higher education expansion and SOE

[5]The China Labour Statistical Yearbook is published annually by National Statistical Bureau of China.

[6]This research uses data from the China Health and Nutrition Survey (CHNS). I thank the National Institute of Nutrition and Food Safety, China Center for Disease Control and Prevention; the Carolina Population Center, University of North Carolina at Chapel Hill; the National I nstitutes of Health (NIH; R01-HD30880, DK056350, and R01-HD38700); and the Fogarty International Center, NIH, for financial support for the CHNS data collection and analysis files since 1989. I thank those parties, the China-Japan Friendship Hospital, and the Ministry of Health for support for CHNS 2009 and future surveys.

[7]The CHNS was collected in nine years: 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009 and 2011. The data for 1989 was not used in this study.

[8]The CIE data comes from the annual record of the National Statistical Bureau of China and the version used in this study is an important outcome of the elaborate work by Nie et al. (2012). I thank Professor Nie, Renmin University of China, for his help with this data.

[9]CHIP data is a joint work by Chinese and international institutions. It has five waves of household surveys, in 1989, 1996, 2003, 2008 and 2013. The surveys before 2002 were conducted by the National Bureau of Statistics of China. Those ones after 2002 were part of Rural-Urban-Migrant in China and Indonesia (RUMiCI) project, organized jointly by the National Bureau of Statistics of China and private institutions.

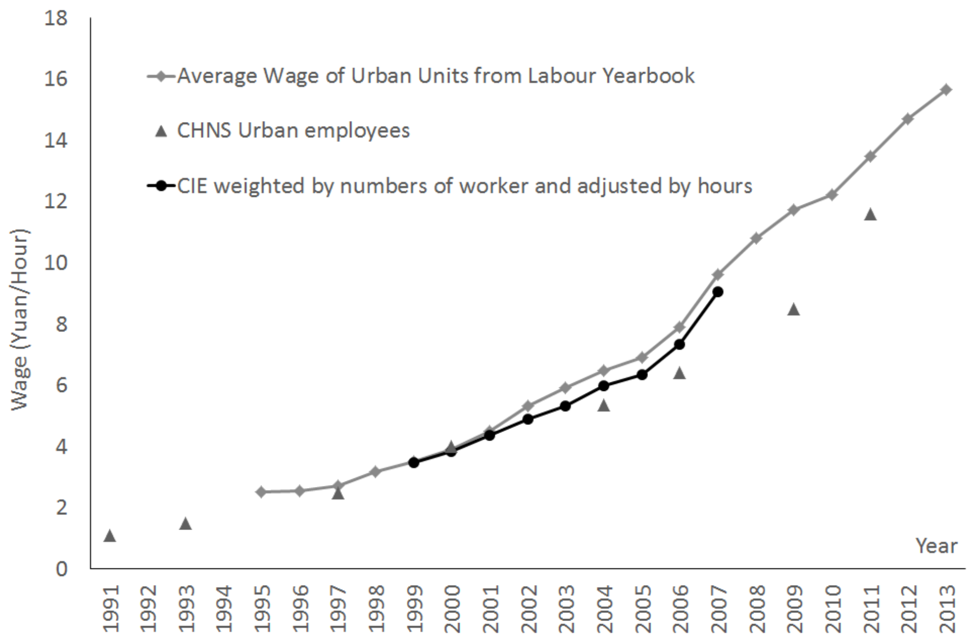

Figure 1.1: Average Real Hourly Wage Rates From 1991 To 2013
The urban units in the Labour Yearbook are employers that registered in urban areas, the employees of which may come from any part of China. The CHNS urban employees refer to individuals in CHNS, who have an urban hukou ID. The wages from CIE are annual average firm-level wages weighted by the number of workers in the firm dividing the average hours worked (from the Labour Yearbook) in that year. All wages are real wages adjusted by the national CPI of China at the price level of 1998.

reform. The main reason for this is that the CHNS data is very comprehensive in the individual profile, and it is therefore possible to track the compositional changes in education and firms' ownerships. In addition, CHNS covers a relative long period of time and contains samples before and after important institutional changes. The disadvantage of CHNS is that, it is a household survey that covers selected urban and rural areas from only twelve provinces in China. A potential alternative to CHNS is CHIP, which has the advantage of including migration data. It, however, lacks data in important years. A detailed description of CHNS, and comparisons with the Labour Yearbook and CHIP is provided in Chapter 2.

To exam the effect of minimum wage policy and trade liberation in Chapters 3 and 4, CIE data is used. The reasons are: 1) CIE data has "above-the-scale"[10] industrial firms which are more compliant with the labour law and minimum wage policy; 2) CIE is the only data that has export data together with wage data. To serve the purpose of the studies in Chapters 3 and 4, CIE is the best data. The drawback is also clear, however. It is only about the industrial sector and cannot

[10] Earning more than five million sales each year.

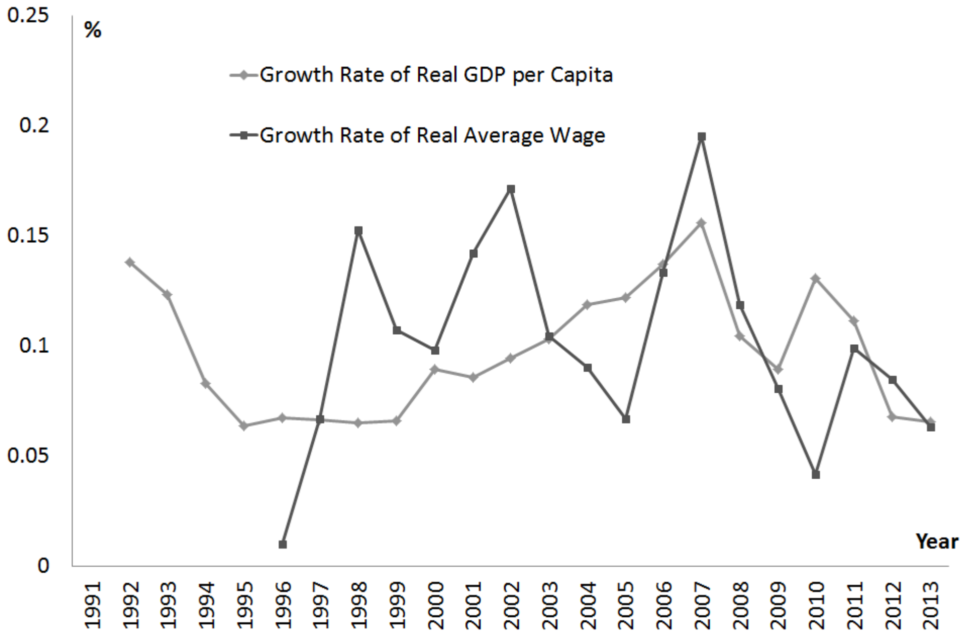

Figure 1.2: Growth Rate of Real GDP and Real Average Wage
The real average wage comes from the China Labour Statistical Yearbook and the real GDP per capita comes from the China Statistical Yearbook. Both published by the National Bureau of Statistics of the PRC.

represent the whole Chinese labour market. A further discussion comparing the CIE data with the CHNS data and the Labour Yearbook data is included in Chapter 3.

The wage dispersion movements in China are more difficult to calculate. There is no nationwide individual wage data; therefore wage dispersion is calculated using CHNS and CIE data. There are also many measurements of wage dispersion, one of which is the standard deviation of wages, and is presented in Figure 1.3.

There are clear differences between the wage dispersion in CHNS and that in CIE. For example, in 2000, average wages in CHNS and in CIE were almost the same ($ln(3.64) - ln(3.84) = -0.05$ logarithm wage point difference), while the logarithm wage standard deviations were 0.64 and 0.79 logarithm wage points respectively. The trends in wage dispersion in the two datasets are different as well: there was a drop in wage dispersion from 2003 to 2004 in the CIE data, which persisted in later years. This is consistent with the changes to minimum wage policy change in 2004, which will be discussed in Chapter 3. On the other hand, in the CHNS data, the wage standard deviation in China was increasing in the first decade of the twenty-first century.

A short answer to the main question of this thesis, therefore, is: that Chinese workers had benefited, but not equally, from the economic growth and reform

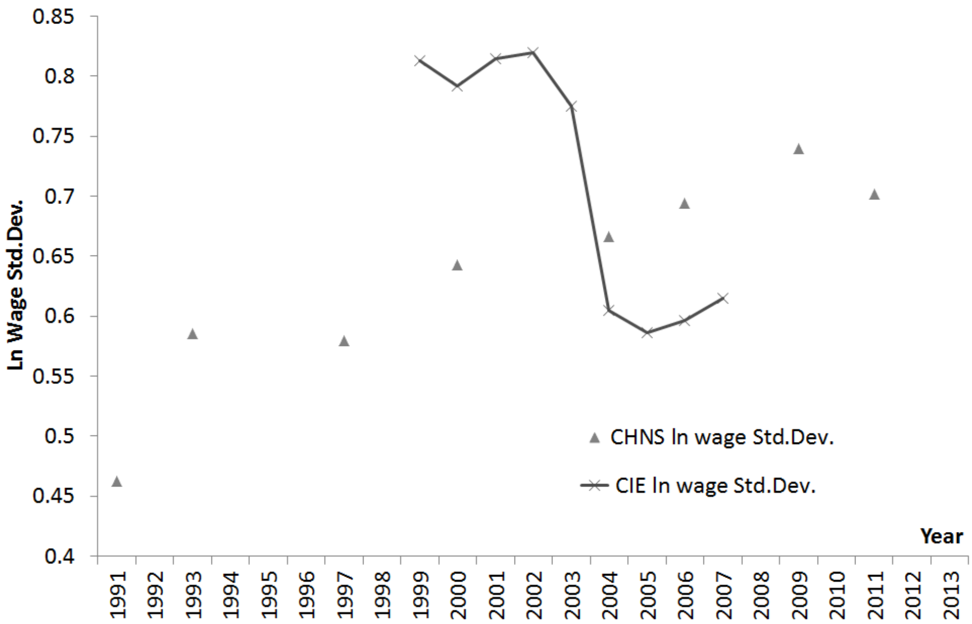

Figure 1.3: Standard Deviations of Ln Wages
All wages in the CHNS data are used in this graph, including both urban and rural residences. In CIE, wages are at firm-level. This graph uses firm-average wages weighted by the number of workers in each firm to calculate the standard deviations of logarithm wages.

experienced in the early twenty-first century. The question that remains to be answered is: what is the role of institutional changes in this changing wage inequality? In the next section, the candidate institutional factors are introduced.

1.2 Institutional Changes up to 2004

Before the 1990s, a large proportion of the non-agrarian labour market was employed by the government as part of the centrally-planned economic system whereby workers were matched with public employers. From 1987, China started to move towards a more market-oriented economic system. Within ten years, the planned matching system for labour employment only existed in a handful of instances, e.g. military students hiring (Christiansen, 1990; Chan and Zhang, 1999). Meanwhile, the *hukou*-system-based social insurance system is a geographic and public-private sectoral barrier in the labour market. The reform of this social insurance system in China in 1999 has increased the geographical integration of labour market, and is likely to have eased migratory movements within the country. In the labour supply side, the expansion in higher education enrolment since 1999 has also reshaped the composition of labour force in China

(Figure 1.7). On the other hand in the labour demand side, in 1997, the institutional reform of SOEs was a shock to the system for the burgeoning labour market, which motivated firms to perform efficiently and reduce employment in the public sector (Yueh, 2004). China's accession to the World Trade Organization (WTO) in 2001 can also be speculated to have had an impact on Chinese manufacturing production and employment. In 2004, the minimum wage policy was strengthened.

1.2.1 *Hukou* System and Social Insurance

The establishment of the labour market does not mean labourers and employers have a complete freedom in China. The *hukou* system is one of the major forces hindering labour mobility, and the associated social insurance system (which was introduced at a later stage) has only served to strengthen the effect (Christiansen, 1990; Chan and Zhang, 1999).

Similar systems have existed in many dynasties of China for at least 2000 years; all sharing the purpose of (partly) preventing residents from unauthorized migration or changing occupations. The contemporary *hukou* system consists of two parts, the location and the rural-urban ID. The location records one's place of registration, which can be a city, a town or a county. Previously, one usually could not work outside his/her place of registration. The rural-urban ID shows that one person is registered in a rural or urban type of family. Under the planned economy, rural ID workers could not take industrial jobs. On the other hand, an urban ID resident cannot take a piece of land and be a farmer (Christiansen, 1990; Chan and Zhang, 1999). Both restrictions have been gradually eased since the "reform and open-up" policy introduced in 1980s (Leung, 2003; Rickne, 2013). This led to a large surge in urbanization and in associated migratory movements of workers.

It can be seen in Figure 1.4 that both urban population and employment shares have been increasing since 1995. Since the pure private firms are excluded in the data, the urban employment share has been clearly undermined. Nevertheless, it is clear that China is gradually urbanizing.

Though workers are technically free to move and to choose jobs, there is still some degree of discrimination according to their *hukou* type. Local governments usually subsidize companies and other organizations to employ local residents, and there is also a pronounced tendency to restrict social services to local people (e.g. cheaper education fees and cheaper housing) (Leung, 2003; Rickne, 2013). It is difficult to change one's *hukou* registration unless the local government con-

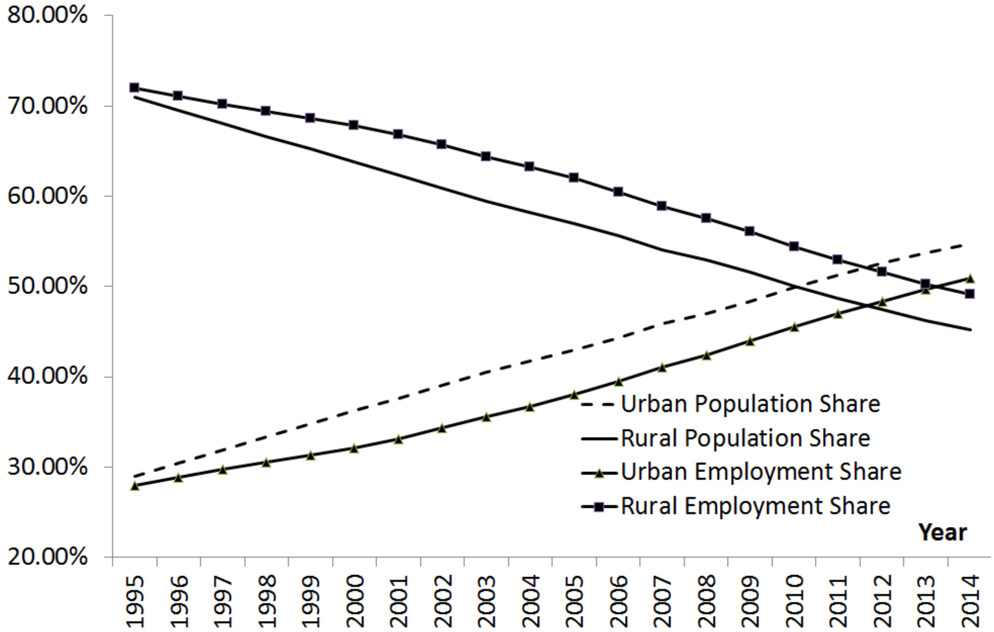

Figure 1.4: Rural and Urban Population and Employment Shares
All data in this graph comes from the Labour Yearbook. The urban employment does not include workers in pure private firms.

siders that person to be 'valuable', and a good higher-education degree would be helpful in this regard.

In 1998, the Chinese government decided to reform the system to cover more workers (Figure 1.5). Until 2004, only a proportion of urban workers were able to enjoy a complete social insurance package[11], with most rural-ID workers only receiving a pension(Christiansen, 1990; Chan and Zhang, 1999; Leung, 2003). Pensions in China consist of two accounts per employee – a personal one and a public one. Every month, both the employee and the employer pay a given percentage of the wage, which varies according to different locations and wage levels, into the two accounts. When workers want to move or migrate to other places which are different from their original registration, they cannot transfer their insurance accounts to new locations. They can withdraw their money from personal accounts and start new ones in new destinations, but this would mean that they would lose the money held in the public account. Alternatively, they may decide not to move the *hukou* registration, although this would lead to significant restrictions and complications when it comes to redeeming compensations.

As shown in Figure 1.5, in 1999, the pension coverage and the medical insurance coverage started to rise. The coverage of work injury insurance and

[11] A typical social insurance package normally includes pension, unemployment insurance, medical insurance, work injury insurance and maternity insurance.

maternity insurance began rising since 2004. The unemployment insurance coverage, meanwhile, started to rise in 1999, but declined again after 2000 before stabilizing.

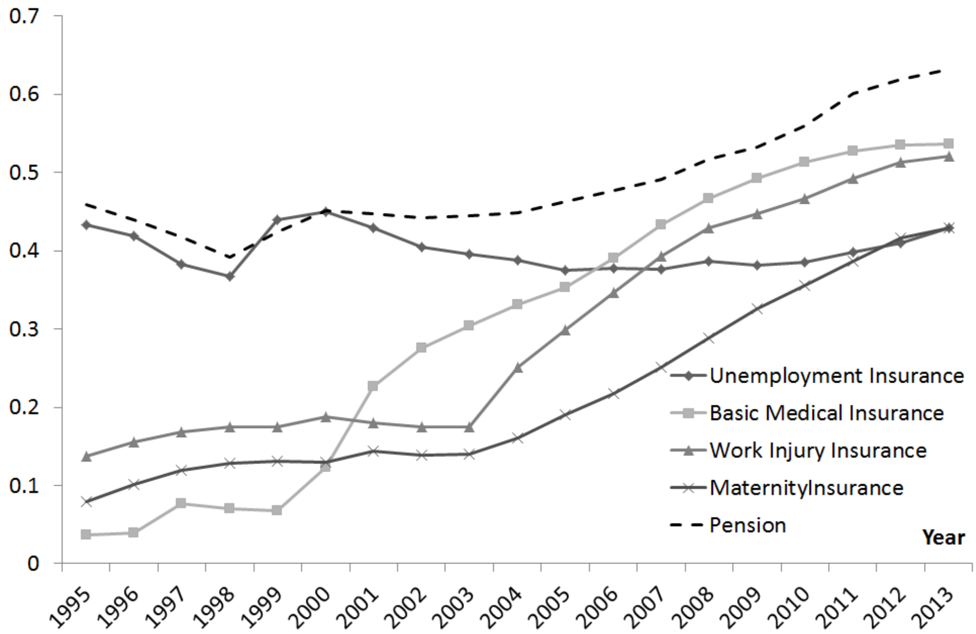

Figure 1.5: Insurance Coverage
All data in this graph are taken from the Labour Yearbook. It shows total insured urban workers divided by total urban employment.

The *hukou* system and *hukou*-based insurance system is believed to have restricted internal migration in China (Christiansen, 1990; Chan and Zhang, 1999; Leung, 2003). Moreover, Whalley and Zhang (2007) argued through a numerical simulation that those restrictions played a significant role in supporting inequality in Chinese regional growth.

To summarise, the *hukou* system, together with the social insurance system, has not completely stopped migration, but it constitutes a barrier to labour mobility. From 2000 to 2004, however, as more people pursued higher education and the government extended the social insurance system to more workers, market frictions were eased, resulting in higher labour mobility and an easing in the wage gap between rural and urban workers.

1.2.2 The Expansion in Higher Education

Until 1995, students were fully funded by the government in higher education and graduates were appointed to jobs in state-owned working units by the Chinese government. The enrolment rate was 5% of senior high school graduates (Yao et al., 2010). Neither the supply nor the demand side of the labour market had much freedom. In 1995, the first Chinese labour law was introduced, and the planning-based system was broken down.

In addition to the adoption of market principle, in 1999, the Chinese government sought to expand the provision of higher education. Since the majority of colleges and universities are owned by the government, the government exerts a strong degree of control over enrolment rates in higher education. As a result of the planned expansion, therefore, the enrolment in higher education (both in absolute and relative terms) increased hugely until 2006, after this, the government maintained an less aggressive enrolment growth (Figure 1.6).

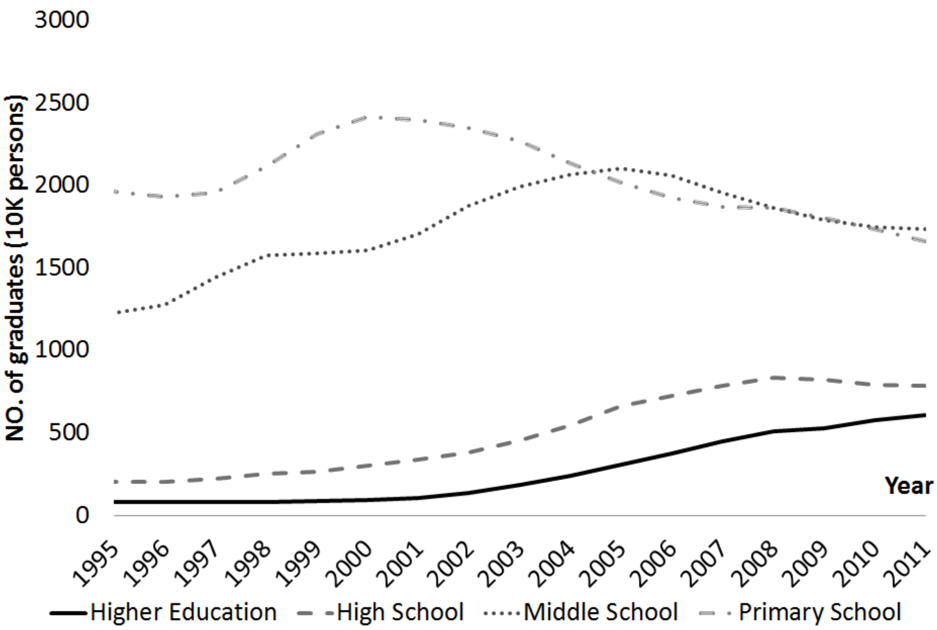

Figure 1.6: Number of Graduates from Each Level of Education
All data in this graph are from the National Statistical Yearbook of China.

In terms of the educational effect on the labour force, Figure 1.7 shows employment share by level of education in each year in China. It is clear that, the share of higher education graduates in labour force increased since 2002, three years after the higher education enrolment increase. After the expansion, the education levels of Chinese labour became less concentrated in secondary level.

On the other hand, there were significant returns to education (Yao et al., 2010; Meng et al., 2013; Li et al., 2008). The increase in the number of higher education graduates can change the equilibrium wage premiums of education. The change in the wage dispersion resulting from education is therefore a combined effect of the employment share change and wage premium change.

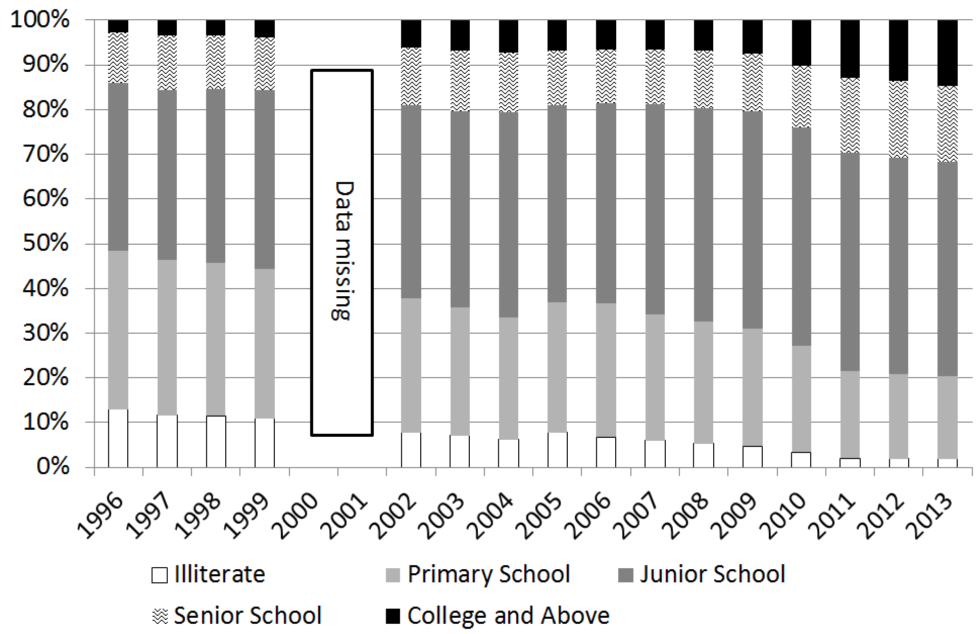

Figure 1.7: Employment Share at Each Level of Education
All data in this graph are from the Labour Yearbook.

1.2.3 The Institutional Reform of SOEs

Before the institutional reform in 1998, SOEs were managed in a planned economy fashion. Workers and staff in an SOE benefited little from the profit generated. Also, they did not suffer much from its debts, which would ultimately be paid by the government. SOEs did not have many incentives to carefully evaluate the productivity of their employees or pay high wages for good workers and most SOEs were very inefficient (Zhang, 2006).

Before joining the WTO in December 2001, an institutional reform at both firm and government level was carried out to increase the efficiency and competitiveness of the Chinese economy. The government decreed that it was no longer responsible for SOE losses, thereby eradicating the soft budget constraint(Zhang, 2006). As a result, SOEs started to have the incentive to be more efficient and to conduct a careful evaluation of worker productivity, whilst also reconsidering the wages on offer (Yueh, 2004). Such reforms gradually spread from SOEs to other local public firms. As a result, the wages paid by the public sector became more flexible (Yueh, 2004). If the public sector became more adaptive at evaluating employee productivity and linking wages accordingly, the wage dispersion in the public sector should have risen.

Meanwhile, as required by the WTO, the Chinese government relaxed regulation on domestic markets. It also introduced policies to encourage the estab-

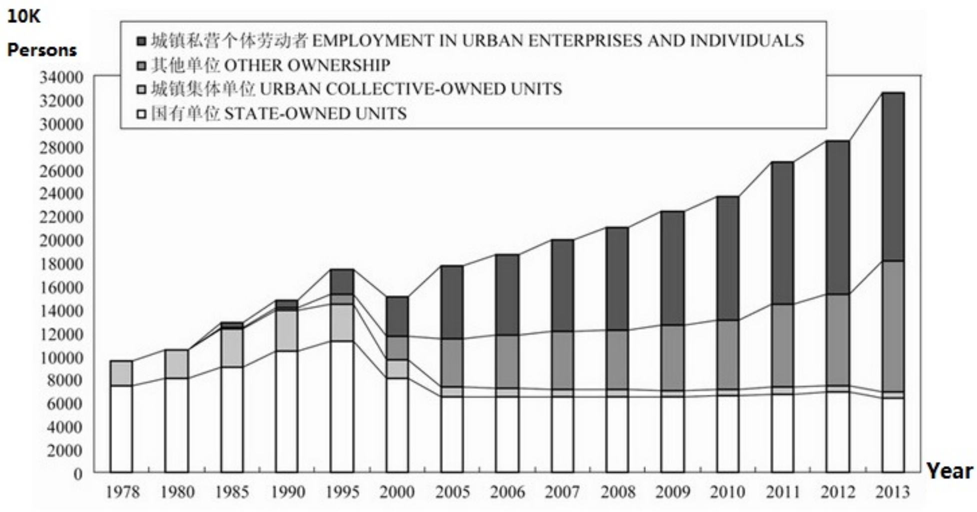

Figure 1.8: Urban Employment Share by Ownership Type of Firms
This graph is from the Labour Yearbook 2014. "Urban enterprises and individuals" refers to purely private firms. Other ownership types include firms not classed as either public or private sector, e.g. foreign firms, mixed ownership firms, etc.

lishment of 'good' private firms, capable of competing with foreign imports. As a result, the Chinese private sector has expanded considerably since 2000. As can be seen in Figure 1.8, in terms of employment share, SOEs shrank considerably from 1995 to 2005, while employment in private and other non-public firms grew dramatically since 2000.

This could change the wage distribution in two ways. First, the deregulation weakened the monopoly power of SOEs in the commodity market, which in turn decreased the rents the public sector paid to their workers. On the other hand, the decrease in the public-private wage gap could reduce part of the potential wage dispersion. the deregulation could have caused an increase in the range of firms, thus increasing the private sector wage range and dispersion.

1.2.4 Minimum Wages

China first started the discussion on the introduction of a minimum wage in 1993, and this was legislated for in 1994. By 1995, however, only 130 cities (out of more than 600) had adopted it (Ma et al., 2012). The minimum wage policy was not enforced nationwide in China before the establishment of the"Minimum Wage Provision" in 2004.

In China, the minimum wage appears in two forms – a per month minimum wage for full time contracts and a per hour minimum wage for part-time and temporary workers. Each local government has autonomy to some extent in

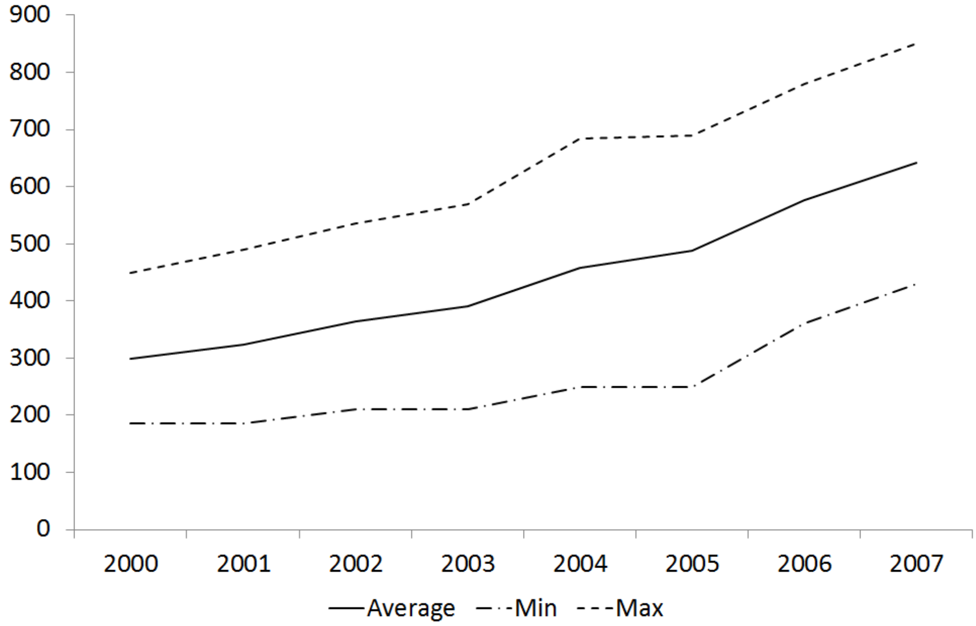

Figure 1.9: Minimum Wages in China
The data to produce this graph comes from Wang and Gunderson (2011), who derived it from the labournet (zhong guo lao dong wang), which is supervised by the Ministry of Human Resources and Social Security of the Peoples Republic of China. Only registered members (annual membership fee 3,500 Yuan) can access the information. Minimum wages in China are different across cities and counties. The minimum wages shown in this graph are provincial minimum wages. Average, min and max refers to the average, minimum and maximum provincial minimum wage for that year in China.

deciding its minimum wage and, indoing so, consideration is normally given to the local poverty line, labour market conditions and social insurance funds. Figure 1.9 shows that minimum wages have been growing in China in the early twenty-first century, with slightly more marked changes in 2004 and 2006.

There is, however, a non-compliance issue in Chinese minimum wage policy. According to the CHNS data, in 2000, 2004 and 2006, respectively, 8.97%, 18.21% and 19.22% of workers earn below the national average minimum wage. Since the CHNS data does not record the working destination of these individuals, it is difficult to calculate non-compliance rates at the provincial level. The non-compliance issue probably occurs due to the fact that there are a considerable number of temporary workers working without formal contracts, which are difficult to monitor, although it appears that such problems occur more often in small, private firms and businesses.

Still, the minimum wage policy in China is effective to some extent. For large firms and non-purely-private firms, the minimum wage policy is a powerful influence. In the CIE data, minimum-wage-compliant above-the-scale industrial firms grow from 86.2% in 2000 to 92.2% in 2007[12]. Due to the increasing minimum-wage-policy compliance in the CIE data, it is chosen in preference to the CHNS data to discuss the minimum wage effect in Chapter 3. It should be noted, however, that the CIE doesnot give full coverage of the Chinese labour market and therefore the minimum wage effect is likely to be partial.

1.2.5 International Trade Liberalization

China joined the WTO on 11 December, 2001. Several years before that, in 1997, China's international trade had already started accelerating (Figure 1.10), but joining the WTO gave China another trade boost. The growth rate of Chinese international trade was struck by the financial crisis, and has fluctuated greatly ever since.

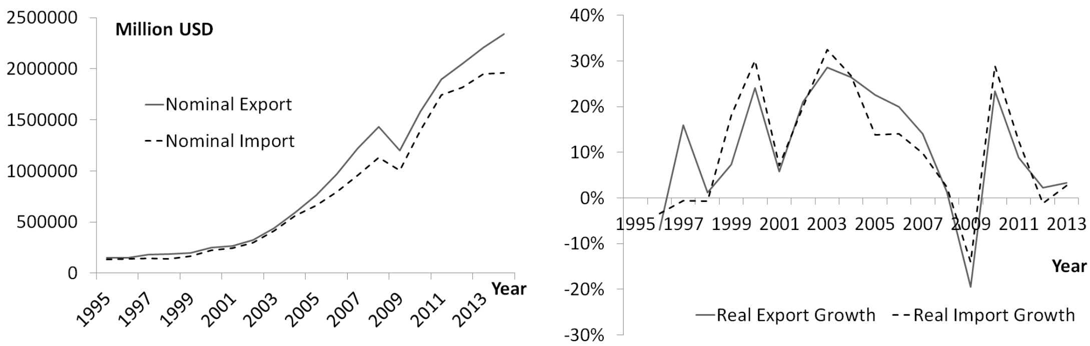

Figure 1.10: Exports, Imports and their Growth Rates in China
The data comes from the National Statistical Yearbook of China.

As an immediate consequence of joining the WTO, 90 out of 97 of the "Harmonized System (HS) two-digit average Most-Favoured-Nation (MFN) applied" tariffs of China were lowered in 2002 (Figure 1.11). The reduction in tariffs continued for five years until 2007, when the Chinese government increased an significant number of MFN tariffs. In 2012, the number of tariff-raised categories exceeded those of the tariff-reduced categories for the first time since China joined the WTO. The Chinese government cut the tariffs again in 2014, and on the 1 July, 2015, China's protection period officially ended.

Tariffs can affect both exports and imports, but it is difficult to match firm data with tariff data. Although researchers have made efforts to merge the Chinese customs data with the CIE data, as mentioned by Wang and Yu (2013), these two datasets do not use the same company ID system. Thus, they had to

[12] Calculation and more details are reported in Chapter 3.

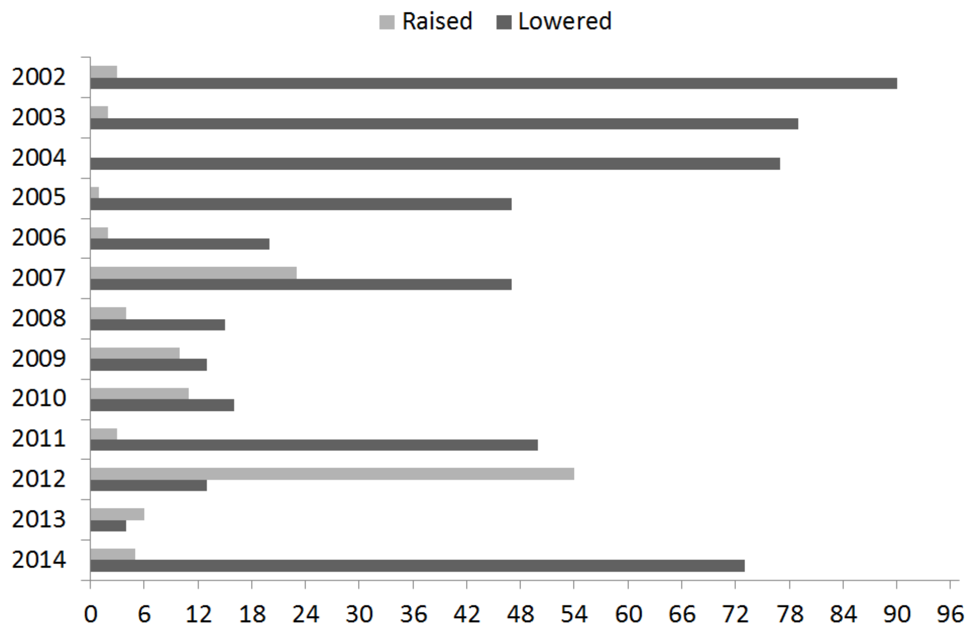

Figure 1.11: Number of Changed Average MFN Applied Tariff of China
The data comes from the tariff data of the World Trade Organization. There are 97 HS two-digit categories of traded goods. The average tariff in each category is used in calculation. Raised records the number of average tariffs that were higher than in the previous year. Lowered is the number average tariffs that were lower than in the previous year.

match datasets by companies' names, addresses and telephone numbers. Using this method they were able to match 21% of the firms in CIE data, covering 47% of exports during the period 2002-2006. These difficulties in accessing reliable data mean that the effect of tariff changes is not considered in this thesis. . Although this may affect the validity of the final analysis of the effect of trade on wages, this would be no more acute than that entailed in using unreliable data.

In 2005, China also changed its currency policy from pegging with the US dollar to a bounded floating regime (Figure 1.12). Since then, the Chinese Yuan has been mainly appreciating against the US Dollar and Euro. For any exporting firms, this means that they earn less from a unit of export or face lower demand for their goods. On the other hand, the Chinese domestic market is likely to demand more foreign goods as they became cheaper.

The effect of international trade on the domestic labour market depends on many factors. In short, changes in trade can change the demand for domestic goods, either final or intermediate goods, and substitute for labour. Such changes can affect the demand for average labour or for any specific type of labour, which, in turn, changes the wage distribution and inequality. This is discussed in Chapter

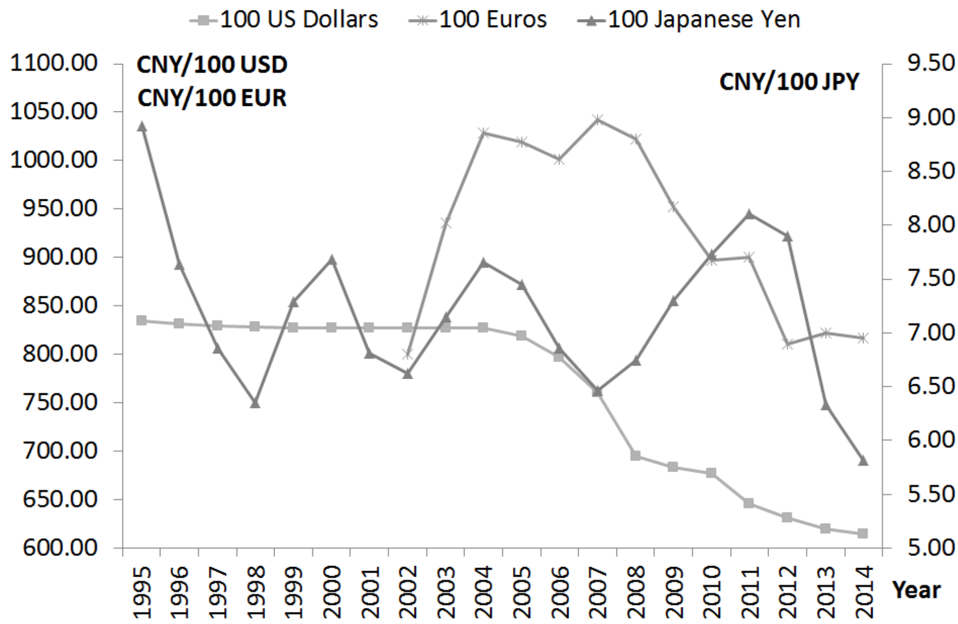

Figure 1.12: The Exchange Rate of CNY
The data comes from the National Statistical Yearbook of China. The exchange rate is the annual average value.

3.

1.3 Summary

To summarize, the rapid economic growth experienced in China since the 1990's has gone hand-in-hand with a growth in the wages. This growth in the wage rate was not pro-cyclical prior to the recent financial crisis, indicating the influence of other important factors. In addition, wage dispersion increases in CHNS data, but have a sudden drop in CIE data. It is important, therefore, to understand what can account for these wage dispersion changes, and what is responsible for the differences in the two datasets.

Market structural changes, labour supply changes and labour demand changes are considered in this thesis.

One of the market structural changes is the *hukou*-based social insurance system reform, which displayed a growth in coverage since 1995, and has been a barrier for labour migration. The expansion in higher education since 1999 serves as an important labour supply change. The changing patterns of labour supply by educational level has an influence on the respective wage premiums together with the employment share. These two changes are discussed in Chapter 2 using the CHNS data. It is difficult to incorporate these two changes in Chapters 3 and

4 because of the limitation of the CIE data.

The institutional reform of SOEs resulted in a smaller public sector and a growing private sector in terms of employment. It also motivated public sector firms to better assess the productivity and wages of their employees. Both movements can change the nature of wage dispersion in China. In Chapters 2 and 3, the SOE reform is included in the decomposition of wage dispersion using the CHNS and CIE data respectively to study whether its effect is consistent in two different samples.

The minimum wage policy installed in 2004 is another important market structural change in China. It increased local minimum wages and imposed a stricter enforcement on the firms. Due to the high non-compliant rate in the CHNS data, the minimum wage effect is discussed in Chapter 3 using the CIE data.

Joining the WTO is a labour demand side change. It reduced most tariffs, and has had a positive effect on Chinese international trade, both in terms of exports and imports. In addition, the appreciation of the Chinese Yuan against the US Dollar can have negative impact on Chinese exports and weakened some demand for labour in China. The effect of labour demand change due to exports on wage dispersion is discussed in Chapters 3 and 4.

Building on this work there is still a need to answer the questions of whether these institutional changes affect Chinese wage inequality? Who benefited or suffered from those policies in the labour market? These issues will be addressed in the following chapters.

Chapter 2

What Drives Wage Dispersion? Evidence from CHNS Data, 2000-2004

2.1 Introduction

As shown in Chapter 1, Chinese workers have benefited from the country's economic growth and reform. Whether workers have benefitted equally from the policy changes remains unknown, however. In this chapter, the relationship between the institutional reform of the SOEs, increasing enrolment rates in higher education, the *hukou* system changes and the wage distribution is discussed.

Employment and wages are the two basic components in the labour market dynamics at the core of the discussions. Most studies discuss one or two of them separately, but few put both into one picture to consider the wage dispersion. A significant portion of the literature has focused on the manner and extent to which individual attributes, the firm and industry variables and the search frictions contribute to wage gaps (Postel-Vinay and Robin, 2002).

Fleisher and Chen (1997) studied the income gap between coastal and non-coastal areas in China and argued that education is a crucial factor through total factor productivity (TFP) in explaining the income gap. DÉmurger (2001) analysed Chinese regional disparities in income per capita growth using parametric panel models. They found less investment in education is correlated with lower income growth. Chen and Feng (2000), Zhao (1997), Heckman and Li (2004) and Kumar Narayan and Smyth (2006) also found consistent results. The occupational attainment and employment of Chinese workers are also positively correlated with higher education level (Bauer et al., 1992; Zhang et al., 2002).

Many studies have shown that the *hukou*-system has an effect on the regional income difference (Christiansen, 1990; Chan and Zhang, 1999; Whalley and Zhang, 2007; Yao et al., 2010). Hertel and Zhai (2006) showed that the rural-urban ID[1] and migration are important factors for wages and employment in China. Some other studies have examined industrial wage differentials between non-agricultural jobs and agricultural jobs in China (Knight and Song, 1997; Meng, 2000; Michelson et al., 2000; Sicular and Zhao, 2004).

Dong and Putterman (2003) argued that there was over-staffing in the public sector in China in early 1990's, which can be attributed to the social burdens of SOEs under hardening budget constraints. The 1999 reform not only led to a significant number of workers in SOEs being made unemployed, but probably also permitted more productivity-related pay (Yueh, 2004). There has been little research on the changes of the public sector and the private sector wage dispersions in China. Evidence from the US labour market showed that the public and the private sectors are different in their wage levels (Appleton et al., 2005) and wage dispersions (Katz and Krueger, 1991).

These studies revealed that higher education expansion, *hukou* system and the reform in SOEs were important in wage determination or employment. However, there was little discussion about the wage dispersion movements in China. The correlation between those institutional changes and wage distribution was not discussed in previous studies.

This chapter follows the method developed by DiNardo et al. (1996) to decompose the change in wage dispersion in China. They decomposed the changes of wage structure in the US between 1979 and 1988. According to their semi-parametric estimation, in addition to the substantial effects of labour demand and supply shocks (Juhn et al., 1993; Murphy and Welch, 1992; Katz and Murphy, 1992; Bound and Johnson, 1992), institutional changes (minimum wage decrease and de-unionization) also influenced the wage distribution remarkably and unevenly.

This chapter discusses the changes in the *hukou* ID, social insurance, higher education enrolment, and public sector, and decomposes their effect on the wage dispersion in China. Short run analysis focused on period 2000-2004, when these changes have come into effect. The long term effects are discussed as well. The long it is after the institutional changes in question, the less plausible is the assumption on demographic non-biased demand change. The results suggest that more detailed analysis is required for wage premium changes for more extended

[1]Rural-urban ID is part of the *hukou* system.

periods after 2000.

The advantage of DiNardo et al.'s (1996) method is quite clear: it is able to provide more detail of the effect various factors have on wage distribution. The results of their decomposition, however, depend on the sequence in which the factors are incorporated into the analysis. What is more, if factors are collinear (especially with some unobservables), the results of one or some factors are likely to be biased. Nonetheless, it is a useful tool to understand and compare the effect of factors on the shape of wage distribution.

Due to a lack of sufficient information about firms, the effects of some demand shocks like international trade liberalisation on wage distribution cannot be estimated. These are left to be discussed in later chapters using CIE data.

In section 2.2 of this chapter, the methodology of the empirical analysis is constructed. Section 2.3 contains a description of the CHNS data, and discussion on potential bias in the sample. Section 2.4 sets out the empirical results, while section 2.5 checks the robustness of the results; a conclusion is provided in section 2.6.

2.2 Methodology: Kernel Density, Counter-factual Density and Reweighting Function

The method of DiNardo et al. (1996) is used to find the extent to which each of the discussed factors can account for changes in wage distribution. The basic idea of the method is to find what the wage distribution would look like if the distribution of the factor(s), e.g. age, education or gender, did not change over time, holding the relative wage premiums constant over time.

First, the density of log real wages is estimated with the weighted kernel density estimation. $\hat{f}_h(w)$ is the weighted kernel density estimation of log real wage rate w, which is based on a random sample of log wages W_1,...,W_n of size n, with frequency weights θ_1,...,θ_n. It is calculated as:

$$\hat{f}_h(w) = \frac{\sum_{\mathrm{i}=1}^{n} \frac{\theta_i}{h} K(\frac{w-W_i}{h})}{\sum_{\mathrm{i}=1}^{n} \theta_i} \tag{2.1}$$

where h is the bandwidth and $K(.)$ is the kernel function. The selection of an appropriate bandwidth h is of imperative importance in this context. If h is too small, it will generate an overly-scattered density, which makes it difficult to capture the main trend in the transition of wage distribution. On the other hand, if h is too large, this yields overly-smooth densities, which ignores important differences between specific effects of variables on wage distribution. 0.1 is chosen as the bandwidth for this study and the robustness of the results using this will be discussed later. The frequency of each observed wage W_i is set as its weight θ_i.

Denote $f_t(w)$ as the density function of w at time t, and x as the vector of the critical variable(s) of interest. t_x is the time the distribution of x stays at, i.e. the distribution of x in the calculation takes the value when it is at time t_x. Similarly, the distribution of w takes the value when it is at time t_w. The joint distribution of w, x and time is $F(w, x, t)$. The conditional density of w over the distribution of x is $f(w|x, t_w)$. It is easy to show that:

$$\begin{aligned} f_t(w) \equiv f(w; x, t_{w,x} = t) &= \int_{x \in \Omega_x} dF(w, x|t_{w,x} = t) \\ &= \int_{x \in \Omega_x} f(w|x, t_w = t) dF(x|t_x = t) \end{aligned} \tag{2.2}$$

The density function of log real wage in year 2004 can therefore be written as $f(w; x, t_{w,x} = 2004)$. The counter-factual density function of w, if the distribution of x remained the same as that in 2000, is $f(w; x, t_w = 2004, t_x = 2000)$. By assuming taht the conditional density of wage on x did not change over time, we get:

$$\begin{aligned} f(w; x, t_w = 2004, t_x = 2000) &= \int_{x \in \Omega_x} f(w|x, t_w = 2004) dF(x|t_x = 2000) \\ &= \int_{x \in \Omega_x} f(w|x, t_w = 2004) \Psi_x(x) dF(x|t_x = 2004) \end{aligned} \tag{2.3}$$

where

$$\Psi_x(x) \equiv \frac{dF(x|t_x = 2000)}{dF(x|t_x = 2004)} \tag{2.4}$$

is the reweighting function of x at each level of x. Employing the Bayesian rule, equation 3.4 can be rewritten as:

$$\Psi_x(x) \equiv \frac{Pr(t_x = 2000|x)}{Pr(t_x = 2004|x)} \cdot \frac{Pr(t_x = 2004)}{Pr(t_x = 2000)} \tag{2.5}$$

The probability of being in time t conditional on the status of x is then estimated using the probit model. Since, in most cases all dummies are used in x, the probit model becomes equivalent to a "cell-to-cell" non-parametric model. In addition, $Pr(t_x = t)$ is just the share of observations of time t.

After $\hat{\Psi}_x(x)$ is estimated, the reweighted density of the wages can be recalculated as follows:

$$\hat{f}(w; x, t_w = 2004, t_x = 2000) = \frac{\sum_{i=1}^{n} \frac{\theta_i}{h} \hat{\Psi}_x(x_i) K(\frac{w-W_i}{h})}{\sum_{i=1}^{n} \theta_i} \tag{2.6}$$

where x_i is the x attribute(s) of the i^{th} observation. Repeating the above steps using different x vectors, it is possible to produce reweighted densities for several variable factors so as to obtain the measures for wage dispersion and density function changes in order to compare each variable's individual effect.

The implementation of the model so far is straightforward. The original density function comes from the kernel density estimation using actual frequencies as weights. Then, probit estimates are used to generate a reweighting function (parameter). Finally, the reweighting parameters are multiplied with frequencies to form counterfactual weights and to calculate the counterfactual distribution, once again using kernel density estimation.

For measuring dispersion, certain wage percentiles are used, e.g. 10^{th}, 50^{th} and 90^{th} percentiles. Sometimes, they fall between two estimated points on the support. For accuracy, if that happens, it is assumed that there is a linear cumulative distribution function between the two neighbouring points. The approximate results, therefore, is calculated using the linear function.

Changes in the supply and demand of labour can, however, result in changes in relative equilibrium wages, which in turn affect the wage dispersion. For example, high school graduates and college graduates have different productivities and earn differently. Over time, their wages can increase at an equal or different pace. If their wages grow at the same rate, *ceteris paribus*, the wage distribution will simply move along the wage axis without changing the shape of the density function. In that case, the wage inequality will not change for there will be no relative wage changes. On the other hand, if the wages of college graduates grow faster than those of high school graduates, *ceteris paribus*, the wage dispersion will increase as the wage inequality between the two groups will be larger than before. This principle can be easily extended to a multi-attribute combination. To that end, this paper divides the labour market into 30 “cells” by gender, education and employer ownership type. The counterfactual density function will be what “the wage distribution in 2004 would be like, if the wage premiums were at their original levels in 2000, when holding the composition by factors constant”, i.e.:

$$
\begin{aligned}
& f(w; x, s, N, t_s = t_N = 2000, t_w = t_x = 2004) \\
& = \int_{x \in \Omega_x} f(w|x, s_{c_x}, N_{c_x}, t_s = t_N = 2000, t_w = 2004) dF(x|t_x = 2004) \\
& = \int_{x \in \Omega_x} f(w - \Delta w_{c_x}|x, t_s = t_N = t_w = 2004) dF(x|t_x = 2004)
\end{aligned} \tag{2.7}
$$

where c_x is the type of sub-market, in which the character of employers and workers is x, and Δw_{c_x} is the change in the mean $ln(wage)$ in "cell" c_x due to the change in relative labour supply N_{c_x} and relative labour demand s_{c_x}. In my case, $c = 1, 2, ...30$ characterized by firm ownership type, gender and education.

To test if there is significant change in relative wage premiums, I will use the Welch's t-test[2] to test the null hypothesis that:

$$H_0 : \Delta ln \frac{w_i}{w} = 0, i = 1, 2, ..., 30.$$

As shown in Table 2.1, when H_0 is rejected, the effect of changes in relative wages on wage dispersion cannot be totally ignored. More specifically, the change in relative wages is significantly higher than zero for "Vocational educated Females working in SOEs" (VFS) and "Higher educated Females working in SOEs" (HFS). An F-test of a simple fixed-effect model of log real wages from 1997 to 2009 also shows that the coefficients of gender and firm ownership type are jointly insignificant, conditional on barrier variables, year dummy and other individual and firm attributes. In addition, the related studies on the Chinese labour market cannot conclude whether the demand shifts had a significant effect on relative wages, or agree on the resulting sign of any wage dispersion change (Yu, 2008; Shao and Liu, 2010a; Xu, 2010).

Given the very limited firm information in the CHNS data and the ambiguous results from previous studies, here, it is simply assumed that there is no demand shift or education-biased demand change during 2000-2009. Following the model and notation of Bound and Johnson (1992), let N_i be the employment share of workers in a specific education by gender group i, and D_j be the dummy variable of the firm ownership type j. The relative wage premium $ln\frac{w_i}{w}$ is thus a linear function of $ln(N_i)$ and D_j.

[2]Welch's t-test is an adaptation of Student's t-test. It is used to test for the significance of difference between the mean values of two samples having possibly unequal variances.

Table 2.1: Changes in relative wages, Welch's test

	2000-2004			2000-2006			2000-2009		
Cell[ab]	Diff[c]	Std.Err.	T-value	Diff	Std.Err.	T-value	Diff	Std.Err.	T-value
PFS[d]	-0.073	0.219	-0.333	0.115	0.243	0.474	-0.585	0.299	-1.959
PFC	-0.193	0.187	-1.035	-0.335	0.188	-1.781	-0.305	0.183	-1.669
PFO	-0.353	0.165	-2.138	-0.457	0.148	-3.077**	-0.372	0.146	-2.543
PMS	-0.106	0.149	-0.712	-0.415	0.170	-2.448	-0.154	0.193	-0.797
PMC	-0.241	0.224	-1.075	-0.543	0.145	-3.741**	-0.194	0.354	-0.549
PMO	-0.296	0.132	-2.236	-0.090	0.111	-0.817	-0.155	0.110	-1.404
JFS	-0.125	0.096	-1.298	-0.138	0.105	-1.319	-0.279	0.120	-2.336
JFC	-0.170	0.111	-1.528	-0.075	0.092	-0.817	-0.413	0.108	-3.843 **
JFO	-0.038	0.097	-0.393	-0.241	0.073	-3.312**	-0.264	0.073	-3.638 **
JMS	0.069	0.068	1.004	0.068	0.090	0.750	0.129	0.071	1.816
JMC	-0.217	0.101	-2.146	-0.088	0.095	-0.923	-0.012	0.128	-0.095
JMO	-0.089	0.072	-1.241	-0.124	0.072	-1.720	-0.097	0.067	-1.442
SFS	-0.032	0.071	-0.446	0.032	0.076	0.418	-0.117	0.085	-1.368
SFC	0.039	0.134	0.292	-0.069	0.144	-0.480	-0.165	0.213	-0.775
SFO	-0.070	0.108	-0.644	-0.158	0.112	-1.406	-0.168	0.103	-1.632
SMS	0.020	0.068	0.291	0.026	0.067	0.394	0.074	0.070	1.054
SMC	-0.063	0.122	-0.513	-0.084	0.101	-0.830	-0.115	0.158	-0.730
SMO	-0.106	0.120	-0.888	-0.071	0.118	-0.606	-0.004	0.126	-0.032
VFS	0.255	0.064	4.003**	0.198	0.071	2.779*	0.224	0.068	3.279 **
VFC	0.010	0.234	0.043	-0.209	0.261	-0.801	0.007	0.218	0.030

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Cell	2000-2004 Diff	Std.Err.	T-value	2000-2006 Diff	Std.Err.	T-value	2000-2009 Diff	Std.Err.	T-value
VFO	-0.201	0.170	-1.180	-0.236	0.160	-1.473	-0.150	0.173	-0.868
VMS	0.090	0.061	1.477	0.141	0.063	2.253	0.240	0.067	3.589 **
VMC	0.037	0.167	0.219	0.016	0.234	0.070	-0.016	0.186	-0.083
VMO	-0.024	0.259	-0.094	0.011	0.231	0.049	0.072	0.236	0.305
HFS	0.324	0.083	3.888**	0.278	0.068	4.093**	0.336	0.072	4.654 **
HFC	-0.331	0.245	-1.349	-0.244	0.154	-1.582	-0.502	0.148	-3.387 **
HFO	0.193	0.259	0.746	-0.046	0.215	-0.214	-0.019	0.214	-0.087
HMS	0.125	0.066	1.886	0.265	0.072	3.671**	0.383	0.069	5.534 **
HMC	-0.055	0.253	-0.216	0.208	0.214	0.974	-0.007	0.227	-0.030
HMO	0.123	0.225	0.548	0.275	0.213	1.288	-0.052	0.237	-0.219

** is 1% significance level, ** is 0.5% significance level.*

[a] *The Cell Welch's test is conducted under the assumption that two samples are not from the same distribution.*

[b] *Cells are the 30 sub-labour-market groups by education × firm size × ownership.*

[c] *Differences are the changes of relative wage premium of each cell with respect to the sample mean wage each year over time. A positive number means that the later year has a higher relative mean wage, and vice versa.*

[d] *Three letters represent the education level, gender and the ownership type of the sub-market respectively. The first letter is education level, with P for primary school, J for junior school, S for senior high school, V for vocational school, H for higher education and above. The second letter indicates it is female (F) or male (M) sub-market. The third letter shows whether the firms are SOEs (S), collective-owned (C) or other (O).*

The sequence of decomposition is also important, since the factors can be correlated with one and another (DiNardo et al., 1996). The primary sequential decomposition of this chapter is the *Barrier*, including rural-urban ID and insurance; the *Firm type*, including ownership type and size; the individual attributes, including age, education, gender and occupation; and labour supply and demand, referring to the changes in the wage premiums. The reversed sequential decomposition is also presented for the sake of robustness.

Finally, several measures were used to measure dispersion. One natural measure is the standard deviation, whereby a higher standard deviation indicates more dispersion. In practice, 0.5% observations were excluded from both ends of wage distribution (i.e. 1% of the observations in total) when calculating the standard deviation so as to avoid any influence from outliers. The robustness of the standard deviation results will be discussed in a later section. To investigate the more detailed shape changes, the log of the real wage gaps amongst the 10th, 25th, 50th, 75th and 90th percentiles were also considered. A decrease in, say, 10th to 50th percentile gap from the original distribution of 2004 to the counterfactual distribution means that the gap should have been lower if the distribution of the critical variable(s) remained the same as it had been at 2000. The ratio of that decrease to the density change between 2000 and 2004 implies the extent to which the actual density change between the two years can be explained by the distributional change in the critical variable(s).

2.3 The Data

2.3.1 Data Description

The China Health and Nutrition Survey (CNHS) data is used in this chapter. The CHNS has been conducted nine times in urban and rural areas of twelve China provinces since 1989, with the 9^{th} survey having been undertaken in 2011. The sample of the CHNS was drawn in a multistage, random cluster process. In each province, four counties and two cities were stratified by their levels of income using a weighted sampling scheme. Subregions within the counties and cities were selected randomly. In each community, all members in the randomly selected 20 households were interviewed. The main reason for using the CHNS is that it provides information on hourly wage rates. Also, there is long series of records which enable a more precise tracking of changes and developments over the last two decades.

The main weakness of the CHNS for the purposes of this study is that it was not designed to be representative of the Chinese labour market as a whole, and does not implement sampling weights to correct for sample bias (Popkin et al., 2010). A second weakness is that it does not have data specifically on migration, which has become a key issue in the Chinese economy. In addition, it does not have observations from the largest two Chinese cities, Beijing or Shanghai, until its very last survey in 2011. All of the above can cause sample bias problems in the following discussion about the Chinese labour market during 2000 and 2004.

CHIP data were also considered. This has more information on labour and occupational characteristics, the most important of which are work experience, on-the-job training, migration and the industrial categories of the jobs. It also has important disadvantages, however. There are only surveys for CHIP data: 1989, 1996, 2003, 2008 and 2013. This made it difficult to capture short-run effects. The timings of the surveys were also less suitable for discussing the targeted institutional changes of this chapter. The Asian financial crisis occurred in 1997 and could have had an important effect on the Chinese labour market, but CHIP data does not have detailed firm information to account for that. The wage data collected in CHIP is also not consistent. For example, in 1988, there was no information on the hours worked by each individual, while in latter waves, apart from 1995, the wage data collected includes bonus and allowances.

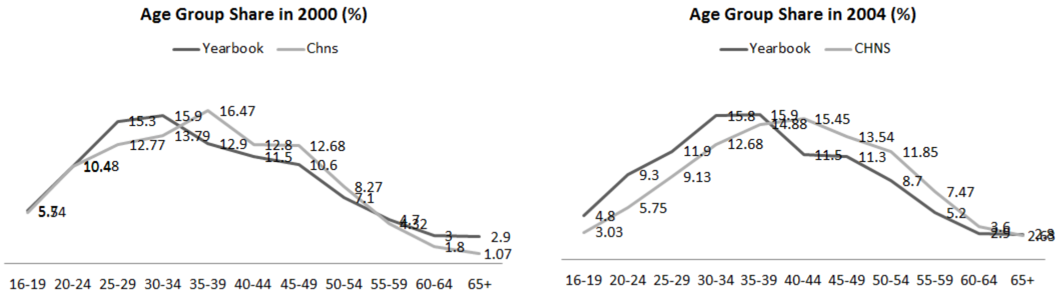
For the purposes of this chapter, therefore, CHNS was chosen. Since the short-run impact of the policies under discussion fall between 2000 and 2004, these two surveys are the focus of the discussion. In addition, one prior wave (1997), and two subsequent waves (2006 and 2009), were included to depict trends and relative long-run effects.

2.3.2 Representativeness of the CHNS Sample

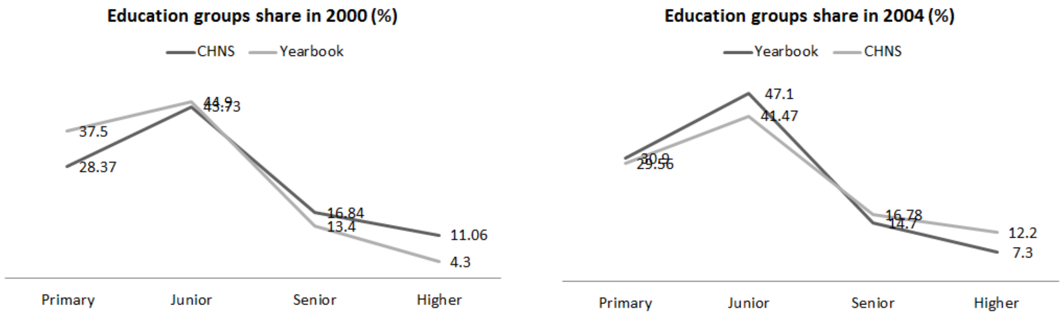
Before commencing the statistical summary of the CHNS data, the representativeness of the CHNS sample will be discussed. One natural check would be for consistency with the national aggregate data, but the Labour Yearbook does not cover the total labour force in many measures, which is also the problem when checking the sample representativeness of the CIE data in next chapter. The two data sets cannot, therefore, be compared directly; instead comparisons are attempted using the closest possible measurements within the two datasets.

In the Labour Yearbook, there are two main measures of employment:

1. The number of people engaged in socio-economic activities that generate income;



(a) Age



(b) Educational

Figure 2.1: Age and educational distributions in 2000 and 2004
Illiterate workers were excluded from both datasets, which was mixed with missing entry in CHNS. In the Labour Yearbook, the employment measure included all workers in agrarian and non-agrarian sectors. In CHNS, all working age non-students are included to match the measurements in the Labour Yearbook.

2. The number of workers and staff, which refers to those who work in and receive income from working units with state ownership, urban collective ownership, joint ownership, share holding stock ownership, limited liability corporations, foreign and Hong Kong, Macao, and Taiwan Chinese funds or other forms of ownership and their affiliated units.

The former measure includes agrarian labourers, for whom there was no hourly wage rate information, while the latter measure is narrower. Thus, in order to compare the two data sets, new sub-samples were constructed from the CHNS sample to be as close as possible to the two Labour Yearbook employment measures. Since the main analysis of this chapter focuses on the short-run effects of institutional changes on the labour market between 2000 and 2004, this discussion of the extent to which the sample is representative is also focused on this time period.

In terms of the age, educational and gender distributions of workers, the CHNS data is quite consistent with the Labour Yearbook in both distributions in 2000 and 2004 (Figure 2.1a, 2.1b and 2.2). To be more specific, the working population in the CHNS sample is slightly older and better educated in general. Overall, though, both the age and educational comparisons can be seen as evidence that CHNS is a representative sample for the total labour market in China. The gender composition of employment for 2000 and 2004 is also very close in the CHNS and in the Labour Yearbook.

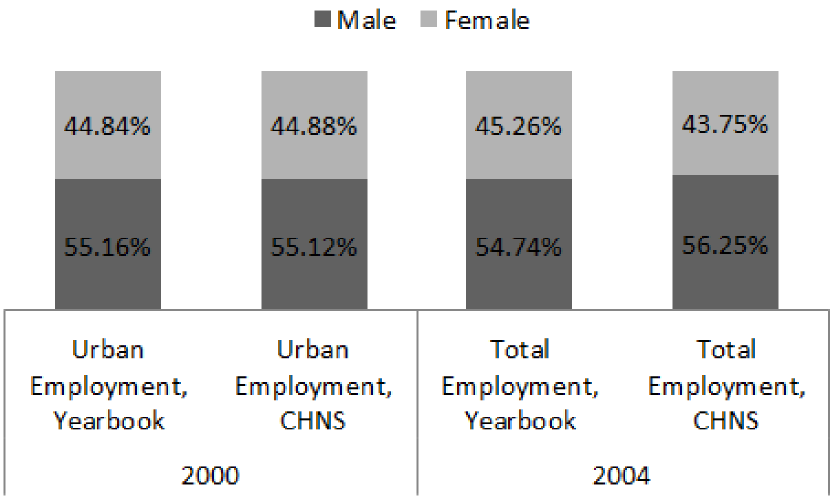


Figure 2.2: Gender distribution in 2000 and 2004
In the Labour Yearbook, both gender share in urban employment and the gender share of total employment are recorded.

Comparing distributions of employers by ownership from the CHNS and the Labour Yearbook in Figure 2.3, these can be seen to be similar in both data sets in 2000. There is, however, a difference in the ownership share in 2004, with CHNS observing more workers from SOEs but fewer in the other categories. This suggests that less privatization is recorded in CHNS and thus if privatization had an effect on wage dispersion, that effect would be underestimated in CHNS.

In summary, the CHNS data is very consistent with the Labour Yearbook apart from the SOE employment share in 2004. Since the CHNS data recorded a smaller decrease in SOE employment, the effect of privatization on wage dispersion change could be underestimated.

2.3.3 Wage Inequality in China

According to the CHNS, the distribution of log real wages moved rightwards and grew fatter (see Figure 2.4) since the early 1990s. The period of interest is 2000-2004, when the shape of the wage distribution changed from a single-peak to a double-peak.

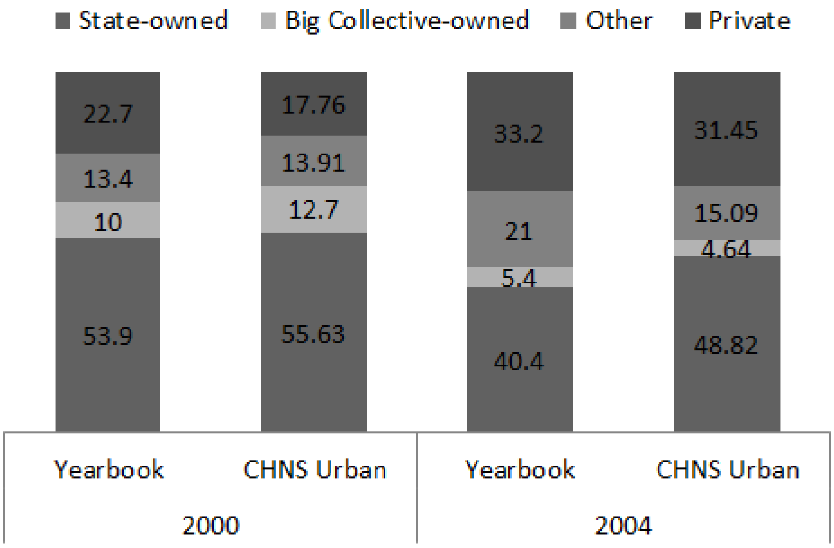


Figure 2.3: Employment share (%) by ownership in 2000 and 2004
The Labour Yearbook only measured urban employment. In addition, small collective-owned enterprises were put in the "other" category in the Yearbook. The CHNS data is adjusted accordingly.

From 2000 to 2004, the real hourly wage in China increased by 29.24%, the real wage standard deviation grew by 54.37% and the standard deviation of log real wage increased by 3.71%. Table 2.2 shows the changes in the 10^{th}, 50^{th} and 90^{th} percentiles of log wage rate. The gaps between different percentiles can be seen to have widened during the period between 2000 and 2004. The gap between the 50^{th} and 10^{th} log real wage was 0.692 in 2000, which became 0.839 in 2004. Also, the wage distribution became more dispersed in the lower half than in the upper half. On the other hand, the dispersion in the upper part of the wage distribution is relatively small. That is to say, the workers at the bottom of the wage distribution were getting further behind the average.

Table 2.2: Change of log wage percentiles from 1997 to 2009

(ln points)/Year	1997	2000	2004	2006	2009
10th Percentile	0.755	1.052	1.202	1.37	1.642
50th Percentile	1.444	1.744	2.04	2.185	2.449
90th Percentile	2.111	2.465	2.815	2.985	3.375

All figures are calculated from CHNS full sample.

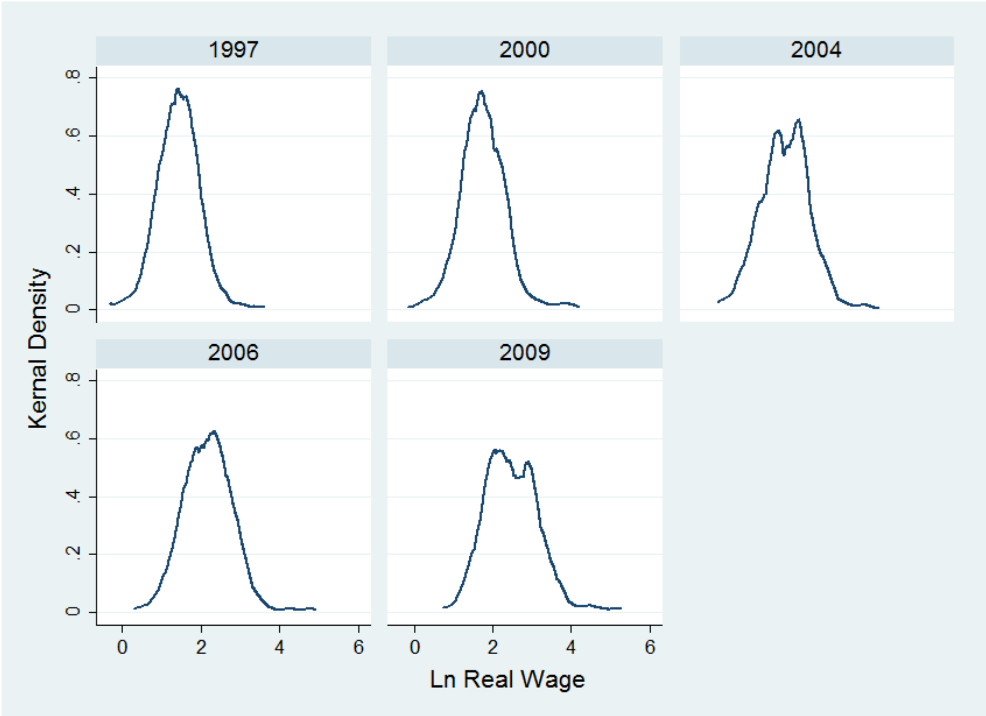


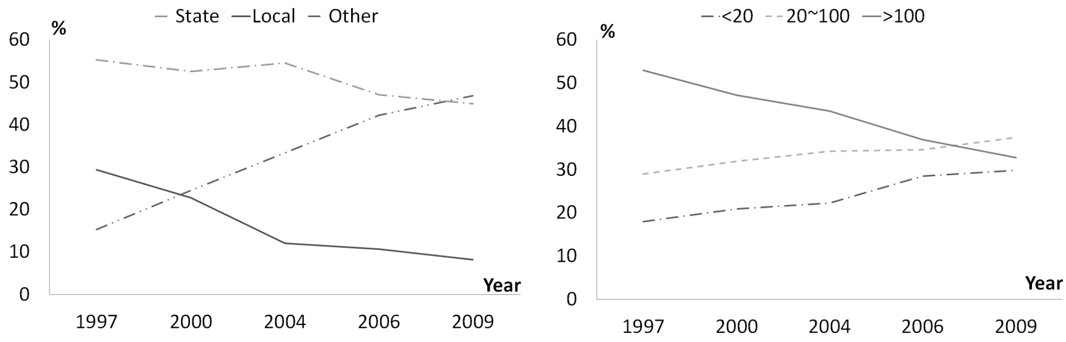
Figure 2.4: Distribution of log real wages from 1997 to 2009
The logarithm of real wages is generated by deflating the hourly wage rate by the annual CPI, with 1998 as the base year. Data from CHNS.

2.3.4 Statistics of Individual and Firms' Attributes

Three groups of variables were considered to explain the transition in the wage distribution. The first group is employer characteristics, including size and ownership. The second group is individual attributes like age, gender, education and occupation. The last group of variables consists of mobility barriers, encapsulated by rural-urban ID and type of medical insurance coverage.

The employer ownership is sub-divided into three categories: state-owned, collective-owned and others. According to Figure 2.5a, non-SOEs and non-collective-owned firms had expanded a lot in terms of employment. Between 1997 and 2009, the employment share of collective-owned firms had declined 21.42 percentage points, while that of the SOEs decreased by 10.50 percentage points. The employment share of different sizes of firms changed significantly as well (Figure 2.5b). More and more people started to work in medium and small firms, rather than big ones.

The individual attributes group is used as reported (Figure 2.6). With the onset of an aging population, the age distribution of labour has become less dispersed (standard deviation decreased from 10.901 to 10.489). Meanwhile, gender



(a) Ownership* (b) Firm size**

Figure 2.5: Change in the employment share of ownership and firm size

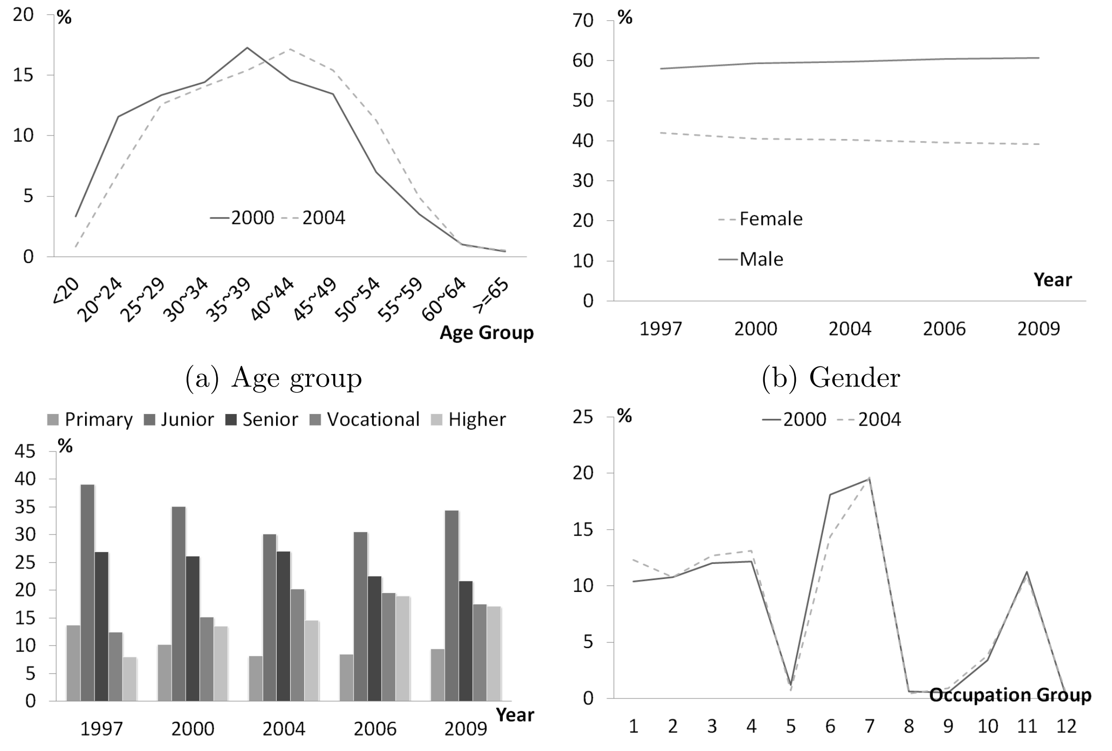
** State refers to employees working in SOEs. Local means people working in enterprises and organizations that were owned by all levels of local governments, i.e. collective-owned. Others can be considered as employees of all other types of firm ownership, including private owned, joint ownership, share-holding stock ownership, limited liability corporations, foreign and Hong Kong, Macao, and Taiwan Chinese fund and other private business.*
*** Firm size is measured by the number of employees in each firm. There are three categories as recorded in the CHNS data: small – less than 20 workers; medium – 20 to 100 workers; large – over 100 employees.*

shares in the labour market have not changed much since 1997.

During 2000-2004, the educational distribution of labour became more dispersed due to the higher education expansion policy. Previously, most workers were educated just to the junior school level. Junior school education is the end of the Chinese nine-year compulsory education system. After 2006, however, when the government eased the expansion programme, the educational distribution of workers started to re-condense to junior school level.

There are 12 categories of occupation groups in CHNS, as listed in Table 2.3. The main distributional change in occupation from 2000 to 2004 was a decrease in the proportion of skilled workers and an increase in the proportion of employees in all other non-agrarian occupations, including managerial jobs and unskilled jobs.

The last group is named barriers (to migration), which includes the rural-urban ID of the *hukou* system and social insurance. The *hukou* system includes region and rural-urban ID registration. Since the CHNS data is sampled controlling for geographical registration, however, the effect of migration cannot be captured. The rural-urban ID is highly correlated with the geographical registration but is not controlled for, and it can therefore give some information about the hukou barrier. From 2000 to 2004, employees became more condensed in



(a) Age group (b) Gender

(c) Education* (d) Occupation**

Figure 2.6: Age, gender, education and occupation distributions over time, CHNS
** Primary means 5 or 6 years primary school education; junior is 2 or 3 years middle school education; senior refers to 3 years high school education; vocational school is normally 3 years education for a specific occupation; higher education is 3 or 4 years college and above.*
*** The occupation groups on X-axis are as defined in Table 2.3.*

urban ID (Figure 2.7). After 2004, however, the trend in the employment share between rural and urban IDs is not consistent with that of Labour Yearbook after 2004. This means that there is a potential issue of bias when considering relatively long-run effects.

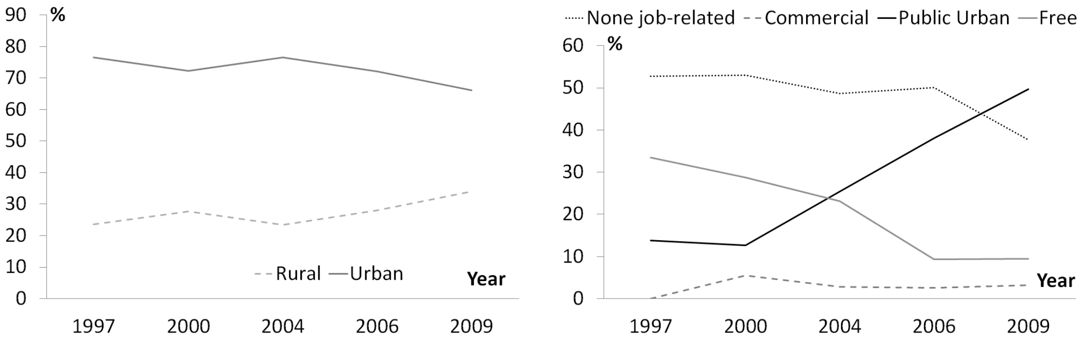
The medical insurance, as part of social insurance, can be grouped into four types – free medical services, the cooperative medical insurance,[3] commercial insurance and non-job-related medical services. The distribution of insurance types became more dispersed over the period 2000-2004.

[3]The cooperative medical insurance was replaced by urban employee medical system in 2006 and further expanded as urban employee and resident insurance in 2009.

Table 2.3: Occupation categories in CHNS

No.	Occupation	No.	Occupation
1	senior professionals (e.g. doctors, professors, lawyers, engineers, etc.)	7	un-skilled workers
2	general professionals (e.g. nurses, teachers, etc.)	8	generals and commanders
3	administration officials	9	soldiers and polices
4	administration staff	10	drivers
5	farmers*	11	service workers
6	skilled workers	12	athletes, actors and musicians

**Note that only those farmers who report their wages are included in the data. The majority of farmers received cash or non-cash earnings but not wages.*



(a) (b)

Figure 2.7: Distributional change of of (a) rural-urban ID and (b) ID and insurance types

2.4 Empirical Results

2.4.1 Short-run Effect: 2000-2004

The primary sequential decomposition is summarized in Table 2.4. The first column reports the actual total changes of wage dispersion measurements from 2000 to 2004. The standard deviation measures the overall change in wage dispersion. More detailed changes in wage distribution are measured by percentile gaps. For example, 05-95 measures the change between the 05^{th} and the 95^{th} percentile. All specifications indicate that the wage dispersion in China increased during the period 2000-2004. The most intensely dispersed part in the wage distribution is the lower tail, i.e. the 10^{th} and 25^{th} percentile gap.

The counterfactual effect is reported in logarithm points, along with how much this is in terms of the percentage of the total change (in parentheses underneath).

A large percentage suggests a strong explanatory power for that factor. For example, in Std. Dev. row and the Firm Type column, the effect of firm type change on the standard deviation is 0.010 log wage points. That means, if the firm type in 2004 remained stayed at the same level as it was in 2000, the increase in the log real wage standard deviation would have been 20.20% less. That is to say, the change in firm type can account for 20.20% of the increase in the wage dispersion. Among all the factor groups, the total effect of firm type and the individual attributes were stronger than that of the barriers, which only accounts for 1.81% of the increase in wage dispersion. For labour supply and demand, it is a negative number, -12.98%, which means that rather than having a dispersion effect on the wage, supply and demand had an opposite effect. If labour supply and demand had not shifted the wage premiums, the wage dispersion would have increased by 12.98%.

According to the primary sequential decomposition, all the considered factors together can explain about 25% of the total wage dispersion increase between 2000 and 2004. The top tail of the distribution is better accounted for by these factors than the bottom tail. In total, 96.97% of the 75^{th}-90^{th} percentile gap increase and 14.50% of the 10^{th}-25^{th} percentile gap increase can be explained. For the middle part, 25^{th}-75^{th} percentile gap, only 9.75% of the increase can be explained. Figure 2.8 shows the overall conterfacutal wage distribution.

Change in the individual attributes is the most powerful explanatory variable for the increase in the 75^{th}-90^{th} percentile gap and the 50^{th}-90^{th} percentile gap. The change in the firm type is most useful in explaining the change in the 10^{th}-50^{th} percentile gap. Apart from in the top tail of the wage distribution, labour supply and demand changes tend to counteract wage dispersion. If the change in the barrier had not occurred, the wage bottom tail would have been more dispersed but the top tail would have been less dispersed. Both effects are small, however, and, in general, the effect of each factor on the wage distribution is not consistent: one factor can have a dispersive effect on one tail and an opposite effect on the other tail.

As mentioned in Section 2.2, the sequence of the decomposition can be very important. In Table 2.5 , therefore, a reversed sequential decomposition is presented. This shows that the effects of factors are mostly consistent with those in the primary sequence. In contrast to the results of primary sequential decomposition, however, the overall effects of change in the barrier factors are larger in the reversed sequence, and some signs of the effects of the barrier factors are opposite in two sequences. Apart from inconsistency in the barrier, the effect of

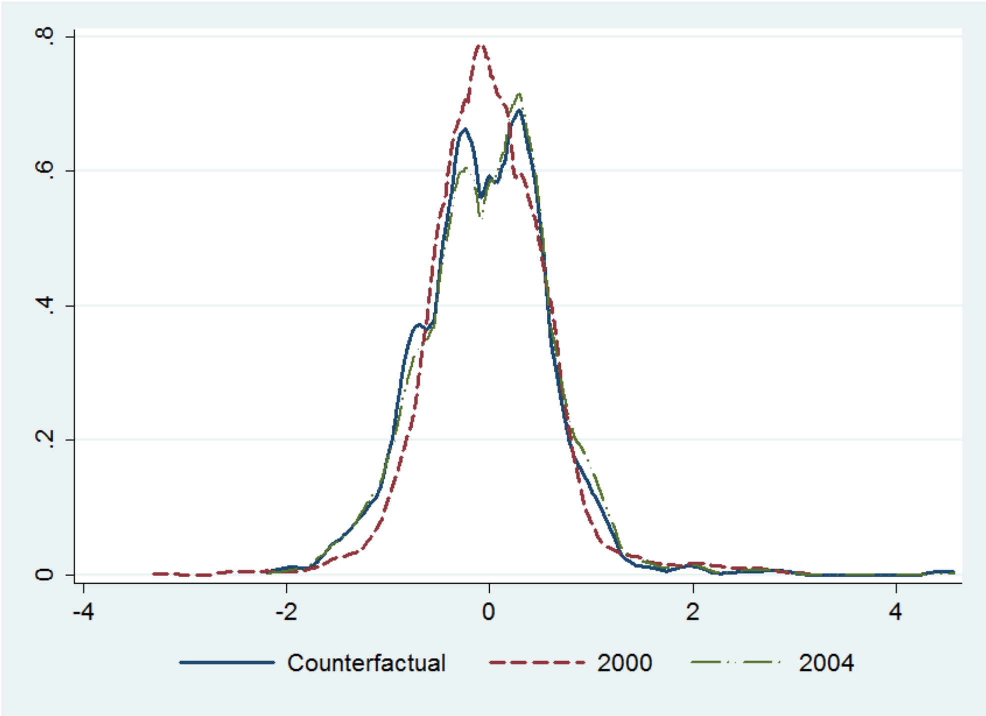


Figure 2.8: Wage Distribution in 2000, 2004 and the Counterfactual Wage Density

change in individual attributes on the top half of the wage distribution is also inconsistent in the two sequences.

Nevertheless, it can be seen from Tables 2.4 and 2.5 that the change in the distribution of individual attributes and firm type is important in explaining the increase in the wage dispersion during 2000 and 2004.

In essence, the change of x variables – barrier, firm type and individual attributes – can increase the wage dispersion in two ways. Firstly, there were wage gaps between labour groups caused by x variable(s) and thus the distribution of the x variable(s) became more dispersed. Thus, the dispersion in the x variable(s) would cause an increase in the wage dispersion. The second way in which the wage dispersion could change is due to the difference in the extent of wage dispersion within each labour group. If the wage rates of a particular group of workers, say females, were more dispersed than those of the other group(s), i.e. male, an increase in female employment would also serve to increase the total wage dispersion.

In respect to changes of firm characteristics, the employment shares of different types of ownership became less dispersed (Table 2.7).But in terms of public-private sectoral dispersion, ownership became more dispersed. As shown in Figure 2.5a, there was a higher share of employees in private firms and a lower proportion of employees in collectively-owned companies in 2004 than in 2000. The wages between these two sectors are slightly different, but more importantly, the within-sector wage dispersions in these two sectors are very different (Table 2.6).

On the other hand, the proportion of employees in firms of different sizes became more dispersed (Table 2.7). There were differences in average wages between large, medium and small firms. While more and more people were employed in small firms, the wage dispersion in small firms were larger than median and big firms in 2004.

There are two possible reasons to explain the observed phenomenon: the increased numbers and types of enterprises and the increased flexibility of labour contracts.

Institutional reform led to a booming private sector in China, which resulted in the proliferation of a vast range of firms with different technological and efficiency levels, and, in turn, a greatly increased range of wages. According to Yang and Jiang (2012), the TFPs of firms in industrial sector have converged from 1999 to 2007. Liu and Zhang (2010) showed that the regional TFP in the service sector was also converging in the early 21^{st} Century. Research on sectoral TFP gaps between service and industrial sectors in China is lacking in the literature probably due to a lack of data. The value-added per worker growth rates, however, were diverging between the two sectors. The real value-added per worker grew 32.60% in the service sector and 40.49% in the industrial sector between 2000 and 2004[4]. Given the significant effect of TFP on wages (Yang and Jiang, 2012), 2012), it is likely that productivity divergence between these sectors resulted in growing wage dispersion in China.

In addition, wages in the private sector and in small firms are more dispersed, probably due to more flexible labour contracts. In big firms and in the public sector, workers are usually classified in several levels with the same wage for each level. In small firms and in private firms, however, contracts on wages is likely to be more personalized and flexible, and thus may better reflect labour productivity. Thus, increasing the labour share of private sector and small firms can result in more dispersed wages. It is difficult, however, to analysis within firm wage dispersion because the data is not available. More research into the within firm movements will be beneficial to understanding this issue.

[4] Data calculated using the National Statistics Yearbook.

Table 2.4: Changes of wage distribution from the 2000 to 2004 decomposition

	Total Change[a]	Effect of[d]				Unexplained Changes
		Barrier[e]	Firm Type[f]	Individual Attributes[g]	Supply & Demand	
Std. Dev.[b]	0.048	0.001	0.010	0.008	-0.006	0.036
		(1.81)	(20.20)	(15.63)	(-12.98)	(75.34)
05-95	0.284	-0.001	0.037	0.037	-0.005	0.217
		(-0.46)	(13.19)	(12.96)	(-1.88)	(76.19)
10-90	0.233	0.004	0.032	0.037	-0.019	0.181
		(1.50)	(13.65)	(15.78)	(-8.35)	(77.42)
25-75	0.103	0.001	0.009	0.018	-0.019	0.093
		(1.41)	(8.97)	(17.42)	(-18.05)	(90.25)
10-25	0.197	-0.003	0.027	0.008	-0.003	0.169
		(-1.51)	(13.77)	(3.81)	(-1.58)	(85.50)
10-50	0.036	0.001	0.005	0.003	-0.002	0.029
		(2.09)	(14.47)	(9.07)	(-5.58)	(79.95)
50-90	0.101	-0.002	0.009	0.053	-0.024	0.064
		(-1.70)	(9.20)	(52.21)	(-23.39)	(63.68)
75-90	0.029	0.004	0.009	0.015	0.001	0.001
		(12.37)	(30.03)	(51.89)	(2.69)	(3.03)

[a] *The decomposition uses data from CHNS, as described in Section 2.3. It is the primary sequential decomposition.*
[b] *This is the standard deviation of log real wages. The top and bottom 0.5% of observations are excluded.*
[c] *This refers to the percentile gaps. For example, 05-95 is the gap between the 5th and the 95th wages, 10-90 is the gap of 10th and 90th wages and so on. The 95th wage is on the top tail of the wage distribution.*
[d] *The effect of each group of factors are presented in log digits, and the respective percentages of explained total change are in parentheses.*
[e] *Barrier refers to the rural-urban ID and insurance type of a person.*
[f] *Firm type includes the ownership type and the size of a firm.*
[g] *Individual attributes include gender, age, education and occupation of a worker.*

Table 2.5: Changes of wage distribution from 2000 to 2004 decomposition, reversed sequence[a]

	Total Change	Effect of[d]				Unexplained Changes
		Supply & Demand	Individual Attributes[e]	Firm Type[f]	Barrier[g]	
Std. Dev.[b]	0.048	-0.003	0.003	0.006	0.006	0.036
		(-7.18)	(7.22)	(12.50)	(12.11)	(75.34)
05-95	0.284	-0.009	0.024	0.029	0.024	0.217
		(-3.06)	(8.48)	(10.10)	(8.29)	(76.19)
10-90	0.233	-0.012	0.029	0.025	0.011	0.181
		(-5.04)	(12.38)	(10.63)	(4.60)	(77.42)
25-75	0.103	-0.009	0.006	0.014	-0.001	0.093
		(-8.66)	(5.83)	(13.81)	(-1.24)	(90.25)
10-25	0.197	-0.006	0.029	0.002	0.003	0.169
		(-2.86)	(14.95)	(1.11)	(1.30)	(85.50)
10-50	0.036	-0.001	0.006	0.003	0.000	0.029
		(-3.97)	(17.06)	(7.03)	(-0.07)	(79.95)
50-90	0.101	-0.011	-0.013	0.031	0.030	0.064
		(-10.83)	(-13.01)	(30.16)	(29.99)	(63.68)
75-90	0.029	0.000	0.008	0.009	0.011	0.001
		(0.31)	(26.89)	(32.63)	(37.15)	(3.03)

[a] *The decomposition uses data from CHNS, as described in Section 2.3. The sequence is the opposite to that in Table 2.4*

[b] *This is the standard deviation of log real wages. Top and bottom 0.5% of observations are excluded.*

[c] *This refers to the percentile gaps. For example, 05-95 is the gap between the 5th and the 95th wages, 10-90 is the gap between the 10th and 90th wages, and so on. The 95th wage is the top tail of the wage distribution.*

[d] *The effect of each group of factors are presented in log digits, and the respective percentages of explained total change are in parentheses.*

[e] *Individual attributes include gender, age, education and occupation of a worker.*

[g] *Barrier refers to the rural-urban ID and insurance type of a person.*

[f] *Firm type includes the ownership type and the size of a firm.*

Table 2.6: Change in within-group mean and Std.Dev. of log real wage

	1997		2000		2004		2006		2009	
	Mean[a]	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Ownership										
State[b]	0.707	0.458	1.148	0.546	1.555	0.508	1.796	0.528	2.261	0.595
Local[c]	0.680	0.534	0.988	0.541	1.211	0.543	1.357	0.465	1.815	0.703
Other	0.827	0.588	1.016	0.594	1.277	0.592	1.386	0.630	1.796	0.661
Firm Size[c]										
<20	0.763	0.563	1.026	0.617	1.309	0.623	1.431	0.649	1.809	0.694
20-100	0.661	0.463	1.051	0.484	1.480	0.526	1.648	0.566	2.111	0.680
>100	0.733	0.504	1.121	0.581	1.432	0.547	1.620	0.584	2.065	0.616
Age Group										
<20	0.439	0.516	0.786	0.490	1.082	0.339	1.211	0.532	1.629	0.749
20–24	0.570	0.467	0.944	0.532	1.133	0.476	1.415	0.513	1.722	0.486
25–29	0.613	0.540	1.030	0.557	1.329	0.587	1.456	0.518	1.943	0.599
30–34	0.754	0.478	1.046	0.544	1.410	0.590	1.510	0.575	1.939	0.621
35–39	0.722	0.474	1.162	0.644	1.402	0.483	1.561	0.577	2.022	0.668
40–44	0.783	0.508	1.064	0.494	1.488	0.547	1.620	0.663	2.008	0.698
45–49	0.815	0.479	1.122	0.473	1.451	0.563	1.592	0.569	2.071	0.681
50–54	0.877	0.437	1.165	0.607	1.539	0.546	1.764	0.633	2.141	0.654
55–59	0.952	0.534	1.341	0.569	1.606	0.628	1.664	0.585	2.112	0.797
60–64	1.183	0.939	1.304	0.508	1.352	0.633	1.514	0.769	1.754	0.640
≥65	0.625	0.378	1.430	0.945	1.592	0.765	1.577	0.937	2.446	1.198

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	1997		2000		2004		2006		2009	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Gender										
Female	0.608	0.473	0.982	0.510	1.354	0.564	1.445	0.588	1.848	0.645
Male	0.797	0.513	1.145	0.585	1.466	0.555	1.663	0.599	2.108	0.676
Education[d]										
Primary	0.703	0.496	1.008	0.541	1.165	0.591	1.234	0.523	1.629	0.624
Junior	0.682	0.515	0.979	0.559	1.259	0.566	1.351	0.584	1.811	0.664
Senior	0.739	0.502	1.126	0.559	1.428	0.556	1.580	0.581	1.993	0.669
Vocational	0.736	0.472	1.101	0.506	1.519	0.463	1.693	0.518	2.169	0.559
Higher	0.813	0.522	1.276	0.583	1.747	0.480	1.966	0.527	2.455	0.555
Occupation Group[e]										
1	0.833	0.482	1.250	0.576	1.771	0.458	2.002	0.522	2.510	0.550
2	0.724	0.483	1.228	0.637	1.590	0.498	1.778	0.517	2.245	0.499
3	0.833	0.513	1.244	0.557	1.600	0.563	1.840	0.596	2.269	0.627
4	0.667	0.449	1.103	0.533	1.506	0.490	1.711	0.499	2.138	0.658
5	0.821	0.454	0.922	0.597	1.695	0.671	2.028	1.249	2.294	0.965
6	0.744	0.533	1.072	0.554	1.288	0.444	1.493	0.539	1.914	0.597
7	0.603	0.454	0.915	0.457	1.090	0.483	1.289	0.503	1.734	0.606
8	0.809	0.184	1.175	0.451	1.737	0.212	2.057	0.464	2.586	0.605
9	0.524	0.480	1.146	0.540	1.636	0.905	1.545	0.495	1.895	0.963
10	1.172	0.638	1.263	0.623	1.612	0.600	1.643	0.606	2.207	0.831
11	0.616	0.502	0.817	0.483	1.194	0.582	1.229	0.598	1.562	0.525
12	0.728	0.323	1.794	0.077	1.643	0.699	1.415	0.698	1.760	0.000
Rural-Urban ID										
Rural	0.718	0.577	0.965	0.508	1.166	0.566	1.320	0.541	1.775	0.684

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	1997		2000		2004		2006		2009	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Urban	0.717	0.481	1.123	0.575	1.499	0.536	1.676	0.598	2.125	0.640
Insurance										
None job-related	0.687	0.533	0.981	0.568	1.242	0.557	1.365	0.598	1.740	0.685
Commercial	-	-	1.023	0.518	1.369	0.444	1.427	0.561	1.857	0.500
Public Urban	0.732	0.459	1.152	0.589	1.577	0.543	1.787	0.527	2.135	0.613
Free	0.759	0.474	1.244	0.495	1.637	0.473	1.887	0.505	2.439	0.594

[a] *Wage means and standard deviations are calculated using CHNS data, excluding the 0.5% top and bottom tail of wage distribution.*

[b] *State refers to employees working in SOEs. Local means people working in enterprises and organizations that were owned by all levels of local governments, i.e. collective-owned. Others can be considered as employees of firms characterised by all other ownership types, including private-owned, joint ownership, share holding stock ownership, limited liability corporations, foreign and Hong Kong, Macao, and Taiwan Chinese fund and other private business.*

[c] *Firm size is measured by the number of employees in each firm. There are three categories: small – less than 20 workers; medium – 20 to 100 workers; large – over 100 employees.*

[d] *Primary means 5 or 6 years primary school education; junior is 2 or 3 years middle school education; senior refers to 3 years high school education; vocational school is normally 3 years education for a specific occupation; higher education is 3 or 4 years college and above.*

[e] *The occupation number is as defined in Table 2.3.*

Table 2.7: Changes in the factorial dispersion

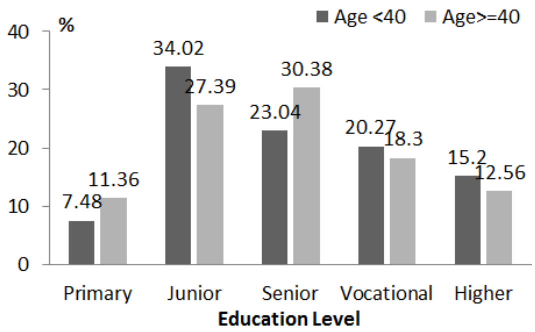
	1997	2000	2004	2006	2009
Barrier:					
Insurance*	23.160	21.319	19.819	22.996	22.136
R/U ID**	0.428	0.451	0.428	0.452	0.474
Firm Type:					
Ownership*	20.146	16.372	20.326	19.654	21.610
Firm size*	17.826	13.045	9.281	3.611	3.009
Individual Attributes:					
Age**	10.393	10.617	10.214	10.229	10.500
Gender**	0.494	0.492	0.492	0.490	0.490
Education*	13.084	10.379	8.795	7.859	9.309
Occupation*	7.718	6.887	6.778	6.946	6.879

** These variables are categorical. Their dispersions are calculated as the standard deviations of the relative frequency by types of the variable. This measurement decreases in dispersion.*
*** The standard deviations of variables are reported. These increase with the dispersions of the variables.*

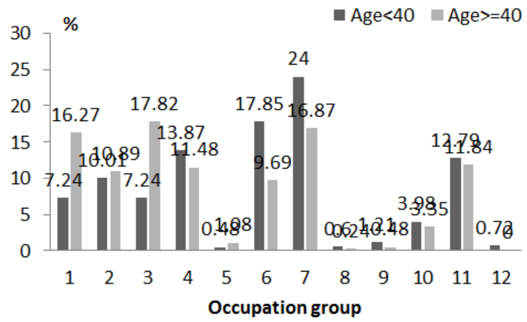
As shown in Table 2.7, individual attributes change in different directions in terms of dispersion. From 2000 to 2004, the employment share by age of the Chinese labour force became less dispersed, which was probably a result of more years of education on average among the young generation and the "one-child policy".[5] This in turn dispersed wages during the period, because there was an increase in the share of employment held by those aged between 40 and 60 years old, whose wages were more dispersed on average. There are several possible reasons for that: one is that 40 to 60 years old workers in 2004 had higher education dispersion than average (Figure 2.9); another potential reason is that older workers were more dispersed in their occupations (Figure 2.9), while younger workers were more concentrated in entry-level jobs.

Nevertheless, the results of improvement in education tell another story. If the distribution of education alone remained the same as in 2000, the increase in wage dispersion in 2004 would have been higher. As shown in Table 2.7, although the overall education of employees became more dispersed from 2000 to 2004 wage dispersion among workers sharing higher levels of education was lower (i.e. there was lower within-group wage dispersion (Table 2.6)). In regard to educational wage premiums, therefore, by 2004, higher education expansion appeared to result in more people entering a less wage dispersed group, serving to reduce the overall

[5]The "One-child policy" officially started in 1979.



(a) Education by age group



(b) Occupation* by age group

Figure 2.9: Education and occupation distributions by age groups in 2004
**The occupational category numbers are consistent with the data description in Table 2.3*

Chinese wage dispersion. From the CHNS data, higher-educated workers were more often young, male, holding managerial jobs and working in SOEs.

Workers with higher education may also be converging in unobserved productivity-related attributes. These attributes include experience, individual intrinsic endowments and things like alumni networks. For employers, recruiting employees with higher education may allow more secure estimations of their employees productivity (Altonji and Pierret, 1998). From the workers point of view, after they obtain higher education, they will get not only a higher wage premium, but also a more certain wage. In terms of utility functions, therefore, the value of education does not only come from higher wages but also from less uncertainty about those returns.

The increase in the occupational dispersion (Table 2.7) derives mainly from a decrease in the share of skilled workers and an increase in the share of of senior professionals, administration jobs, unskilled workers and service workers. This increased occupational dispersion appears also to generate some wage dispersion. A plausible reason for this transition can be the increasing use of computers, which can substitute for workers performing routine tasks while complementing workers doing non-routine jobs (Autor et al., 2003). As computers have become cheaper, their use has proliferated, particularly as a direct replacement for semi-skilled workers who are typically involved in routine tasks. On the other hand, occupations requiring non-routine tasks could not be substituted by computers but were complemented by them, meaning that labour market shares in these jobs actually increased. The non-routine jobs include high wage occupations like lawyers and doctors and also low wage ones like babysitting. Solid research in the Chinese labour market of technology change on labour demand focused on skilled and unskilled workers, which cannot fully explain the observed change in occupation. More research is needed into this area.

Another plausible explanation is that such a change in occupational distribution is a joint outcome of the institutional reform and the improvement in education. There was surplus in some industries for quite some years that, in the SOE reform, excess workers, who were mainly skilled, were laid off. Those workers found new roles in other occupations, mainly low wage and non-managerial ones. At the same time, the extension of higher education produced more people eligible for high wage jobs like administrative occupations and professionals. This is consistent with the positive correlation between higher education, SOEs and managerial jobs.

The share of overall employment held by female has declined slowly (Figure 2.6). As Yao and Tan (2005) have discussed, decreasing female labour market participation is less correlated with husbands' incomes than it is with business cycles. On average, the male/female wage gap declined since 1997 until 2004 in CHNS data, and increased afterwards, which is consistent with Gustafsson and Li's (2000) conclusions using CHIP data, but different from Zhang et al.s (2008) work using two provincial-sectoral data. Males also appear to have had more dispersed wages in most years (Table 2.7). In general, the change in the employment share of males and females has very little effect on the changing wage dispersion.

The overall effect of changes in barrier variables on the increase in wage dispersion is moderately positive, although this could have been underestimated using CHNS data. As mentioned in Section 2.3, the survey has controlled for rural-urban area and the individual ID is highly correlated with that. In the CHNS data, more employees have an urban ID, and these were also generally earning more and with less dispersed wages, which is consistent with previous literature on rural-urban differentials in China (Christiansen, 1990; Chan and Zhang, 1999; Whalley and Zhang, 2007; Yao et al., 2010; Hertel and Zhai, 2006; Knight and Song, 1997; Meng, 2000; Michelson et al., 2000; Sicular and Zhao, 2004). Urbanization can therefore reduce wage dispersion by increasing urban employment. Nevertheless, in the Labour Yearbook, more people were in rural employment (Figure 1.4) in 2004. The results of change in rural-urban ID from the CHNS data, therefore, can be biased. Nevertheless, given that people with urban ID are more privileged in the labour market than those with rural ID, a considerable proportion of the wage gap can easily be eliminated by abandoning the rural-urban ID differentiation system (Hertel and Zhai, 2006). This can also help reduce a substantial part of the reported wage dispersion.

On the other hand, with the expansion of public medical insurance, the distribution of insurance became more dispersed (Figure 2.7b). This, in turn, has had a positive effect on the wage dispersion, given the wage gaps between different insurance groups (Table 2.7). There has been little study of the effect of insurance on wages or wage dispersion, however, although one possible explanation is that being forced to participate in public insurance could be a disadvantage for a firm in the labour market. Buying insurance is expensive and, therefore, to save costs firms prefer to pay a considerable premium in order to opt out of insurance. Such a contract can be also attractive to some workers if they have a high discount rate. According to Bärnighausen et al. (2007), in Wuhan, a middle-sized city in the central area of China, informal workers were willing to pay 4.6% of their income for health insurance. Firms, however, would have to pay 8%[6] of their wages for the basic health insurance. Therefore, those employers who did not participate in the provision of public insurance systems, and have other disadvantages in production, have an incentive to compete with participating employers by raising wages. In that case, the wage differences between the employers with different productivities can be smaller than would be the case without the influence of insurance. As the take-up of insurance expansion spread gradually from government-related enterprises to private firms, and from good firms to the others during the 2000-2004 period, this incentive or "advantage" disappeared and the total wage dispersion increased.

Supply and demand shifts have shown a considerable effect on the reduction in wage dispersion between 2000 and 2004. As explained in Section 2.2, the change in relative wages was significant in two out of thirty sub-labour-markets (Table 2.1). Using the gender-education-ownership factors explained relative wage change as the supply and demand change, and such change actually counteracts wage dispersion to a considerable degree. The effect of labour demand change on relative wage, however, may be biased due to lack of firm information in the CHNS data. More research is thus required to understand the effect of labour demand shifts on relative wage premiums.

2.4.2 Long-run Effect: 2000-2006 and 2000-2009

The longer term effect of changes in the investigated factors on changes in wage distribution are summarized in Table 2.8. Both the primary sequence and re-

[6] Quote from Wuhan government website <http://www.wuhan.gov.cn/hbgovinfo/szfxxgkml/fggw/zfgz/201505/t20150515_29810.html>.

versed sequence are presented. Since 2000, wage dispersion is getting larger in all measurements expect for two: the $10^{th} - 25^{th}$ percentile wage differential from 2004 to 2006, and the $50^{th} - 90^{th}$ percentile wage differential from 2006 to 2009.

Comparing the two sequences of decomposition in the 2000-2006 period, it can be found that changes in the employment share of firm types and individual attributes became even stronger in accounting for the increase in the wage dispersion. The effect of barriers such as urban-rural ID and social insurance and labour supply and demand shifts were unclear. The changes in the lower half of the wage distribution are better explained, in that the change in the barrier variables played an important role.

Moreover, results from the 2000-2009 decomposition show that the investigated factors were no longer capable of accounting for the increase in Chinese wage dispersion. In both the primary and reverse sequence, the effect of changes in the types of firms becomes inconsistent. The effect of movements in individual attributes also becomes unclean in the bottom half of the wage distribution. As shown in 2.1, in the long-run, relative wage premiums changed significantly. It is likely here that relative demand shifts had become very important. The global financial crisis occurred during the 2006 to 2009 period and Chinese wages started to behave procyclically (Figure 1.2). Ignoring demographic-biased labour demand shifts can be very unrealistic during a crisis.

To summarize, the longer it is after the institutional changes, the less certain of the effects of them on wage dispersion change. One possible reason is the fail of assumption that labour demand shifts were not demographically biased. It is therefore important to consider the relative wage changes caused by demand shifts in that sense. Another possibility is the sample selection biasness, which cannot be completely rule out.

Table 2.8: Decomposition of change in wage dispersion, 2000-2006 and 2000-2009

	Total Change	Primary Sequence Effect of[c]: Barrier	Primary Sequence Effect of[c]: Firm Type	Primary Sequence Effect of[c]: Individual Attributes	Primary Sequence Effect of[c]: Supply & Demand	Reversed Sequence Effect of: Supply & Demand	Reversed Sequence Effect of: Individual Attributes	Reversed Sequence Effect of: Firm Type	Reversed Sequence Effect of: Barrier	Unexplained
Decomposition of 2000-2006 change:										
Std. Dev.[a]	0.052	-0.011	0.025	0.005	0.030	-0.009	0.006	0.030	0.009	0.017
		(-20.19)	(47.88)	(9.34)	(57.82)	(-17.35)	(10.67)	(56.94)	(16.89)	(32.85)
05-95[b]	0.212	-0.033	0.050	0.019	0.029	-0.031	0.014	0.054	0.028	0.147
		(-15.31)	(23.64)	(9.07)	(13.47)	(-14.56)	(6.77)	(25.64)	(13.01)	(69.14)
10-90	0.225	-0.018	0.061	0.027	0.009	-0.029	0.026	0.069	0.012	0.146
		(-8.04)	(27.18)	(11.79)	(4.03)	(-12.72)	(11.63)	(30.64)	(5.42)	(65.04)
25-75	0.129	-0.032	0.036	0.032	-0.002	-0.020	0.033	0.035	-0.014	0.096
		(-25.11)	(28.18)	(24.59)	(-1.80)	(-15.73)	(25.28)	(27.23)	(-10.93)	(74.15)
10-25	0.149	0.033	0.041	0.009	-0.001	-0.015	0.008	0.030	0.057	0.068
		(22.14)	(27.51)	(5.81)	(-0.94)	(-9.87)	(5.52)	(20.45)	(38.41)	(45.48)
10-50	0.076	0.003	0.020	0.013	-0.002	-0.008	0.010	0.020	0.014	0.041
		(4.59)	(26.60)	(16.75)	(-2.35)	(-10.71)	(12.49)	(26.00)	(17.81)	(54.41)
50-90	0.061	-0.020	0.017	0.001	0.010	-0.010	0.006	0.024	-0.011	0.052
		(-32.70)	(28.30)	(2.10)	(16.49)	(-16.66)	(9.93)	(39.69)	(-18.78)	(85.81)
75-90	0.035	0.001	0.008	-0.009	0.012	-0.002	-0.010	0.021	0.003	0.023
		(2.43)	(22.86)	(-25.38)	(34.51)	(-6.55)	(-28.52)	(61.28)	(8.22)	(65.58)

continued on next page

[a] *This is the standard deviation of log real wages. The top and bottom 0.5% of observations are excluded.*

[b] *This refers to the percentile gaps. For example, 05-95 is the gap between 5th and the 95th wages.*

continued from previous page

		Primary Sequence Effect of:				Reversed Sequence Effect of:				
	Total Change	Barrier	Firm Type	Individual Attributes	Supply & Demand	Supply & Demand	Individual Attributes	Firm Type	Barrier	Unexplained
Decomposition of 2000-2009 change:										
Std. Dev.	0.125	-0.046	-0.024	0.047	0.004	-0.005	0.027	0.014	-0.055	0.143
		(-36.65)	(-19.45)	(37.77)	(3.51)	(-3.75)	(21.67)	(11.03)	(-43.77)	(114.82)
05-95	0.414	-0.151	-0.151	0.118	0.002	-0.017	0.063	-0.002	-0.225	0.596
		(-36.35)	(-36.48)	(28.47)	(0.50)	(-4.21)	(15.29)	(-0.57)	(-54.37)	(143.86)
10-90	0.366	-0.094	-0.093	0.129	0.018	-0.017	0.086	0.042	-0.150	0.406
		(-25.73)	(-25.33)	(35.22)	(5.00)	(-4.67)	(23.42)	(11.45)	(-41.04)	(110.84)
25-75	0.237	-0.017	0.022	0.061	0.001	-0.011	0.069	0.040	-0.030	0.169
		(-7.09)	(9.24)	(25.84)	(0.41)	(-4.57)	(28.95)	(16.77)	(-12.75)	(71.60)
10-25	0.168	-0.127	-0.325	-0.152	0.088	-0.008	0.016	-0.056	-0.469	0.684
		(-75.81)	(-193.31)	(-90.52)	(52.34)	(-4.53)	(9.71)	(-33.55)	(-278.93)	(407.30)
10-50	0.198	-0.041	-0.090	-0.030	0.039	-0.008	0.052	0.005	-0.171	0.320
		(-20.59)	(-45.51)	(-15.20)	(19.83)	(-4.01)	(26.24)	(2.32)	(-86.01)	(161.47)
50-90	0.045	-0.014	-0.004	0.035	-0.003	-0.002	0.009	0.009	-0.001	0.031
		(-30.09)	(-8.25)	(77.90)	(-7.56)	(-5.23)	(21.04)	(19.18)	(-2.98)	(68.00)
75-90	0.085	-0.043	-0.028	0.109	-0.006	-0.004	0.013	0.017	0.005	0.054
		(-51.21)	(-32.76)	(128.01)	(-7.29)	(-5.05)	(15.28)	(20.45)	(6.07)	(63.24)

[c] *The effect of each group of factors are presented in log digits, and the respectively explained percentages of total change are in parentheses. Individual attributes include gender, age, education and occupation of a worker. Barrier refers to the rural-urban ID and insurance type of a person. Firm type includes the ownership type and the size of a firm.*

2.5 Robustness of Results

2.5.1 Bandwidth: Issue of Mass Points

As mentioned in Section 2.2, choosing a bandwidth for the kernel density estimation is important in this model. The aim is to find a bandwidth that is large enough to capture only the important trends in the distribution, but not too wide that it may ignore important distributional changes in the counterfactual densities. Ultimately, the selected bandwidth was 0.1. A sensitivity check was run to analyze the influence of bandwidth selection on the results. The explainable change in wage gaps changes faster at bandwidth values between 0.08 and 0.1 than between 0.10 and 0.12 (Figure 2.10). Also, the optimal bandwidths chosen by Stata program were 0.116 and 0.103 for the wage distributions in 2000 and 2004. It was concluded, therefore, that 0.1 is a good bandwidth to extract important information from the noise.

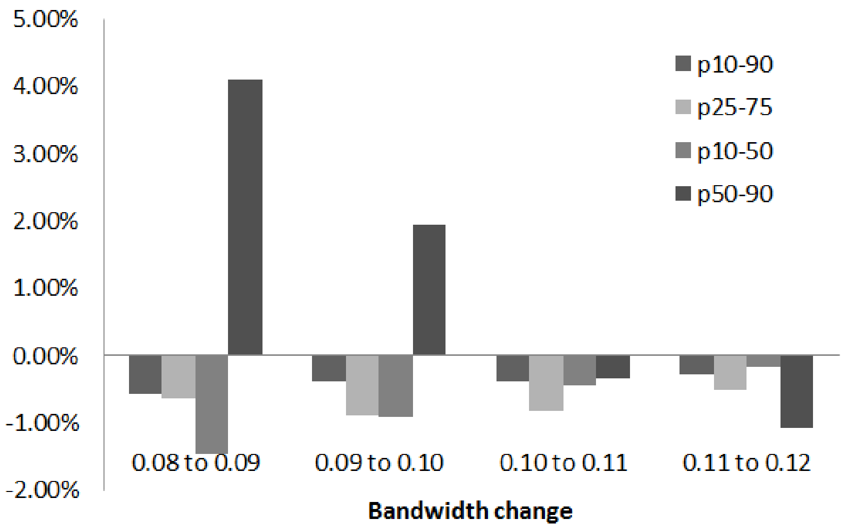


Figure 2.10: Changes in explainable percentile gap increase by bandwidth[a]

[a] *Bandwidth change is on the X-axis. The Y-axis is the percentage change in the explained fraction of measurements. The four measurements are percentile gaps. p10-90, p25-75, p10-50 and p50-90 represent the gaps of* $10^{th} - 90^{th}$, $25^{th} - 75^{th}$, $10^{th} - 50^{th}$ *and* $50^{th} - 90^{th}$ *percentiles respectively.*

2.5.2 Outliers

Standard deviation can reflect the overall inequality of a distribution but is very sensitive to extreme values, which may make the results unreliable. In order to exclude outliers, therefore, some observations from both tails of the wage distribution in each year were ignored. In order not to eliminate important information at the tails of wage distribution, a test was run to analyze the extent to which the standard deviation was influenced by the number of excluded observations (Table 2.9). Each column of Table 2.9 shows the decomposition results of the main model when the highest and the lowest 0%, 0.5%, 1% or 5% of observations are excluded. The results change substantially from 0% to 0.5% of observations were excluded, much more so than in other cases. It seems plausible, therefore, to exclude 0.5% of wages from either end of the distribution when calculating the standard deviation.

Table 2.9: Changes in the explanatory fraction of Std. Dev. of log real wage by fraction of outliers excluded

% Excluded[ab]	0.00%	0.50%	1.00%	5.00%
Total Change	0.039	0.048	0.056	0.068
Supply & Demand	-2.21%	1.81%	1.09%	17.37%
Individual Attributes	28.33%	20.20%	17.18%	11.43%
Firm Type	2.91%	15.63%	16.73%	-34.96%
Barrier	-29.40%	-12.98%	-10.49%	18.99%
Unexplained	100.38%	75.34%	75.50%	87.17%

[a] *In this table, results from the 2000-2004 period is reported. The decomposition takes the primary sequence. All calculations are based on CHNS data.*
[b] *The percentage is the fraction excluded from the two ends of the wage distribution in each year. For example, 0.50% means there were 0.50% of observations excluded from both bottom and top ends of the wage distributions in 2000 and in 2004. 0.50% has been chosen for the main analysis.*

2.6 Conclusion

This chapter ahs focused on the underlying forces that have characterized wage dispersion in China over the period 2000 to 2004. It was shown that if all the considered factors were kept constant over this period, around 25% of the increase in the wage distribution's standard deviation would have eliminated. In addition, the change in employment share by firm type and individual attributes were shown to be strong driving forces behind the observed wage dispersion. On the other hand, changes in the relative wage premium of different demographic groups is likely to have undermined the expanding wage dispersion.

Increasing labour share of private sector and small firms can account for a considerable fraction of wage dispersion. There are several possible explanations. One is that the institutional reform and policy adjustments to the WTO agreement allowed the private firms with different performance levels to develop. This, in turn, increased the range of wages. In addition, while in big public enterprises, workers are usually classified in several levels with the same wage for each level, in small or private firms, wage contracts wages are more likely to be personalized and flexible, and are therefore more likely to reflect productivity levels. Thus, increasing labour share of private sector and small firms can result in more dispersed wages. More research is needed to study whether there is productivity diversification between industrial and service sectors, and whether that difference has affected Chinese labour market. Moreover, within firm wage dispersion can be another interesting topic to understand the wage dispersion issue.

On the other hand, as the educational levels of employees became more dispersed, potential wage dispersion dropped. That is because highly educated groups have low within group dispersion of wages. As barriers to educational attainment have fallen, the marginal utility of education outweighed its marginal cost, meaning that individuals demand for education increased and the educational distribution of labour became less skewed to the right. As for the employers, these changes facilitated their assessment of the actual employee productivity rates, which had become more uniform due to the proliferation of higher education.

The change in occupational shares is very likely to be evidence in support of the model proposed by Autor et al. (2003). As computers have become cheaper, their use has proliferated, particularly as a direct replacement for semi-skilled workers who are typically involved in routine tasks. On the other hand, occupations requir- ing non-routine tasks could not be substituted by computers - indeed some of them are actually complementary to computer use - meaning that labour market shares in these jobs actually increased. Since the non-routine occupations are very dispersed in terms of wages, as a result, wages have become more dispersed. Another possible explanation is that these changes in occupational distribution are a joint outcome of institutional reform and educational improvements. The workers laid off in the reform found new roles in other occupations, mainly low-paid ones. At the same time, the extension of higher education produced more labourers eligible for high wage jobs like administrative occupations and professionals.

A drawback of this study is the lack of migration analysis. The acquisition of data related to the number of migrant workers would have rendered the discussion on barriers to labour mobility somewhat more reliable and robust. Another shortcoming is the lack of data on work experience. Although it is suggested that age can act as a proxy for experience it is clearly not a perfect one. This also has to do with the mobility of labourers and years of schooling. Moreover, the absence of samples from large cities like Beijing and Shanghai (where high wage rates and high wage inequality are both prevalent) may have led to underestimation of the wage dispersion. In addition, because of insufficient information about the employers in the CHNS, the equilibrium effects of the demand and supply shocks in the labour market cannot be estimated. Given the short time span and the stable industrial labour shares, those effects are not likely to overturn the main findings, however.

Chapter 3

The Effect of the Minimum Wage on Wage Distribution in the Industrial Sector: Evidence From Chinese Industrial Enterprises Data

3.1 Introduction

According to the 2004 minimum wage provision, each local government in China can set its own minimum wage, and should strictly enforce it. An important question then is whether the increase/enforcement of the minimum wage affects Chinese wage inequality at all? If so, which part of wage distribution and how much of it is affected?

DiNardo et al. (1996) decomposed the effects of the demand-side and supply-side shocks, individual attributes, unions and the minimum wage on the wage distribution in the US in the 1980s. Unlike Brown et al. (1982) and Card and Krueger (1994), they found the minimum wage to be a powerful explanatory variable, especially at the lower tail of wage distribution, based on three assumptions about how minimum wage affects wage density. They assumed no spillover or disemployment effect and a minimum-wage-dependent-only lower tail, which will be discussed in detail in this chapter. As will be shown, the results are assumption-dependent. In the case of the US, the minimum wage was decreased, which makes DiNardo et al.'s (1996) results conservative under their no spillover or disemployment effect assumptions. For China in 2004, however, it was the opposite situation. It is important, therefore, to consider how results change when different assumptions are made.

Lee (1999) further discussed whether the minimum wage has a spillover or disemployment effect on wage distribution in the US in the 1980's. Instead of testing the correlation between minimum wage and wage dispersion measures, the relationship between the minimum-median wage gap and the wage dispersion measures was tested. It was found that a vast majority of the observed growth in inequality in the lower tail of wage distribution could be attributed to the erosion of the minimum wage rate. In addition, the minimum wage could explain over 60% of growth in the "within-group" wage inequality during the 1980's.

Teulings (2000) addressed the issue indirectly, using a production function with a Distance-Dependent-Elasticity of Substitution (DIDES) structure, where an increase in the minimum wage leads to a compression of relative wages. Although these results were generally consistent with the conclusions of Lee (1999), they were mostly attributed to the general equilibrium effects, making the effects of the return to education even more pressing. Teulings (2003) then used a two stage model, wherein the first step used workers' attribute parameters to model wage distribution and the second related the parameters to the minimum wage. The results rejected the assumption of DiNardo et al. (1996) that there is no spillover effect and further extended the effect of the minimum wage on wage distribution through individual attributes.

Unlike the US, which has had an effective minimum wage for many decades, the UK minimum wage was partial and ineffective until 1999, when the national minimum wage was introduced (Dickens and Manning, 2004a,b). Dickens and Manning's work in the UK context is consistent with DiNardo et al. (1996): the national minimum wage in the UK has a detectable effect on the lower tail of wage distribution. Contrary to Lee (1999) and Teulings (2000), however, Dickens and Manning (2004a) found that the minimum wage had virtually no effect on the pay of workers in the higher tail. On the other hand, Stewart (2004) estimated the disemployment effect of the introduction of the national minimum wage in the UK on low-wage workers among four demographic groups (male/female and old/young) using logit difference-in-difference estimation, where individuals with marginally higher wages were taken as the control group. He found no significant results to support the disemployment effect in the UK.

In the case of China, many studies used a provincial panel to discover the relationship between minimum wage and the aggregate wage level and employment. Ma et al. (2012) were the first to use panel data models at firm-level to estimate the minimum wage effect on firms' wages and employment. Controlling for time, firm specific factors, and local labour market characteristics, the local minimum wage was found to have a significant positive effect on firm-level wages, and a significant negative minimum wage elasticity of employment. The research of Jia and Zhang (2013) also showed a significant positive spillover effect of the minimum wage after 2004.

It is controversial to argue that increasing the minimum wage causatively increases firm-level wages, however. According to the Chinese "Minimum Wage Provision", minimum wages are calculated by the government and are conditional on the average expenditure of households below the local poverty line, the minimum standard of living, the average level of earnings, the local level of pensions, and the local economy. The labour contracts may also be pre-set according to market conditions. It is, therefore, rational to believe that both firm-level wages and minimum wages are the result of previous economic development, which was not discussed in Ma et al. (2012) and Jia and Zhang (2013).

In addition, the empirical results of Ma et al. (2012) for the disemployment effect of minimum wages could have been overestimated. The variation of minimum wages across the regions and the large amount of worker migration between regions in China indicate a substantial possibility of a spillover effect of an increase in one region's minimum wage increase on other regions' employment. In extreme cases, where both labour and capital are fully mobile nationwide, only the lowest regional minimum wage will be binding. Both minimum wages and industrial firm-level employment could be correlated with the development of nonindustrial sectors: as nonindustrial sectors grow to pay marginally higher wages, the average income will increase, minimum wages will be adjusted accordingly, and the original industrial workers will be attracted to the non-industrial firms.

This chapter employs a semi-parametric model similar to that of DiNardo et al. (1996) to estimate the effect of the minimum wage on wage dispersion, assuming no minimum wage effect on firm-level wages or firm-level disemployment to start with. Rather, minimum wages will be assumed only eliminating the ineligible firms in an aggregate term under the main assumptions. The assumptions of no spillover effect or disemployment effect will then be discussed, and a comparison of different assumptions will be presented.

This chapter is structured as follows: section 3.2 sets out the methodology; section 3.3 describes the CIE data, including a comparison with other datasets; section 3.4 presents and discusses the empirical results; sections 3.5 and 3.6 provide a robustness check and conclusion.

3.2 Methodology

The method used in this chapter is based on the semi-parametric model of DiNardo et al. (1996). Two parts will be considered: institutional changes and minimum wage increases. Here, institutional changes are changes in firm size, ownership and export status.

The notation in this chapter is consistent with that in Chapter 1. The weighted kernel density estimator is used to calculate log real wage density, where $\hat{f}_h(w)$ is the weighted kernel density estimation of log real wage rate w, based on a random sample of W_1,...,W_n of size n, and frequency weights θ_1,...,θ_n:

$$\hat{f}_h(w) = \frac{\sum_{\mathrm{i}=1}^{n} \frac{\theta_i}{h} K(\frac{w-W_i}{h})}{\sum_{\mathrm{i}=1}^{n} \theta_i} \tag{3.1}$$

where, h is the bandwidth and $K(.)$ is the kernel function. Unlike with CHNS data, where the bandwidth is 0.1, 0.02 has been chosen as the bandwidth for this CIE. The main reason is that the CIE data is less dispersed than the CHNS data after 2004. More useful details can be drawn from the CIE data with a small bandwidth. The number of workers in firm i is used as its weight θ_i, and the firm's log average real wages as W_i.

The implementation of the model is similar to that described in Section 2.2. The primary sequence of decomposition is, firstly, the effect of institutional changes and, secondly, that of minimum wage changes, while the reversed sequence is the opposite.

3.2.1 Effect of Institutional Changes

The counterfactual wage density of institutional changes can be defined as the wage density that would be ultimately revealed if one or more of the composition of firms' characters did not change over time. The effect of a factorial change is then the difference between the respective counterfactual wage density and the real wage at the end of the time period.

Recall from Chapter 2 that the unconditional wage distribution $f_t(w)$ at time t is the integral of the conditional wage density $f(w|x, t_w = t)$ over the institutional factors set x:

$$f_t(w) \equiv f(w; x, t_{w,x} = t) = \int_{x\in\Omega_x} f(w|x, t_w = t)dF(x|t_x = t) \tag{3.2}$$

Therefore, the density function of log real wage in the year 2004 can be written as

$f(w; x, t_{w,x} = 2004)$. The counterfactual density function of w, if the distribution of x remained the same as that in 2000, is $f(w; x, t_w = 2004, t_x = 2000)$. By assuming the conditional wage distribution of x did not change over time:

$$f(w; x, t_w = 2004, t_x = 2000) \quad = \int f(w|x, t_w = 2004)\psi_x(x)dF(x|t_x = 2004) \tag{3.3}$$

where

$$\psi_x(x) \equiv \frac{dF(x|t_x = 2000)}{dF(x|t_x = 2004)} \tag{3.4}$$

is the reweighting function of x at each level of x. Employing the Bayesian rule, it can be rewritten as:

$$\psi_x(x) \equiv \frac{Pr(t_x = 2000|x)}{Pr(t_x = 2004|x)} \cdot \frac{Pr(t_x = 2004)}{Pr(t_x = 2000)} \tag{3.5}$$

The probability of being in time t conditional on the status of x $(Pr(t_x|x))$ is estimated by a logit model. Meanwhile, $Pr(t_x = t)$ is just the share of observations of time t. In this chapter, x's are the ownership of firms, sizes of firms (as a result of SOE reform) and the export status (as the result of joining the WTO).

3.2.2 Effect of the Minimum Wage

To consider the effect of a change in the minimum wage, assumptions have to be made about how overall wage distribution would change with changes in the minimum wage. Similar assumptions are made to those in DiNardo et al. (1996), with the key difference being that, in DiNardo et al.'s (1996) case, the minimum wage decreased from the 1970s to the 80s in the US, while, in China, the minimum wage increased between 2000 and 2004. For the sake of robustness, assumptions are designed to be conservative, minimising the effects of the minimum wage. Alternative assumptions have also been discussed.

Default Assumptions

Assumption 1: A change in the minimum wage does not have spillover effects on wage distribution above the highest minimum wage. *This means, if the minimum wage changes from m_0 to m_1, wage distribution $f(w|x, t_x)$ where wage $w > max\{m_0, m_1\}$ will not be affected.*

In the case of the Chinese labour market, where $m_{04} \geq m_{00}$, this means:

$$[1 - I(w \leq m_{04})]f_t(w|x, t_w; m_{00}) = [1 - I(w \leq m_{04})]f_t(w|x, t_w; m_{04}) \qquad (3.6)$$

where the indicator function $I(.)$ is equal to 1 if the terms in the brackets apply, and equal to 0 otherwise.

This assumption is effectively the same as in DiNardo et al. (1996). In reality, when minimum wage increases, not only do the wages below the new minimum wage rise because of the legislation, but the wages above too. This could be due to the incentive compatibility constraint of workers or to firm-union negotiation.

According to Ma et al. (2012), a 10% increase in minimum wage will result in a 1.29% increase in firms' logarithm wage in those firms with the lowest 20% capital per worker. Such an effect decreases as the quantile of firms increases. For firms that have wages higher than the average, the minimum wage effect becomes negative. In summary, the lower quantile increases faster than the higher ones under an increasing minimum wage. In other words, the gap between logarithm wages becomes smaller as a result of an increase in the minimum wage. Ma et al. (2012) did not consider whether this would entail a structural break in considering the minimum wage effect on wages, however, because of the better enforcement of minimum wage policy in 2004.

The results from Jia and Zhang (2013) tested the effect of the minimum wage with a structural break in 2004. They showed that the minimum wage had a significant positive effect on in the lowest 20% of individual wages. Especially after 2004, the impact of the minimum wage became significant on the whole wage distribution. The effect of minimum wage decreases in real wage. For the wage distribution above the minimum wage level, however, the coefficients are very close for males. In such cases, the relative log wage does not change much, and the wage dispersion will not change.

It is clear that there was spillover effect in the Chinese labour market. What is not consistently revealed in the two studies, however, is whether that spillover effect resulted in different growth rates between different quantile wage groups. In addition, neither study considered the education or skill changes in the labour supply, nor the demographic-biased labour demand shifts, meaning that their results in respect to the spillover effect could be biased.

If the results of Jia and Zhang (2013) are taken as the valid estimation of the spillover effect and applied to wage dispersion decomposition, the effect of the minimum wage will tend to reduce wage dispersion more than when using Assumption 1. As the empirical results will show, the effect of increasing the minimum wage was to reduce wage dispersion between 2000 and 2004, whereas if a spillover effect is factored in, such a reduction in wage dispersion would be larger.

Given the uncertainty of spillover effects, Assumption 1 will be used as a conservative assumption, meaning that the results shown will be a lower bound of the minimum wage effect.

To simulate complete counterfactual wage distribution, an assumption about the wages below the minimum wages is needed. According to Jia and Zhang (2013), the effect of the minimum wage on wages below the minimum wage in China is very significantly positive. A plausible assumption about the wage distribution below the minimum wage, therefore, would be that it depends on the minimum wage. An apparent complication is that the minimum wage before 2004 may or may not have been binding. The assumption for below-minimum-wage changes under those situations will be discussed separately.

If "minimum reference wages" were binding before 2004, the counterfactual wage density should reflect what it would have been like in 2004 if the minimum wage had not risen from m_{04} to m_{00}.

Assumption 2: The shape of conditional wage distribution at or below the highest minimum wage should depend only on the minimum wage. *For two years, t_0 and t_1, with minimum wages, m_0 and m_1 ($m_0 \leq m_1$), the conditional density $f(w|x, t_1; m_0)$ that would prevail at t_1 if m_1 were brought down to m_0 is proportional to the shape of the conditional density $f(w|x, t_0; m_0)$ for the wages below the highest minimum wage m_1.*

Assumption 2 implies that the counterfactual conditional wage distribution between minimum wages m_0 and m_1 would have a similar shape to the conditional wage distribution at time t_0. The logic of this is that, without being restrained by a higher minimum wage, a worker in time t_1 should earn the same wage as his counterpart in t_0. For wages below m_0, the lack of compliance with labour legislation has not changed. An alternative assumption could be that for wages below m_0 the counterfactual conditional wage density equals that in m_1. Such an assumption would bring additional complexity, however, since it needs to be considered whether m_0 is binding in the first place. This, therefore, is considered only as a robustness check, and Assumption 2 will be used to obtain the main results.

In the case of China between 2000 and 2004, therefore, if the minimum wage in

2004 m_{04} were brought back to the 2000 level, m_{00}, the counterfactual conditional wage density would be proportional to the conditional wage density in 2000:

$$\begin{aligned} I(w \leq m_{04}) f_t(w|x, t_w = 2004; m_{00}) \\ = \psi_w(x, m_{04}) I(w \leq m_{04}) f_t(w|x, t_w = 2000; m_{00}) \end{aligned} \tag{3.7}$$

where $\psi_w(x, m_{04})$ is the reweighting function to be discussed later in this section.

If "minimum reference wages" were NOT binding before 2004, the result would be equivalent to that in the case where $m_{00} = 0$. Because the reweighting function $\psi_w(x, m_{00})$ does not depend on m_{00}, the result is the same as if m_{00} is binding. Under Assumption 2, whether m_{00} is binding or not should not affect the empirical results.

Assumption 3: The minimum wage has no effect on employment probabilities.

This assumption is exactly the same as that in DiNardo et al. (1996).

In summary, Assumptions 1, 2 and 3 together present a full set of assumptions that can build up the counterfactual wage distribution if the minimum wage did not change. The counterfactual wage density can be estimated by combining the wage density above m_{04} in 2004 and the wage density below m_{04} in 2000:

$$\begin{aligned} f_t(w|x, t_w = 2004; m_{00}) =& \psi_w(x, m_{04})[I(w \leq m_{04})] f_t(w|x, t_w = 2000; m_{00}) \\ &+ [1 - I(w \leq m_{04})] f_t(w|x, t_w = 2004; m_{04}) \end{aligned} \tag{3.8}$$

where

$$\psi_w(x, m_{04}) = \frac{Pr(w \leq m_{04}|x, t_w = 2004)}{Pr(w \leq m_{04}|x, t_w = 2000)}. \tag{3.9}$$

Finally, the overall counterfactual wage distribution for lowering the minimum wage from m_{04} to m_{00} is obtained by integrating the conditional counterfactual wage densities over the distribution of attributes:

$$\begin{aligned} & f_t(w; t_w = 2004, t_x = 2004, m_{00}) \\ &= \int \psi_w(x, m_{04}) I(w \leq m_{04}) f_t(w|x, t_w = 2000; m_{00}) dF(x|t_x = 2004) \\ &\quad + \int [1 - I(w \leq m_{04})] f_t(w|x, t_w = 2004; m_{04}) dF(x|t_x = 2004) \end{aligned} \tag{3.10}$$

$$= \int \psi_w(x, m_{04}) I(w \le m_{04}) f_t(w|x, t_w = 2000; m_{00}) \psi_x(x)^{-1} dF(x|t_x = 2000)$$
$$+ \int [1 - I(w \le m_{04})] f_t(w|x, t_w = 2004; m_{04}) dF(x|t_x = 2004). \quad (3.11)$$

where $\psi_w(x, m_{04})$ is as defined in equation (3.9), and $\psi_x(x)^{-1}$ is the reciprocal of $\psi_x(x)$ in equation (3.5).

Using the Bayes' rule, the product of the two reweighting functions will be:

$$\begin{aligned}\psi(x, m_{04}) &\equiv \psi_w(x, m_{04}) \cdot \psi_x(x)^{-1} \\ &= \frac{Pr(t_w = 2004|x, w \le m_{04})}{Pr(t_w = 2000|x, w \le m_{04})} \cdot \frac{Pr(t_x = 2000)}{Pr(t_x = 2004)}.\end{aligned} \quad (3.12)$$

The conditional probabilities for a firm's average wage to be observed in 2000 or 2004, given that it is below the 2004 minimum wage, and given the respective firm's character vector x, are estimated by a logit model.

After $\hat{\psi}(\cdot)$ is estimated for various cases, the reweighted density of the wages can be calculated as follows:

$$\hat{f}(w; x, t_w = 2004, t_x = 2000) = \frac{\sum_{i=1}^{n} \frac{\theta_i}{h} \hat{\psi}(\cdot) K(\frac{w - W_i}{h})}{\sum_{i=1}^{n} \theta_i} \quad (3.13)$$

If the former steps are repeated using different x vectors, reweighted densities for several variable factors can be produced. By comparing the real wage densities and counterfactual wage densities, the measures of the counterfactual effect of each set of variables can be obtained.

Assumptions 1, 2 and 3 are therefore used as the defaults in the empirical analysis.

Alternative Assumptions

In Assumption 2, the wage distribution only depends on the minimum wage level in 2004. It could have been the case, however, that firms below the minimum wage in 2000 were not affected by the minimum wage increase. The alternative assumption to Assumption 2, therefore, contains two parts: one for the wages between the old and the new minimum wages ($w \in (m_0, m_1]$), the other for the wages below the smallest minimum wage ($w \in (-\infty, m_0]$).

Assumption 4: Conditional wage density between the lowest and the highest minimum wages should only depend on the highest minimum wage. *For two years, t_0 and t_1, with minimum wages, m_0 and m_1 ($m_0 \le m_1$),* *the conditional density $f(w|x,t_1;m_0)$ that would prevail at t_1 if m_1 were brought down to m_0 is proportional to the shape of the conditional density $f(w|x,t_0;m_0)$ for the wages between the highest minimum wage m_1 and the lowest minimum wage m_0.*

Assumption 5: Conditional wage density below and at the lowest minimum wages should not be affected by the change in the minimum wage. *For two years, t_0 and t_1, with minimum wages, m_0 and m_1 ($m_0 \leq m_1$), the conditional density $f(w|x,t_1;m_0)$ that would prevail at t_1 if m_1 were brought down to m_0 is the same as the shape of the conditional density $f(w|x,t_1;m_1)$ for the wages below and at the lowest minimum wage m_0.*

Replacing Assumption 2 with Assumptions 4 and 5, the conditional wage density below the minimum wage in 2004 m_{04} can be written as:

$$
\begin{aligned}
&I(w \leq m_{04})f_t(w|x,t_w = 2004; m_{00}) \\
&\qquad = \psi_w(x, m_{00}, m_{04})I(w \leq m_{04})(1 - I(w \leq m_{00}))f_t(w|x,t_w = 2000; m_{00}) \\
&\qquad\quad + I(w \leq m_{00})f_t(w|x,t_w = 2004; m_{04})
\end{aligned}
\tag{3.14}
$$

where $\psi_w(x, m_{00}, m_{04})$ is the reweighting function:

$$
\psi_w(x, m_{00}, m_{04}) = \frac{Pr(w \in (m_{00}, m_{04}]|x, t_w = 2004)}{Pr(w \in (m_{00}, m_{04}]|x, t_w = 2000)}
\tag{3.15}
$$

Therefore, under Assumptions 1, 3, 4, and 5, the overall counterfactual wage distribution can be calculated as:

$$
\begin{aligned}
&f_t(w; t_w = 2004, t_x = 2004, m_{00}) \\
&= \int I(w \leq m_{00})f_t(w|x,t_w = 2004; m_{04})dF(x|t_x = 2004) \\
&\quad + \int \psi_w(x, m_{00}, m_{04})I(w \leq m_{04})[1 - I(w \leq m_{00})] \\
&\qquad\qquad \times f_t(w|x,t_w = 2000; m_{00})dF(x|t_x = 2004) \\
&\quad + \int [1 - I(w \leq m_{04})]f_t(w|x,t_w = 2004; m_{04})dF(x|t_x = 2004) \qquad (3.16) \\
&= \int I(w \leq m_{00})f_t(w|x,t_w = 2004; m_{04})dF(x|t_x = 2004) \\
&\quad + \int \psi_w(x, m_{00}, m_{04})I(w \leq m_{04})[1 - I(w \leq m_{00})] \\
&\qquad\qquad \times f_t(w|x,t_w = 2000; m_{00})\psi_x(x)^{-1}dF(x|t_x = 2000)
\end{aligned}
$$

$$+\int [1 - I(w \leq m_{04})] f_t(w|x, t_w = 2004; m_{04}) dF(x|t_x = 2004). \tag{3.17}$$

where $\psi_w(x, m_{00}, m_{04})$ is as defined in equation (3.15), and $\psi_x(x)^{-1}$ is the reciprocal of $\psi_x(x)$ in equation (3.5).

Using the Bayes' rule, the product of the two reweighting functions will be:

$$\begin{aligned}\psi(x, m_{00}, m_{04}) &\equiv \psi_w(x, m_{00}, m_{04}) \cdot \psi_x(x)^{-1} \\ &= \frac{Pr(t_w = 2004|x, w \in (m_{00}, m_{04}])}{Pr(t_w = 2000|x, w \in (m_{00}, m_{04}])} \cdot \frac{Pr(t_x = 2000)}{Pr(t_x = 2004)}.\end{aligned} \tag{3.18}$$

which can be calculated using logit estimation.

As discussed, if the minimum wage in 2000 is not binding, Assumptions 4 and 5 are equivalent to Assumption 2. Therefore, only the situation where the minimum wage in 2000 is binding is considered.

Although assumption 3 excludes a disemployment effect, as shown by Ma et al. (2012) and Fang et al. (2010), the wage elasticity of employment in China is significantly negative. As the minimum wage rises, firm-level wages also rise and employment is subsequently reduced. As the results from the fixed effect model of firm-level employment are regressed on the regional minimum wages (Ma et al., 2012), both on average by firms and over time, a 1 log point increase in the minimum wage is found to decrease firm-level employment by 0.059 log points. In addition, according to quintile-subsample (by firm-level capital per worker from low to high) estimations, the minimum wage only decreases employment in the bottom 60% of firms, the effect of which is above 0.069 log employment points per each log point increase in the minimum wage.

Since the minimum wage has a more negative effect on the employment at the lower quantile (Ma et al., 2012), allowing for disemployment will result in a further reduction in the weights of the reweighting function on the lower wage distribution. Assumption 3 is thus conservative, allowing for a smaller effect of minimum wage on wage density.

There are several ways to allow for the disemployment effect on the wage distribution. Given the results from Ma et al. (2012), the disemployment effect can be included in a conservative and simple manner by:

Assumption 6: The change in the minimum wage should only have a disemployment effect on the bottom 50% of conditional wage density at an average disemployment rate. *Given the minimum wage elasticity of employment below the median wage is e_{em} and minimum wages m_0 and m_1 at time t_0*

and t_1, *the employment ratio should be* $\psi_{em} = \frac{EM_1}{EM_0} = \exp(e_{em}(\ln(m_1) - \ln(m_0)))$.

In practice, this is simply to multiply the counterfactual weights with the employment ratio and re-estimate the wage distribution:

$$\hat{f}(w; x, t_w = 2004, t_x = 2000) = \frac{\sum_{i=1}^{n} \frac{\theta_i}{h} \hat{\psi}(\cdot) \psi_{em} K(\frac{w - W_i}{h})}{\sum_{i=1}^{n} \theta_i} \tag{3.19}$$

The results of alternative assumptions will also be shown and compared in the empirical discussion.

3.2.3 Lack of Labour Demand and Supply Shifts

During the period 2000-2004, there were changes in labour supply and demand. In contrast to the CHNS data used in Chapter 2, however, it is difficult for CIE data to account for labour supply shifts. One firm-level wage is not associated with any particular type of labour. Although part of the effect of supply and demand shifts on relative wages will be discussed in the next chapter, more research is still needed to understand wage premium changes with labour demand and supply shifts in CIE data.

According to the results from Chapter 2, supply and demand shifts had a moderate reduction effect (7% to 13%) on wage distribution between 2000 and 2004. Gaps between relative wage premium changes get larger in the longer term, however, although the effect of the shifts is mostly on the upper half of the wage distribution. Under Assumption 1, i.e. no spillover effect, the effect of the minimum wage is orthogonal with supply and demand shifts on the upper half wage distributionwage distribution, and these shifts can only eliminate 1%-3% of the $10^{th} - 25^{th}$ wage gap increase that the minimum wage is assumed to have an effect on.

In summary, the effect of labour demand and supply shifts will be ignored in this chapter and discussed more in next chapter.

3.3 Data Description

To analyse the effect of the minimum wage on wage distribution, the CIE data is used. As mentioned in Chapter 1, the CHNS data is not used to discuss the minimum wage issue because it is highly non-compliant with the minimum wage policy. In addition, there is no information on the working destination of individuals, which makes it impossible to assess minimum wage effects at the provincial level. To better understand the limitation of CIE data and how its results can be related to that of CHNS, it is essential to compare these two datasets.

The CIE data includes all the manufacturing firms "above the scale"[1] and has more than 1.8 million observations in total between 1999 and 2007. It is derived from the annual record of the National Statistical Bureau of China and the version used in this study is an important outcome of the elaborate work by Nie et al. (2012). It includes industries of mining, manufacturing and electricity, gas and water production and supply, with manufacturing firms making up more than 90% of the observations. The variables in the database include payroll, number of workers, total exports, sales, ownership, etc.. Compared to 2004 national economy census data, this database covers 89.5% of national industrial sales. In respect to the labour market, the CIE data covers more than 58% of industrial employment.

Although Nie et al. (2012) made a great effort to match firms across years, the CIE data remains a very unbalanced dataset. After matching through name, address and telephone number etc., only 8% of the firms are matched throughout the whole sample with the remainder being unmatched or only partially matched.

Table 3.1: Differences in the sample characters of CIE and CHNS

	CIE	CHNS
Region	All 34 mainland provinces are included.	Randomly selected households in sub-regional areas in nine mainland provinces are included.
Time Coverage	1999 to 2007	1993, 1997, 2000, 2004, 2006, 2009, 2013
Industry Coverage	Only industrial sectors: mining, manufacturing and electricity, gas and water production and supply.	Not specified.
Wage	Firm-level annual wages.	Individual wage rate per hour.
Workers' Profile	No	Yes (including age, education, occupation...)
Firms' Profile	Employment, income, cost, asset, capital, etc.	Ownership and size.

A brief summary of the differences between the two datasets is set out in 3.1.

[1]Defined by the National Bureau of Statistics of China as the firms earning more than 5 million RMB each year

Since the CIE data is at the firm-level, it does not have the employee profile of each firm. In other words, within-firm wage variations are missing from this firm-level data, as well as workers attribute information.

If within-firm workers are identical, the employment weighted firm-level wage distribution should be the same as the individual wage distribution. This would be unlikely for many firms, however. Within-firm wage distribution could be affected by minimum wage policy, demographic changes and labour supply and demand shifts. Without the employees profile, however, it is difficult to account for the effect on the relative wage premiums of demographic-biased demand or supply shifts.

Nevertheless, the CIE data covers more regions (all the provinces in mainland China) than the CHNS does (seven provinces), which may result in a larger wage dispersion on account of the coverage of more regional differentials. As stated before, CIE data covers three main sectors, while the CHNS probably contains individuals from all sectors, including farming and services. In addition, firms in the CIE data are "above the scale", indicating a lack of the personal and very small businesses in the sample that are most likely to employ the lower-tail workers and to disobey the Labour Law of the China.

All of above suggest the possibility of sample inconsistency, and if the wage structures of the two datasets do not present the same labour market/sub-market, the following assumptions may have been violated: 1) within-firm wages are identical; 2) inter-sector wage distributions are identical; 3) cross-region wage distributions are identical. Such a bias could affect the external validity of the results from CIE data.

3.3.1 Statistics: CIE, CHNS and the Labour Yearbook

As shown in Figure 1.1 in Chapter 1, the average urban wages in CHNS are persistently, although not substantially, lower than those in CIE, but average wages in both datasets are lower than those in the Labour Yearbook. As mentioned in Chapter 1, it is difficult to know which one of the Labour Yearbook, CHNS and CIE is more representative of the Chinese labour market. Nonetheless, they all share a similar increasing trend.

From Figure 1.3, however, it can be seen that the wage dispersion changes differently in the two datasets. In Figure 3.1, the wage distributions calculated from CHNS and CIE in the same years are presented. In 2000, CIE data were more skewed to the left. In 2004, both data were dual-peaked, and CIE data had a much thinner left tail. In 2006, the two distributions became different in medians, widths and heights. The Labour Yearbook does not contain enough information to compute wage density functions.

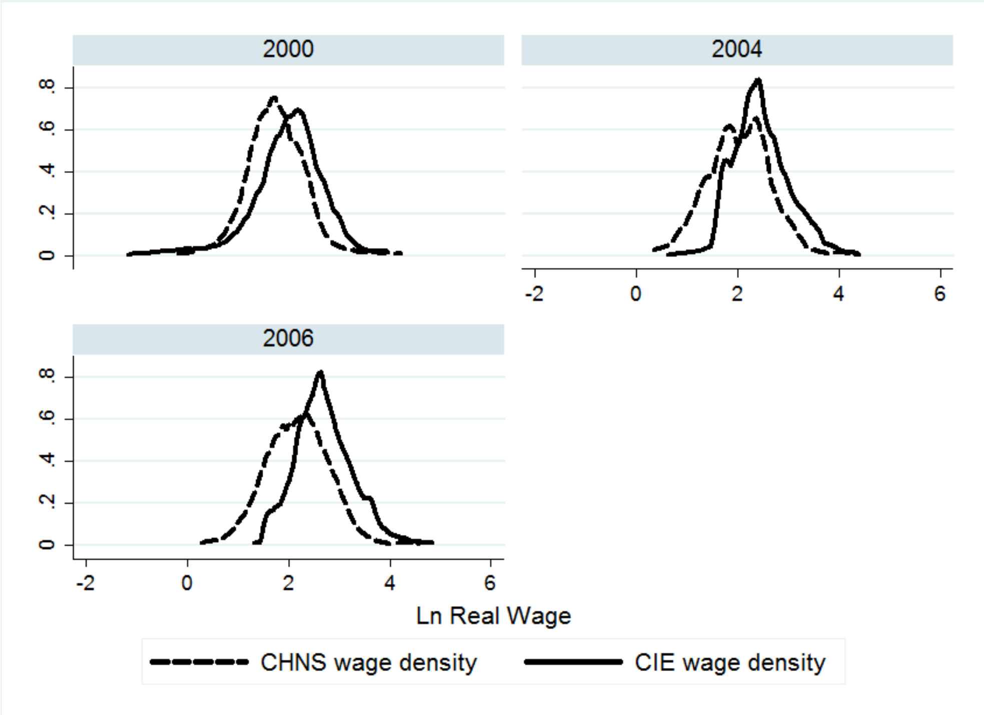


Figure 3.1: Log real wage* distributions in 2000, 2004 and 2006

**Real wages in CIE are firm-level annual averages in the unit of 1000 Yuan at the price level in 1998. CHNS real annual wages are calculated by multiplying hourly wage rates by* $40hrs/week$ *and* $\frac{365}{7}weeks/year$, *and dividing by 1000 Yuan. All figures from CIE data are weighted by the number of workers in each firm. In both datasets, the top and bottom 0.5% of observations are excluded in each year.*

This phenomenon clearly indicates that the two datasets are probably representing different populations. It is therefore important to understand why the CIE data is different from the CHNS data and/or the Chinese national labour market, and what the difference means in respect to what can be inferred from the CIE data about the Chinese national labour market. Considering the differences in data characteristics discussed in previous section, the inconsistency of the wage dispersion between the CHNS data and CIE data may come from five possible sources:

Source 1: The overall increase in the wage dispersion comes from the divergence in non-industrial wages that are not covered in CIE. *Assuming the means of wages are identical, non-industrial firms should take up a significant share of employment and are more dispersed.*

Source 2: Inter-sector wage differentials are widening so as to counteract the contraction of wages in the industrial sector. *Assuming wage variances are identical, the firms not included in CIE should take up a significant share of employment and pay a different wage premium.*

Source 3: Within-firm wages are not identical because of differences in the worker composition. *Under the condition that CIE is an unbiased sample of Chinese firms, within firm wage variances should be skewed due to workers' attributes.*

Source 4: CIE data are more comprehensive than the CHNS data due to included more provinces that are less dispersed in terms of wages than are those in CHNS. *Assuming the regional wage distributions of CIE and CHNS are representative and identical, the difference in the aggregate wage distributions should be the result of missing provinces in CHNS sample.*

Source 5: There is an institutional change in 2004 that has more of an effect on labour in the industrial sector and/or in large firms.

It is difficult to exam directly whether the sectoral differences are the reasons for the inconsistency. It is thus unlikely to find direct evidence for Sources 1 & 2, although an indirect alternative comparison of the difference in the coverage between different types of enterprises in the datasets is possible.

In Table 3.2, the employment share by the ownership type of firms from the CIE, the CHNS and the Labour Yearbook are summarized. The CHNS data is clearly closer to the Labour Yearbook in respect to SOE and other employment types, while the collectively-owned employment figures are similar between the CIE and the Labour Yearbook, but slightly higher in the CHNS.

In Table 3.3, it can be found that very few small firms are included in the CIE. It is thus clear that the CIE covers more non-state-owned firms and more large firms, and is therefore not a representative sample of all enterprises in all sectors in China. There is no similar data for the Labour Yearbook.

By assuming that wages have identical means but different variances across sectors and firm-size groups, the recalculation of the aggregate wage standard deviation, using the within-group wage standard deviations (from CHNS) and employment shares of different type firms, suggests that less than a third of the wage variation difference between the two datasets can be explained.

Table 3.2: The employment share by ownership type

	CIE[a]			CHNS			Labour Yearbook[b]		
year	State-Owned[c]	Collective-Owned	Other	State-Owned	Collective-Owned	Other	State-Owned	Collective-Owned	Other
1997				54.99%	29.86%	15.15%	70.70%	14.10%	15.20%
1999	50.15%	17.18%	32.68%				69.80%	12.90%	17.30%
2000	43.77%	15.34%	40.89%	52.20%	22.86%	24.94%	68.40%	11.60%	20.00%
2001	37.93%	12.98%	49.08%				65.20%	10.20%	24.60%
2002	33.06%	11.36%	55.58%				62.70%	9.10%	28.20%
2003	27.35%	8.64%	64.01%				60.50%	8.10%	31.50%
2004	20.94%	7.42%	71.64%	52.73%	12.19%	35.08%	56.90%	7.10%	36.00%
2005	17.94%	5.17%	76.89%				54.90%	6.50%	38.60%
2006	15.47%	4.80%	79.73%	46.57%	10.75%	42.68%	53.40%	6.00%	40.60%
2007	12.95%	4.35%	82.70%				52.90%	5.40%	41.70%
2009				44.51%	8.42%	47.06%	51.10%	4.90%	44.00%

[a] *Employment share in the CIE data is weighted by the number of workers in each firm.*

[b] *There are only urban employment data available for this measurement. This includes workers working in urban registered units.*

[c] *In CIE data, firms with over half of their capital owned by states are defined as state-owned, the firms with over half of capital owned collectively are collective-owned, and the rest as other. The selection of the capital share thresholds is artificial. Fortunately, the results do not change significantly within the range of thresholds* $(20\%, 50\%)$. *Given that the CIE has less public sector employment, increasing the threshold will make the gap between the CIE and the CHNS data even larger, and may overstate the importance of ownership*

Table 3.3: The employment share by firm size

	CIE[a]			CHNS		
year	< 20	20−100	>100	<20	20−100	>100
1997				18.26%	28.73%	53.01%
1999	0.05%	5.64%	94.32%			
2000	0.05%	6.13%	93.82%	21.23%	31.62%	47.15%
2001	0.06%	7.11%	92.83%			
2002	0.06%	7.66%	92.28%			
2003	0.07%	8.32%	91.61%			
2004	0.11%	11.22%	88.68%	23.96%	33.51%	42.52%
2005	0.09%	10.61%	89.30%			
2006	0.10%	11.30%	88.61%	29.34%	34.29%	36.37%
2007	0.11%	12.04%	87.85%			
2009				30.78%	36.65%	32.57%

[a] *Employment share in the CIE data is weighted by the number of workers in each firm.*

By assuming that wage distributions have identical variance but different means, a similar recalculation of inter-group wage dispersions, using employment share as weights and average wages of groups (from CHNS), shows that up to 60% of the difference in the wage dispersions between the two data sets can be explained.

In addition, if observations in respect to small firms (with less than 20 workers) are excluded from both datasets, wage variations do not change significantly compared to the full samples. Thus, the sample differences come from sectoral labour market differences, but not from the absence of small firms.

Altogether, this supports the contention that Source 1 and 2 are both important sources of sample bias in the CIE. Non-industrial firms bring non-negligible differences to the analysis using CIE data, in terms of the differences of the within-sector wage dispersions, and the wage differentials between sectors.

Source 3, meanwhile, is difficult to test because the CIE data do not record workers attributes. To make it testable, this study assumes that the within-firm wage distributions are independently and identically distributed in each year. In that case, the wage distribution in CIE and the counterfactual wage distribution over individual attributes in CHNS should display similar trends over time. According to the estimation from the CHNS data presented in Chapter 2, individual attributes (age, education, gender and occupation) can account for less than 16% of the change in wage dispersion. Conditional on that, the changes in individual factors and the firms characteristics are orthogonal; if the wage distributional difference between CIE and CHNS merely came from a lack of information of within-firm individual wage differentials, it has to be true that wage dispersion increases in CIE but less than in CHNS.

Source 3 is therefore controversial. On the one hand, it is consistent with the fact that if individual attributes did not change, wage dispersion would have increased less. On the other hand, the effect of keeping individual attributes constant cannot completely offset that of the other factors. At least, the lack of workers information and within firm wage distribution is not the only source for the sample inconsistency.

To check Source 4, this study takes the CIE observations from the nine provinces in which the CHNS survey was conducted to form a sub-sample to compare with CHNS. The results show that the CIE sub-sample is almost identical to the full CIE sample.[2] The difference between wage distributions in CIE and in CHNS cannot be explained at all by regional effects, therefore, and, accordingly, it is not plausible to conclude that differences in the regions is a reason for the wage distributional difference between CIE and CHNS.

For Source 5, two important candidate institutional reforms are: the strengthening of and increases in minimum wages and the international trade liberation experienced in China. Minimum wage legislation affects large firms more probably because that small firms may have informal contracts with workers, and are not registered with the supervision department. The results of Ma et al. (2012) implied that the lower tail of wage distribution is reduced by increasing the minimum wage. It is also consistent with the fact that CIE has a lower wage dispersion than in CHNS. In addition, over 90% of Chinese exports are manufacturing goods. Chinas joining of WTO in 2004 is therefore likely to have affected industrial firms more than the other firms. Under the assumption of competitive markets and a comparative advantage in low-skilled workers, the international trade liberation should have reduced the wage gap between low-skilled and high-skilled workers.

To summarise, apart from the regional factor, sectoral, individual and institutional biases can be sources for the data inconsistency in the CIE. Above all, it is the sample selection bias that is the most important reason for the inconsistency: because the CIE only contains industrial firms, its inter-firm wage dispersion becomes smaller and it is more affected by institutional reforms. The within-firm individual wage differentials may have an effect here as well.

[2] Wage averages and standard deviations in all years of the sub-sample are the same as those of the full sample up to three decimal places.

3.3.2 Summary Statistics of CIE

The characteristics of the firms in question are summarised by year in Table 3.4. The variation of log wages can be seen to have gone down between 2000 and 2004, unlike in the CHNS data. The number of workers per firm, as well as the variation in numbers of workers per firm, have each decreased. This implies that Chinese industrial firms are converging to a smaller size. Nevertheless, the total real sales of each firm are increasing on average and diverging over time. State-owned capital share is converging to a lower level as well. This is consistent with the Chinese governments policy of "marketization" and SOE reform. As a result, government intervention in firms operations, typically in hiring and wage decisions, has decreased.

In Table 3.5, minimum wages[3] are summarised together with the fractions of employment that complies with them each year. It can be seen that the real minimum wage has almost doubled from 2000 to 2007, while the share of workers earning above it has also increased. This implies that not only are workers earning more, but also more firms are complying with Chinese minimum wage policy. In the empirical analysis in this chapter, the counterfactual wage density depends on employment above the minimum wage in 2004. Thus, the last two columns, which indicate an increasing fraction of workers earning above the 2004 minimum wage, were calculated either using the average minimum wage or the provincial wage.

3.4 Empirical Results

The empirical results are summarised in Table 3.6. From 2000 to 2004, the log wage standard deviation decreased by 0.175 (excluding the extreme 0.5% of values from both tails). Wage distribution tended to become more concentrated in the lower half, but to disperse in the upper half. The percentage figures in the table indicate how much of the total change can be accounted for by different factors. Both primary sequence and reversed sequence decompositions are presented.

[3]Minimum wages in China are different between provinces. The national average minimum wage used in this study is therefore the weighted average of the provincial minimum wages. The data on minimum wages comes from Wang and Gunderson (2011), who gained data from the *labournet* (—hong Guo Lao Dong Wang), which is supervised by the Ministry of Human Resources and Social Security of the Peoples Republic of China. Only registered members (annual membership fee: 3,500 Yuan) can access the information.

Table 3.4: Summary of firms' characteristics from 1999 to 2000

	Ln Wage[a]		Worker[b]		Sales (1m Yuan)		State-Owned Capital Share[c]		Export[d]
Year	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
1999	1.853	0.813	372.625	1735.012	1017.491	4227.850	48.28%	0.470	38.31%
2000	1.968	0.792	353.597	1544.334	1162.607	5422.519	42.14%	0.465	40.51%
2001	2.059	0.815	325.420	1421.397	1138.708	4877.122	36.37%	0.452	40.94%
2002	2.167	0.820	310.429	1366.663	1245.360	5099.247	31.36%	0.436	40.98%
2003	2.281	0.775	295.591	1275.329	1498.071	5922.953	25.76%	0.411	42.90%
2004	2.456	0.605	241.745	1092.856	1749.030	7258.052	19.76%	0.377	46.94%
2005	2.567	0.586	254.651	1187.210	2369.392	10077.231	16.76%	0.352	46.20%
2006	2.695	0.596	245.236	1193.332	2914.694	12747.998	14.51%	0.331	46.24%
2007	2.824	0.615	234.282	1155.572	3355.521	14425.195	12.41%	0.311	43.97%

[a] *Ln wage and sales are reported in real terms at the 1998 price level, weighted by the number of workers in the firms.*
[b] *Worker summarises the number of workers employed in a firm each year.*
[c] *State-owned capital share is the average fraction of state-owned capital over the total capital of firms, weighted by the number of workers in the firm.*
[d] *Export is the fraction of workers employed in any firm that exports.*

Table 3.5: Statistical summary of minimum wage and relative employment share

Year	National Average Minimum Wage[a] (1000 Yuan)	Fraction of Workers above National Average Minimum Wage[b] (%)	Fraction of Workers above Provincial Minimum Wage[c] (%)	Fraction of Workers above 2004 National Average Minimum Wage[d] (%)	Fraction of Workers above 2004 Provincial Min Wage[e] (%)
2000	3.915	85.4%	86.2%	63.6%	68.4%
2001	4.172	86.6%	87.3%	69.0%	73.3%
2002	4.679	86.8%	87.1%	74.7%	78.2%
2003	5.185	87.0%	88.4%	80.1%	82.9%
2004	6.004	89.5%	92.4%	89.5%	92.4%
2005	6.403	91.2%	92.5%	93.4%	95.2%
2006	7.207	91.1%	93.0%	95.7%	97.4%
2007	7.798	91.4%	92.2%	97.1%	98.6%

[a] *National average minimum wage is the average provincial minimum wage weighted by the number of workers. It is reported in real terms, deflated to the 1998 price level.*

[bc] *These two measure the size of labour earnings above the national average and the provincial minimum wage of the respective years.*

[de] *These two measure the share of employees earning above the national average and the provincial minimum wage in 2004.*

Table 3.6: Effect of institutional changes and minimum wage on wage distribution, 2000-2004

	Std. Dev.[b]	05-95[c]	10-90	25-75	10-25	10-50	50-90	75-90
Total Change[a]	-0.175	-0.575	-0.202	-0.087	-0.196	-0.285	0.083	0.081
Primary Sequence:								
Institution	2.83%	-1.60%	-31.91%	-12.73%	-15.53%	-6.11%	56.80%	28.35%
National Min Wage	44.58%	59.89%	53.20%	-9.97%	59.72%	38.39%	2.28%	1.09%
Provincial Min Wage	34.65%	44.69%	29.22%	6.77%	27.06%	20.71%	-0.06%	-0.13%
Reversed Sequence:								
National Min Wage	48.56%	54.76%	26.01%	0.00%	26.81%	18.44%	-0.02%	-0.02%
Institution	-2.43%	3.53%	-4.72%	-22.69%	17.38%	13.84%	59.11%	29.46%
Unexplained	52.58%	41.71%	78.71%	122.69%	55.81%	67.72%	40.91%	70.56%
Provincial Min Wage	39.91%	40.51%	24.51%	0.46%	25.03%	17.37%	-0.04%	-0.08%
Institution	-1.14%	2.59%	-27.20%	-6.41%	-13.51%	-2.78%	56.79%	28.30%
Unexplained	62.51%	56.91%	102.69%	105.95%	88.47%	85.41%	43.25%	71.78%

[a] *The effects are presented as the percentage of the total change. A positive number means a negative effect on wage dispersion, and vice versa.*
[b] *This is the standard deviation of log real wage, deflated at the 1998 price level. The top and bottom 0.5% from both tails are excluded.*
[c] *These are the percentile gaps. For example, 05-95 is the gap between the* 95^{th} *and* 05^{th} *wage percentile.*

From Table 3.6, it can be seen that the overall wage dispersion and the lower half of the wage percentile gaps decreased between 2000 and 2004. If the institutional and minimum wage changes had not occurred, 37% to 47% of the decrease in the standard deviation of log wage would not have occurred. Moreover, 15% to 32% of the decrease in the $10^{th} - 50^{th}$ percentile gap can be accounted for.

On the other hand, the $50^{th} - 90^{th}$ percentile gap increased. If the institutional factors and minimum wage remained at their 2000 levels, 57% to 60% of the increase in wage percentile gaps could have been reduced. The effect of change in institutional factors and minimum wages are consistent in sign in both sequential decompositions.

3.4.1 Minimum Wage Effect

Under Assumptions 1, 2 and 3, the minimum wage has a substantial effect on wage distribution, especially on the lower half. In both sequences it is consistent that if the minimum wage did not increase over time, between 35% and 49% of the decrease in log wage standard deviation would not have occurred. In addition, between 17% and 38% of the decrease in the 10^{th}-50^{th} percentile gap would not have occurred. The effect of increasing the minimum wage on the top half of the wage distribution is negative. This means that, if the minimum wages remained at their 2000 levels, the increase in the 50^{th}-90^{th} wage percentile gap would have been 0% to 2% more. This result turns out to be consistent with that in previous studies in both China and overseas that minimum wage increases mainly affect the lower part of the wage distribution.

The effect of the national average minimum wage is about 10% higher than the average effect of provincial minimum wages in accounting for a decrease in wage standard deviation. Given that the more the minimum wage increases, the larger its effect in terms of reducing wage dispersion, it must be the case that the marginal effect of minimum wages is decreasing in firm wages. This also indicates that provinces with higher minimum wages have smaller marginal changes in wage dispersion. This is consistent with large migration in China, and is evidence for weak geographical barriers.

In summary, increases in the minimum wage can reduce the overall wage dispersion. Its effect, however, reduces according to wage level and does not support geographic segregation in labour market. These results rely highly on the assumptions applied to determine how changes in the wage structure are associated with the minimum wage. Alternative assumptions may reveal a different result.

Spillover Effect

As discussed in Section 3.2, there is a positive spillover effect of minimum wages in the Chinese labour market. Studies from the CHNS and CIE data, however, show that the minimum wage effect decreases according to increasing wage levels. This will cause logarithm wage gaps to become smaller, and make the minimum wage effect larger in magnitude.

The spillover effect is not included in this study because there are still unresolved issues relating to supply and demand changes. It is important to distinguish between wage premium changes accounted for by minimum wage and by supply and demand changes. Changes in labour profiles are not available in the CIE data, however, which makes decomposition of wage premium changes very inaccurate. Chapter 4 will discuss this in more detail and solve part of the problem. More still needs to be done, however.

Between Two Minimum Wages

The alternative assumptions for Assumption 2 are Assumption 4 and 5. The results using Assumptions 4 and 5 are presented in Table 3.7 for both national average minimum wage and provincial minimum wages. These are consistent in sign in most measurements with the results using Assumption 2. With Assumptions 4 and 5, the effect of the minimum wage on log wage standard deviation and $10^{th} - 50^{th}$ percentile gap is smaller than when using Assumption 2. Nevertheless, their effect on the $50^{th} - 90^{th}$ wage percentile gap is negative, although the magnitudes ranges from 0% to over 100% depending on the decomposition sequence.

The sequence of decomposition becomes more important when using Assumptions 4 and 5 than when using Assumption 2. A plausible explanation for this is that, under Assumptions 4 and 5, minimum wage changes and institutional changes are not orthogonal. Institutional changes can magnify the effect of the minimum wage on the upper half of the wage distribution by almost truncating the wage tail below the 2002 minimum wage, which makes the wage distribution become more skewed to the right.

These results show that whether the increases in the minimum wage only affected the wage distribution between the minimum wages in 2000 and in 2004, or the whole wage tail below its 2004 level, its effect was a reduction in the wage dispersion. Such an effect is significant on the lower part of wage distribution but may decrease in line with higher wages.

Table 3.7: Effect of minimum wage under different assumptions

Assumptions[b]		Std. Dev.[c]	05-95[d]	10-90	25-75	10-25	10-50	50-90	75-90
	Total Change [a]	-0.175	-0.575	-0.202	-0.087	-0.196	-0.285	0.083	0.081
Primary Sequence									
1, 2, 3	National Min Wage	44.58%	59.89%	53.20%	-9.97%	59.72%	38.39%	2.28%	1.09%
	Provincial Min Wage	34.65%	44.69%	29.22%	6.77%	27.06%	20.71%	-0.06%	-0.13%
1, 3, 4, 5	National Min Wage	26.51%	34.03%	97.84%	118.26%	40.72%	35.04%	-118.16%	-18.46%
	Provincial Min Wage	8.83%	7.19%	42.31%	58.37%	14.93%	2.94%	-93.11%	-6.68%
1, 2, 6	National Min Wage	66.55%	72.70%	113.84%	114.60%	57.32%	44.76%	-123.72%	-22.14%
	Provincial Min Wage	56.75%	57.58%	104.36%	121.28%	43.84%	37.40%	-125.94%	-23.94%
1, 4, 5, 6	National Min Wage	26.51%	34.18%	97.73%	117.77%	38.96%	33.03%	-124.79%	-22.95%
	Provincial Min Wage	9.07%	7.29%	42.42%	58.13%	13.92%	0.82%	-100.67%	-9.67%
Reversed Sequence									
1, 2, 3	National Min Wage	48.56%	54.76%	26.01%	0.00%	26.81%	18.44%	-0.02%	-0.02%
	Provincial Min Wage	39.91%	40.51%	24.51%	0.46%	25.03%	17.37%	-0.04%	-0.08%
1, 3, 4, 5	National Min Wage	6.39%	16.90%	11.08%	0.00%	11.42%	7.86%	-0.01%	-0.01%
	Provincial Min Wage	9.38%	14.82%	14.86%	0.24%	15.22%	10.54%	-0.01%	0.00%
1, 2, 6	National Min Wage	48.94%	55.40%	26.86%	-1.48%	27.80%	18.30%	-2.59%	-1.33%
	Provincial Min Wage	40.17%	42.22%	23.16%	-2.68%	22.85%	15.77%	-2.26%	-5.38%
1, 4, 5, 6	National Min Wage	5.99%	16.04%	10.01%	-1.39%	10.47%	6.43%	-2.30%	-1.13%
	Provincial Min Wage	9.03%	14.46%	12.80%	-0.95%	13.08%	8.33%	-2.58%	-1.32%

[a] *The effects are presented as the percentage of the total change.*

[b] *Assumptions are represented by their number given in Section 3.2*

[c] *This is the standard deviation of log real wage, deflated to the 1998 price level. 0.5% from both tails are excluded.*

[d] *These are the percentile gaps. For example, 05-95 is the gap between the 95^{th} and 05^{th} wage percentile.*

Disemployment

Replacing Assumption 3 with Assumption 6 for the disemployment effect estimated by Ma et al. (2012), it can be seen that the effect of the minimum wage is very similar under the two assumptions. The only difference is that the magnitudes become much larger in the primary sequence under Assumption 6. This is because the disemployment effect allows a reweighting of the wage distribution between the minimum wage and median wage, which is correlated with institutional changes.

In summary, increasing the minimum wage can account for a significant proportion of the reduction in the wage dispersion under different sets of assumptions. Especially in the lower half of the wage distribution, the effect of the minimum wage is large. In the higher wage groups, meanwhile, the minimum wage also has an negative effect on wage dispersion; although it is unclear how much the minimum wage can affect the upper half of the wage distribution. Under different assumptions, such effects can be large or small.

3.4.2 Institutional Changes

Institutional changes include a reduction in the size of firms, a decrease in the employment share of SOEs and increasing exposure to exports. In total, if there were no institutional changes between 2000 and 2004, up to 3% of the wage dispersion reduction would have been eroded (Table 3.6). With reserved sequential decomposition, institutional changes reveal a 2% positive effect on wage dispersion. It is thus unclear whether institutional changes disperse or concentrate wages in the CIE sample between 2000 and 2004.

Looking at the institutional change, however, the effects on the wage percentile gap do change; it is clear that if institutional factors were at their 2000 levels, between 57% and 59% of the dispersion in the $50^{th} - 90^{th}$ percentile gap would have been reduced. This means that institutional changes have a positive effect on wage dispersion at the upper half of the wage distribution. The effect of institutional factors on the lower half of the wage distribution is unclear, however. With a national average minimum wage and a reversed sequence of decomposition, the effect of institutional changes is negative on wage dispersion at $10^{th} - 50^{th}$ percentile gap. In other cases, the effect is positive.

The overall results of institutional changes in the CIE data are consistent with that in the CHNS data in most measurements. Nevertheless, the explanation is different. In the CIE data, small firms are more dispersed in wages (Table

Table 3.8: Within-group average wages and wage standard deviations in 2004

	Ownership			Export		Firm Size		
	SOEs[a]	COEs[b]	Other	N[c]	Y	<20	20-100	>100
Mean[d]	2.661	2.347	2.411	2.376	2.561	2.419	2.334	2.475
Std. Dev.	0.610	0.570	0.517	0.565	0.524	0.584	0.498	0.557

[a] *SOEs are state-owned enterprises; firms with over 50% state-owned capital.*
[b] *COEs are collectively-owned enterprises; firms with over 50% collectively-owned capital.*
[c] *N means that the firm's export is zero. Y means that firm has positive exports.*
[d] *Mean and Std. Dev. are the weighted average and standard deviation of log real wages in 2004.*

3.8). Growing numbers of small firms can therefore increase wage dispersion. In addition, a reduction in state-owned capital meant that more employees were working for the private sector, and firms become less dispersed in ownership type. Given higher within-group wage dispersion in the public sector, the wage dispersion is reduced by privatization.

These results contradict those that were discovered from the CHNS data. Although both datasets show that fewer people are working in public firms, in CHNS, public firms employment does not drop below 50%, i.e. the ownership type becomes more dispersed as opposed to in CIE. Another difference is that in the CHNS data, within-group wage dispersion increases in private ownership, while in the CIE data the opposite is true. A plausible reason for this is that public firms are more diverse in industries in the industrial sector, and private firms are more diverse in other sectors, e.g. services.

The effect of institutional changes on the upper half of wage distribution is larger comparing to in the CHNS data. One reason for this is that the change in export policy has been considered in addition to firm size and ownership. Although exporting firms are less dispersed in terms of wage, the growing number of workers working in the export sector and a high wage premium in export firms meant that wage dispersion increased. Another possibility is that institutional changes affected the CIE sample more than the CHNS sample. For example, the employment share of the private sector increased by 30.75 percentage points in the CIE data, while it increased by 10.14 percentage points in the CHNS data.

In summary, the results from the CIE and CHNS data are, overall, very similar. The explanations for the results that are suggested by the data are different, however. The implications derived from the inconsistency of the privatisation effect on wage dispersion between CIE and CHNS are very important: 1) industrial workers and firms are more homogeneous than those outside the industrial sector; 2) 2000 to 2004 was a time when the industrial and non-industrial sector started to diverge. In addition, higher exposure to exports can cause wage dispersion.

3.5 Conclusion

In this chapter, the effect of the minimum wage on wage dispersion has been analysed, together with the effect of institutional changes. Using a semi-parametric model similar to that of DiNardo et al. (1996), assumptions have been made about wage density movement under an increasing minimum wage. As a result, changes in the minimum wage can explain up to 49% of the decrease in log wage dispersion in the industrial sector.

Estimation of the minimum wage effect shows that increasing the minimum wage can reduce overall wage dispersion by eliminating the lower tail of the wage distribution. The marginal effect of the minimum wage decreases in wage, which also indicates the weak geographical labour market segregation in China.

Assumptions about disemployment, spillover and the wage tail under the minimum wage play an important role in generating the minimum wage effect on wage distribution. From the discussion, the result of the minimum wage effect can be concluded to be robust in terms of their sign, but the magnitudes vary. The minimum wage effect on wage density is minute if the same estimation is applied to the CHNS data, indicating that the government enforces minimum wage policy more strongly in the industrial sector than in other sectors.

The effect of institutional changes disperses wage in the upper half of wage distribution, which is consistent with previous results from the CHNS. However, the reasons are different. In the CIE data, it is workers becoming more dispersed in terms of export exposure and firm size that made wages to be more dispersed. This result also indicates that private firms are less diversified in the industrial sector, but more so in the service sector.

There are two drawbacks of the work presented in this chapter: 1) a lack of consideration of the spillover effect; 2) the inability to take account of labour supply and demand shifts. Both issues derive from the fact that the CIE data does not contain employees profiles. Although there were studies about spillover effect and wage premium changes, without accounting for labour supply shifts and demographic-biased demand shifts, the results could be biased.

Chapter 4

International Trade Liberalization and Wage Distribution in the Chinese Industrial Sector

4.1 Introduction: International Trade and the Labour Market

Many countries, including China, promote exports to stimulate economic growth. China joined the World Trade Organization (WTO) on 11 December, 2001; although the countrys exports had already started increasing long before that. Joining the WTO, however, gave Chinas exports another boost. In line with the agreement, China started to lower its import tariffs from 2002. By 1 January, 2005, most of the commitments on import tariffs had been completed. By 1 January, 2010, all the commitments had been reached, with the aggregate tariff decreased to 9.8% from its pre-WTO level 15.3%.[1] On 1 July, 2015, Chinas protection period officially ended.

The expansion in exports, however, poses the questions of whether the Chinese people have benefited equally from international trade liberalization? If not, how much inequality has been created by the booming international trade? These are important questions because they directly affect social welfare, and thus should be taken into account in policy making. This chapter will address these two

[1]Data quoted from the regular press conference of the Ministry of Commerce of the People's Republic of China on 18 June, 2015. Link: http://www.mofcom.gov.cn/xwfbh/20150618.shtml

questions by focusing on the relationship between exports and relative wages in the Chinese industrial sector.

There have been various studies into the relationship between international trade and the domestic labour market, with most focusing on establishing the connections between trade, labour demand, wages and employment. In theory, increased exports expand the respective demand for labour, whilst more imports compete with domestic production and reduce the respective demand for labour (by lowering product prices and forcing some firms to exit the market). In principle, when labour demand changes, both equilibrium wages and employment may change, conditional on the labour supply. With non-fully-substitutable heterogeneous workers and firms, the change in wages and employment can result in a change in wage dispersion.

Following these ideas, many studies have been conducted in both developed/importing countries and developing/exporting countries on the international trade effect of wage premiums and employment.

Topalova (2010) studied the trade liberalization effects on income distribution in India. He used household survey data initially to show that there was no significant correlation between trade liberalization and labour mobility overall, and then that the greater an individuals level of consumption was, the more likely it was that that person had moved during the preceding ten years. Topalova's study suggests that even where overall income has increased significantly, the more trade-liberalization-exposed Indian rural areas exhibited less poverty reduction and slower consumption growth. These results support the contention that increased international trade has served to increase local income inequality in India. The mechanism Topalova postulated to explain these findings was that, in a labour-immobile and capital-perfect-mobile market, the relative price decrease in the capital-intensive sector will cause a more-than-proportional decrease in labour income in that sector while the income of the labour intensive sector increases; this in turn accelerates income inequality in the trade-liberalized area.

A similar example can be found in Mexico, where the labour is neither homogeneous nor perfectly mobile (Chiquiar, 2008). In 1994, Mexico joined North American Free Trade Agreement (NAFTA), representing its second stage of trade liberalization, having already established regional labour market heterogeneity across the country in wage premiums. Even after 1994, immigration flows between regions were small, especially those from Mexico City to the U.S. border. Given that foreign firms and exporting firms were much more concentrated towards the U.S. border for reasons such as transport costs, Chiquiar (2008) focused on the heterogeneous effect of trade liberalization on the changes in wage gaps in different regions. When the endogenous problems of regions, sectors and labour structures in the wage equation were accounted for by using an IV estimator based on state-level variables like infrastructure, the changes in Mexicos regional wage premiums were found to be strongly correlated with trade liberalization variables. Chiquiar (2008),however, did not discuss whether the IV variables were themselves exogenous. Things like fundamental infrastructure development can be provoked by forward-looking policies of investment to boost international trade. If that is the case, the labour mobility could have been undermined.

Both Topalova's (2010) and Chiquiar's (2008) methods depend greatly on the disconnection between trade liberalization and labour flows, which is unlikely to be the case in China. According to Liu and Qu (2008), using 2004 manufacturing industry survey data, 20%-30% of wage inequality in China can be attributed to industrial, regional and public-private sectoral barriers. Among all the market divisions, 4-digit industrial classification has the largest share of wage inequality accounting, while the share of the region is less than 10%. This is consistent with non-negligible labour migration among regions in China. In this study, therefore, the regional barrier is not an appropriate assumption and will therefore be abandoned.

Given the rapid growth in Chinese exports, research has been done on how that growth might affect the labour market of trade partners in terms of wage premiums and employment (e.g. Autor et al. (2012)), but there has also been increasing interest in the effect of growing exports on the China domestic labour market, especially after Chinas entry into the WTO. China has some unique features that may bring interesting results to the trade-labour literature: substantial labour migration, strict *hukou* restrictions, and powerful governmental interventions.

Previous research on China has mainly focused on the skill-biased demand changes that are associated with international trade and Foreign Direct Investment (FDI) (Shao and Liu, 2010b; Wang and Si, 2011). Because Chinas exports to high-income regions have accounted for the majority of its total export growth, both FDI and exports have served to increase the demand for technology-knowledgeable workforce and this has favoured skilled workers and raised wage inequality. The study of regional market barriers suggests that labour mobility frictions can explain about 20% to 30% of overall wage inequality (Liu and Qu, 2008). Yang and Jiang (2012), meanwhile, found that international trade expanded China's firms' productivity variance, which, in turn, potentially increases wage inequality. When the provincial fixed effect was considered, however, international trade does not seem to have a significant direct influence on the provincial wage Gini coefficient (Qu and Fan, 2012).

Most of these studies used provincial panel data from the China Statistics Year Books series (Shao and Liu, 2010b; Qu and Fan, 2012), although some of used Industrial Survey (in 2004 and/or 2008) firm level panel data (Liu and Qu, 2008; Wang and Si, 2011). A very few studies used Chinese Industrial Enterprises (CIE) data (from 1999 to 2007) on wage inequality accounting (Yang and Jiang, 2012). Given that provincial panel data gives results at the 2-digit industrial level, which is implied to be improper by Liu and Qu (2008) and by the results from this study, only the studies using firm-level data will be discussed in further detail.

Chen and He (2013) used firm level data from 2000 to 2009 to study the effect of exports on the wage premiums of skilled and unskilled workers. They developed a two-stage production version of the Melitz (2003) model, assuming that unskilled workers produce intermediate goods and skilled workers produce the final goods. In their empirical analysis, they used the rural individual income as an approximation for unskilled workers' wages and found a significant positive effect of export/export exposure on the wage premiums of skilled workers, while controlling for labour productivity, capital intensity, employment and the age of the firm etc. As part of their robustness checks, they used the lowest wages in all industries as an alternative measure for unskilled workers' wage and found similar results as before.

One issue with Chen and He's (2013) study, however, is their assumption that the composition of skilled and unskilled workers in each firm in 2004 (the only year that has this figure available) is the average and stable status from 2000 to 2004. As shown later, however, 2004 to 2005 was actually the period with the lowest employment in manufacturing and the smallest real wage gaps between export and non-export firms. One could argue that they had picked the time when unskilled workers employment was at a low point, thus exaggerating the export effect on wage gaps in other years. Whether exports do in fact disperse wages is yet to be concluded, therefore.

Yang and Jiang (2012) studied the effect of total factor productivity (TFP) on wage differences. When technological innovation occurred, good firms (those with more productive workers, who are assumed to have lower learning costs) are more likely to adopt more productive new technology and should pay their employees higher wages than before, which in turn should increase wage inequality. Using 1999 to 2007 manufacturing firm level data in a standard Cobb-Douglas production function, Yang and Jiang (2012) found that average wages and wage inequality increased with TFP. In their calculation, firms' export share out of their total production was controlled, and did not have a significant effect on wages.

Several other papers have also studied the effect of increasing exports and improving technology on wage. They used different datasets and found that exports have a moderately positive effect on wage inequality (Wang and Si, 2011). On the other hand, they could not agree on whether technological upgrading reduces or enhances wage inequality.

In summary, previous studies do not agree on whether export expansion or productivity improvements affect wage inequality. The main problem in these studies is that they did not consider time-variant unobservables, for example, increasing computer and foreign language literacy of labour, and labour supply shifts. This chapter will propose a fixed-effect estimation, using a first-difference model to analyse the issue.

The structure of the rest of this chapter is: section 4.2 will discuss the characteristics of the data to be used; section 4.3 introduces the methodology for empirical analysis; section 4.4 is where empirical results will be discussed; section 4.5 is the conclusion.

4.2 Data Description

4.2.1 CIE Sample

In this chapter, CIE is used as described in Chapter 3. Comparing to the national statistics, the annual total values of exports in the CIE vary between 60% and 71% of the annual national manufacturing exports between 1999 and 2007 (Table 4.1). Within the sample, more than 99% of firms reported a number for exports and about 97% of these seem reasonable (i.e. $exposure = export/sales \in [0, 1]$, denoted as the ep01 sample in the following discussion), no more than 24% of which reported a non-zero exports. It is possible that some firms underreported their exports, or the national statistics on export contained a significant fraction of re-exporting business, neither of which are the focus of this study. Considering just those firms who reported a number for exports, it can be found that a large proportion of them are pure exporters or pure non-exporters (Figure 4.1).

About 2.9% of observations reported an irrational exposure figure. Comparing

Table 4.1: Fraction of the CIE exports to the national exports

Year	1999	2000	2001	2002	2003
EX_{CIE}/EX_{UN}	57.98%	55.79%	59.07%	59.62%	59.81%
EX_{CIE}/EX_{YB}	62.29%	60.34%	63.81%	63.62%	63.46%
Year	2004	2005	2006	2007	
EX_{CIE}/EX_{UN}	66.72%	62.00%	61.51%	61.08%	
EX_{CIE}/EX_{YB}	70.37%	65.23%	64.19%	63.39%	

EX_{CIE} is the total level of exports calculated from the CIE data. EX_{UN} is the total level of manufacturing export calculated from the N Comtrade database. EX_{YB} is the total level of annual manufacturing exports provided by the China National Statistical Yearbook.

the characteristics of firms in the ep01 sample with the remainder, it can be found that those firms with less than 0 or greater than 1 export numbers have smaller sales, assets and average wages and a larger number of workers (Table 4.2). To test the randomness of the ep01 sample, Welch's tests are used on total sales, assets, average wages and number of workers between the ep01 sample and non-ep01 sample, under the least-strict assumption that two samples have different distributions. It turns out that firms outside the ep01 sample are always having fewer assets and lower sales (significant at the 95% confidence level). In terms of average wages and the number of workers at firm level, however, the results are controversial (Table 4.2). In general, the firms that did not report exports, or who reported irrational numbers have more employees, fewer sales and assets, and pay lower wages. The result given by the ep01 sample can be biased, therefore.

4.2.2 Exports

As mentioned previously, less than 25% of firms' exports are positive and can account for about 60% to 70% of the national total industrial exports. From 1999 to 2007, as total sales and exports increased (excluding 2007, probably due to the financial crisis), fewer and fewer workers were employed in the industrial sector, where the average wages and wage variances were getting higher (Table 4.3). So far, there has been no turning point in Chinese population growth, and the agrarian labour force has kept decreasing. It must, therefore, be the case that more and more workers are employed in non-tradable service sectors. It is possible that the service sector offers better pay to workers due to an increase in domestic demand for services and attracts more workers than the manufacturing sector does.

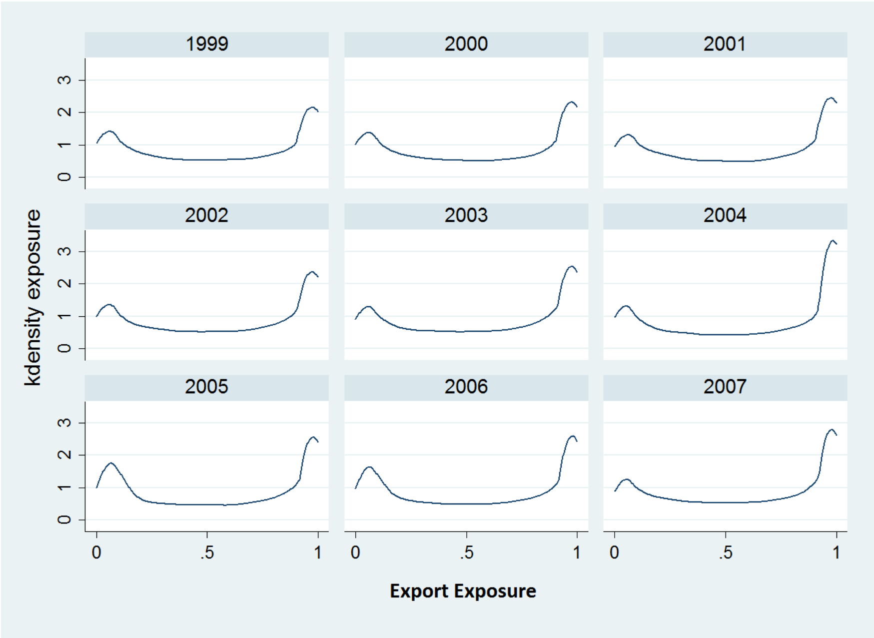


Figure 4.1: Distribution of export exposure, positive export firms only

Using the model of DiNardo et al. (1996), had the export exposure stayed the same as in 1999, the real wage standard deviation would have increased by 2.25% less by 2007, and the log wage standard deviation would have decreased 12.47% less. How to interpret that? The model assumes no significant change in the wage premium between workers in exporting and in non-exporting firms. As a result, the effect of increasing export exposure on wage dispersion by changing industrial employment is very small. This suggests that either the booming of China's exports in the early twenty-first century contributes little to wage dispersion, or it contributes by changing the wage premium of exporting firms, which is the focus of this chapter.

Welch's tests (Table 4.4) show the gaps between non-exporting firms and exporting firms, with the latter persistently having significantly higher sales, more assets, more workers and higher wages. Interestingly, the wage gap (which is very large; usually more than 10% of the average wage) between export firms and non-exporters was decreasing immediately after China joined the WTO in 2001 until 2006. The empirical model will therefore focus on two questions: 1) does the export exposure affect wage premiums; 2) does the change in export status affect the gap of wage premiums?

Table 4.2: Differences[a] between EP01 sample and others

	Sales[b]	Asset[c]	Wage[d]	Worker
1999	-13690.830*	-27721.280*	0.211*	-45.422*
2000	-17264.060*	-25888.540*	0.250*	-17.472
2001	-19581.350*	-29946.050*	-0.146	-11.745
2002	-17189.730*	-27621.380*	0.059	34.446*
2003	-21818.690*	-35335.490*	-0.149	14.430
2004	-25578.830*	-23145.600*	-0.957*	22.939*
2005	-25538.000*	-29843.420*	-0.516*	68.916*
2006	-24271.800*	-20424.900*	0.075	88.900*
2007	-12859.390*	-26709.120*	-0.358*	94.106*

** Denotes the 95% two-sided level of significance to reject the null hypothesis that two samples have the same means, under the assumption of unequal distribution.*
[a] *The differences are calculated using the averages of the non-ep01 sample minus those of the ep01 sample. A negative value means that the non-ep01 sample has a lower mean value in that measure.*
[b] [c] *Sales and assets are at the firm-level and their unit is 1000 Yuan.*
[d] *Wage is annual wage per worker at the firm-level. The unit is 1000 Yuan.*

4.2.3 Exchange Rate

There is a clear turning point in exports (Table 4.3) in 2004. While the total value of exports and the total number of exporting firms kept growing, the percentage of exporting firms and the average export exposure of each firm reached a peak in 2004 and thereafter decreased, perhaps as a result of the abandonment of the RMB exchange rate peg with the USD in early 2005 (Figure 4.2). Nonetheless, more and more workers and firms have become involved in export production since the appreciation of the RMB.

After the abandonment of the strict exchange rate peg, the Chinese government introduced a so called managed floating exchange rate system, where the basic exchange rates of the RMB are set by the Peoples Bank of China (Chinese central bank) based on the demand and the supply of the RMB and the currency basket. The currency basket used by China includes the USD, JPY, EUR, KRW, SGD, GBP, etc.. There are about 20 currencies in total, the weights of which are not declared. Up to 3% variation in the exchange rates are allowed in execution.[2]. In addition, the RMB kept appreciating against the USD until 2012.

The RMB exchange rate serves as a monetary tool to stabilize the Chinese economy, which includes its international trade. According to the concept of

[2]For the RMB-USD exchange rate, the allowance is 0.3%.

Table 4.3: Summary statistics by year of sample EP01

Year	% of Exporters	Total sales[a]	Asset	Export	Worker (person)	Average wage	Wage S.D	Sales per worker	Exposure (%)
1999	0.20	38854.67	65538.71	5508.39	374.56	6.92	3.39	141.36	0.11
2000	0.21	44160.17	66877.16	6737.41	353.25	7.59	3.75	160.33	0.12
2001	0.22	44747.06	64008.61	7162.35	323.22	8.16	3.96	172.31	0.13
2002	0.23	48255.76	63632.04	7941.78	304.93	8.77	4.17	191.40	0.13
2003	0.24	55345.32	64797.26	9928.53	290.02	9.31	4.36	215.72	0.14
2004	0.28	51240.66	50507.73	11122.32	234.10	10.22	4.29	231.02	0.17
2005	0.27	61117.11	55114.67	11853.85	247.31	10.47	4.44	235.31	0.15
2006	0.25	62935.71	53127.61	12109.22	236.07	10.85	4.61	233.27	0.14
2007	0.22	63173.12	50789.01	10989.73	224.90	11.14	4.82	211.07	0.13

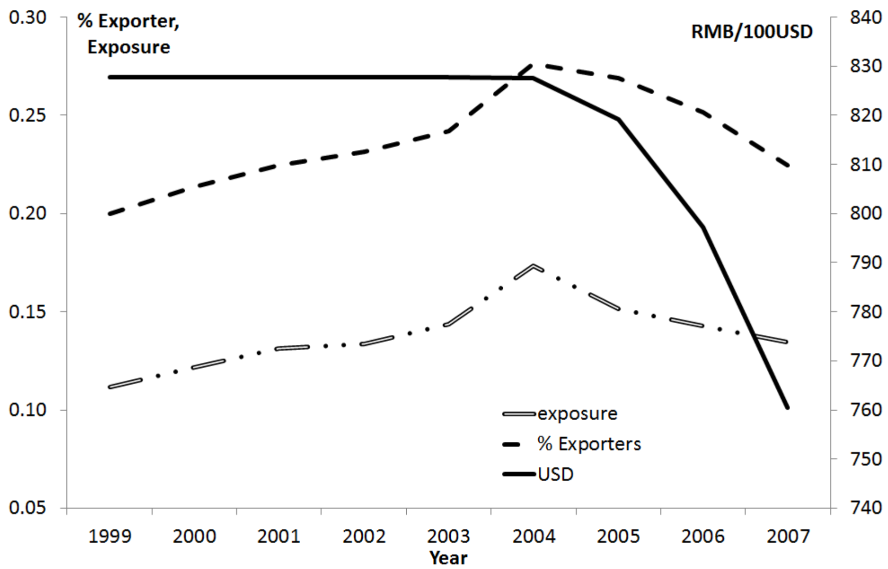


Figure 4.2: The time series of RMB/100USD exchange rate, fraction of export firms, and average export exposure

purchasing power parity, all other things remaining equal, the appreciation of the RMB could lead to a reduction of exports, and can be seen as an external shock to exports.

4.2.4 Productivity

In terms of the channels through which exports can affect wages, it is natural to consult the characteristics of the firms and their respective industries. There could be economies of scale, thus firm sizes are considered, and these can also be correlated with exports. Firms efficiencies or productivities are also important in determining wages in theory, given that wages should be an indicator of the marginal product of labour in a perfect competitive market equilibrium.

One way to measure the productivity of firms is the value-added per worker. The value-added at the firm level was only recorded after 2005, before which, value-added can only be computed from firms outputs, input sand VAT (value-added tax). To obtain a consistent measure of value-added, $VA = output - input + vat$ is used. The value-added per worker is then VA divided by the number of workers in a firm. Comparing this measure with the actual recorded ones after 2005, more than 98% of observations can be matched. In addition, the average error of the level of the measurement used here relative to that of the actual record is about 0.1%. The VA measure can therefore be said to be very accurate. There are observations where VA is positive but VAT is negative. In the year 2004, for example, the measurement error in VA is 2% to 4% higher than in the other years. The apparently outlying observations were excluded from the sample and, overall, measurement error is considered to be low in this study.

Originally, the value-added per worker is not significantly different between exporting firms and non-exporting firms. The value-added per worker for non-exporters, however, becomes increasingly higher than that for exporters (Table 4.4). The possible reasons for this are: 1) Chinas export tax rebate policy made less productive firms survive by exporting; 2) industries have different technologies and more labour intensive ones expand more in exports; 3) workers in non-exporting firms work substantially more hours than their counterparts in exporting firms; 4) the fixed cost to develop and expand in the domestic market is higher than that to export (the opposite to Melitzs model).

To understand how an export tax rebate can rescue less productive firms, it should be noted that, for pure exporters, VA is equal to net VA (VA minus VAT), which is not the case for non-exporters. Comparing two otherwise identical firms, therefore, one of whom is a pure exporter and the other a pure non-exporter, without a tax rebate policy, they should have the same marginal product of labour, thus have the same labour demand curve. With the export tax rebate, however, the labour demand curve of the latter would be lower than that of the former. In a competitive labour market, with the same labour supply, the exporter can provide higher wages or hire more workers. Furthermore, if the exporter is less productive than the non-exporter, with the tax rebate, it can still have a higher labour demand curve, giving higher wages and employing more people. For this reason, net VA is a better indicator to compare the productivity of different firms. From Table 4.4, it can be seen that the net VA gap is less than the VA gap. Nevertheless, the gap is still significantly positive, meaning that there is still some other reason for non-exporters being more productive.

Table 4.4: Welch's test of mean differences between non-exporters and exporters

Year		Sales	Asset	Average Wage	(Wage Diff. in % of Sample Mean Wage)	Worker (person)	Value-added per worker	Value-added net VAT per worker
Non exporter - Exporter Difference[a]								
1999	Means	-61200.12	-96954.52	-1.62	(-23.46%)	-439.48	0.97	0.78
	S.D.	3554.37	6192.73	0.02		19.36	0.55	0.55
2000	Means	-63398.66	-86621.75	-1.75	(-22.99%)	-397.60	1.22	1.13
	S.D.	3065.76	5293.44	0.03		16.21	0.52	0.52
2001	Means	-61784.52	-82333.64	-1.65	(-20.24%)	-350.50	4.40	3.94
	S.D.	2877.26	4655.69	0.03		14.17	0.50	0.50
2002	Means	-63236.26	-75894.19	-1.57	(-17.92%)	-313.59	7.74	6.35
	S.D.	3043.30	4479.58	0.03		12.75	0.55	0.55
2003	Means	-69477.12	-71652.79	-1.60	(-17.21%)	-299.29	12.31	10.20
	S.D.	3227.27	4122.77	0.03		10.73	0.59	0.59
2004	Means	-56312.35	-47523.35	-1.19	(-11.60%)	-233.52	14.24	10.78
	S.D.	2403.44	2022.01	0.02		6.41	0.59	0.59
2005	Means	-66098.14	-54261.12	-0.88	(-8.44%)	-248.10	19.03	15.88
	S.D.	2896.48	2670.67	0.02		7.12	0.78	0.78
2006	Means	-74460.00	-60884.87	-1.18	(-10.89%)	-267.94	22.75	19.22
	S.D.	3450.40	2621.02	0.02		7.42	0.73	0.73
2007	Means	-79129.24	-67268.06	-1.47	(-13.21%)	-283.57	37.92	33.22
	S.D.	4310.76	3548.46	0.02		8.08	0.64	0.64

[a] *The differences are calculated in real terms*

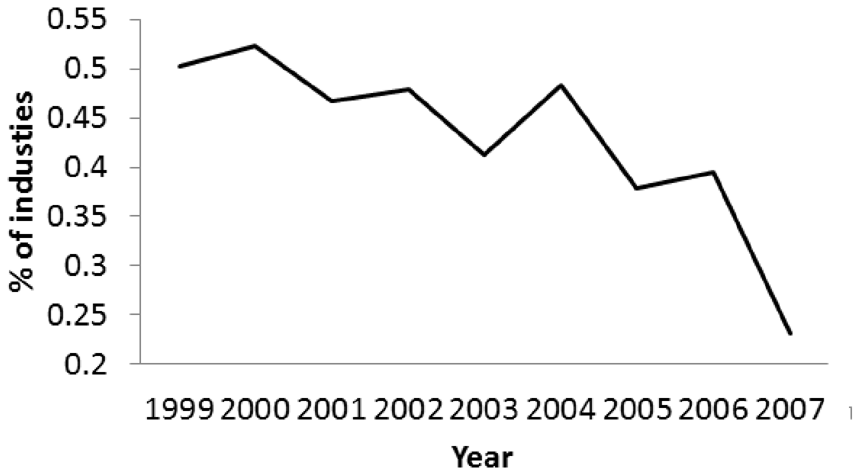


Figure 4.3: Proportion of industries with higher exporting VA per worker than that of non-export firms

To examine whether it is the differences in the industrial distribution of exporters and of non-exporters that matters, the industrial distributions of exporting and non-exporting firms are compared in this study. It is found that there is a distinct difference between the two distributions, with some industries indeed exporting more (Table 4.5). To test if it is the change in the industrial distribution that resulted in the odd value-added gap, the fraction of industries that have higher mean value added per worker for their exporting firms than that of their non-exporting firms is calculated for each year. The result of this calculation shows a clear decreasing time series (Figure 4.3), which means more and more industries are getting less productive in the exporting firms. This is a sign that the difference between industrial distributions is not the main reason for the interesting movement in the value-added per worker.

It is difficult to examine from the manufacturing firm level data whether workers are generally working harder in non-exporting firms, since the question is not asked in any other producer perspective dataset to the authors knowledge. Nevertheless, surveys from an individual perspective usually do not ask for the exporting status of the employers, nor even their specific industries. A very indirect way is to check household data, i.e. CHNS, for the correlation of working hours with the ownership types of firms and average working hours per day and then to check the correlation of firms ownership with their export exposure. The results, however, suggest that the opposite was the case, in that exporting firms have a lower state-owned or collectively owned share of capital, in which people are on average working longer hours. Of course, this is not a sufficient proof of

Table 4.5: Top 10 industries in the employment share of exporters and non-exporters

Top 10 non-exporting			Top 10 exporting		
Rank	Industry	Export Share	Rank	Industry	Export Share
1	Steel rolling processing	4.87%	1	Steel rolling processing	4.92%
2	Electricity supply	3.42%	2	Apparel and Textile Manufacture	3.22%
3	Coal Mining	3.27%	3	Cotton, chemical fibre textile processing	3.13%
4	Processing of crude oil and petroleum products manufacturing	2.76%	4	Computer accessories manufacture	3.09%
5	Cement manufacturing	2.55%	5	Automobile manufacture	2.97%
6	Cotton, chemical fibre textile processing	2.44%	6	Computer manufacture	2.93%
7	Thermal power generation	2.11%	7	Electronic components manufacture	2.85%
8	Automobile parts and accessories manufacturing	1.97%	8	Steel production	2.34%
9	Wire and cable manufacturing	1.97%	9	Coal Mining	1.99%
10	Commonly used non-ferrous metal rolling processing	1.92%	10	Automobile parts and accessories manufacturing	1.78%

longer working hours in either exporting firms or non-exporting firms.

Zhang et al. (2013) have discussed the negative relationship between exports and the value-added ratio[3] of industrial enterprises in China. After accounted for the ownership of firms, government tax rebates and subsidies, and distortions in the local factor markets, exports are still significantly negatively correlated with the value-added ratio. Their result strongly support that Chinese exports do not bring higher productivity to its firms. This is in line with Kaplinsky (2000); Humphrey and Schmitz (2002) and Gereffi (2005), who all show that developing countries can be very well captured in low value-added parts of the

[3]This is calculated as: Value-added Ratio (VAR) = Value-added (VA) / Total Product.

industrial chain and race to the bottom with each other. As Chinese terms-of-trade becomes worse (Zhang and Liu, 2006; Huang, 2008), an inability to change the export structure means Chinese exports becomes less and less profitable. At the same time, exporting firms still need to hire high-productivity workers to maintain their competitiveness in the international market.

A firms exports are therefore correlated with its value-added per worker, which also can affect the wages. It is thus important to notice this in the empirical model

4.2.5 Industrial Classification

There are 546 4-digit industries in the CIE, which produce a large variety of goods with different technologies, efficiencies and types of workers. It is possible that firms and workers compete in the sub-labour-market within each 4-digit industry, and that there is a barrier to migrate between the sub-labour-markets for firms and for workers. It is therefore important to account for these industrial differences. Nevertheless, China changed its industrial classification GB/T4754 from ver.1994 to ver.2002 in 2003. Previous studies used 2-digit industrial classification because the change in the 2-digit level is very small. There is no study concerning classification matching at a 4-digit level, however.

To match the industrial classifications into a consistent new code, a simple version of the Prims algorithm has been used. The fundamental idea of the algorithm is to cluster the connected industries together into the smallest possible groups. More specifically, one industry is taken from GB/T4754-2002 and all corresponding GB/T4754-1994 categories are then added into the set, together with all their linked neighbours until no element in the working set corresponds with one outside the set. Then, this set is given a new industrial classification code.[4] Repeating that procedure, many independent connected graphs are produced that cover every industry in the data. The new groups do not have an equal size but are closely related in terms of production.

As a result, all industries are grouped into 94 categories: one group of industries that were included in the data from the beginning but had been moved out since 2003 and 93 groups that were retained continuously throughout the data period, among which ten groups did not export at all at any time, and two groups exported discontinuously.

[4] A more detailed description of the algorithm can be seen in the Appendix of this chapter.

4.3 Methodology

The standard deviation of log wages $\{w_i\}$ is calculated as the square root of the weighted sum of log wages:

$$SD(w) = \sqrt{\sum_i [p_i(w_i - \overline{w})^2]} \tag{4.1}$$

where p_i is the fraction of workers earning wage w_i, and $\overline{w}$ is the weighted average of $\{w_i\}$. Using the first order total derivative, the decomposition of the change in the log wage standard deviation can be written as:

$$\Delta SD(w) = \frac{1}{2}\frac{1}{SD(w)}\sum_i (\Delta p_i \times \widetilde{w_i}^2 + p_i \times 2\Delta\widetilde{w_i}) \tag{4.2}$$

where $\widetilde{w_i} = w_i - \overline{w}$ was assumed to be time invariant, and the effect of institutional changes Δp_i was estimated as in previous chapters. It has been shown (Chapter 2) that, between 2000 and 2004, relative wage changes were mostly insignificant, and the effect of supply and demand shifts on wage dispersion is moderately negative. In the long run, however, relative wages have become more and more different in the early twenty-first century. It is, therefore, important to understand what has caused these changes.

In this chapter, the effect of exports on $\widetilde{w_i}$ is the main question. An Oaxaca-Blinder style OLS model to estimate the effect of export on wages can be written as:

$$w_{i,t} = \beta_{0,t} + \beta_1 Exposure_{i,t} + \beta_2 Exposure_{i,t}^2 + \rho_1 D_{export,i,t} + \epsilon_{i,t} \tag{4.3}$$

where $w_{i,t}$ is the log wage of firm i at time t, $Exposure_{i,t}$ is the respective export exposure, $D_{export,i,t}$ is the dummy variable indicating whether firm i exported in year t, $\{\beta_i, \rho_i\}$ are the coefficients, and $\epsilon_{i,t}$ are the i.i.d. residuals.

As discussed earlier, the RMB/100USD exchange rate and value-added per worker can affect the exports, and also correlate with wages. It is thus important to take these into account:

$$\begin{aligned} w_{i,t} =& \beta_{0,t} + \beta_1 Exposure_{i,t} + \beta_2 Exposure_{i,t}^2 + \rho_1 D_{export,i,t} \\ &+ \beta_2 Exposure_{i,t} \times USD_t + \beta_3 Exposure_{i,t}^2 \times USD_t \\ &+ \beta_4 VAPC_{i,t} + \beta_5 Exposure_{i,t} \times VAPC_{i,t} + \beta_6 Exposure_{i,t}^2 \times VAPC_{i,t} + \epsilon_{i,t} \end{aligned} \tag{4.4}$$

where USD_t is the annual average RMB/100USD exchange rate at year t, and $VAPC_{i,t}$ is the log net value-added per worker of firm i at year t. The individual term of USD_t is dropped in the model because it is collinear with year specific constants $\beta_{0,t}$.

OLS estimation can be biased if there is unobservable that correlates with wage and export exposure. For instance, export-intensive areas, like Shenzhen, can have high living expense, and firms needs to pay high wages to compensate that. Industrial technology changes can be labour intensive or capital intensive, as well as improving the quality of goods to compete in foreign markets. Different firms can face different financial constraints that affects export and wage (Du and Girma, 2007; Godechot, 2012).

Two fixed-effect models are thus tested to control for unobserved factors. Dividing the error term into two parts, $\epsilon_{i,t} = \alpha_i + u_{i,t}$, α_i is the fixed-effect and $u_{i,t}$ is the i.i.d. error. One fixed-effect model assumes there is an unobserved time-invariant **industrial effect** $\alpha_i = \alpha_{ind}$, i.e. industrial subsidies, regulations, competitiveness in international trade, etc., and the other one assumes there is an unobserved time-invariant **firm effect** $\alpha_i = \alpha_{firm}$, including the firm's market power, effectiveness, etc..

There can still be time-variant unobservables that are export-biased and wage-related, however. For example, the boom in the computer industry and the use of the Internet in business can in principle ease the process of communication and negotiation in international trade (more than that of the domestic trade due to distance and territory issues). Thus, the demand for computer-literate workers will have increased, which in turn will increase the relative wages for those workers (DiNardo et al., 1996; Bound and Johnson, 1992). For instance, let $\epsilon_{i,t} = \alpha_{i,t} + u_{i,t}$. $\alpha_{i,t} = a_{i,0} + a_{i,1} * t$ be a fixed-effect with a time trend, and this accounts for trended movements like skill-biased demand shifts.

To account for trended fixed-effect, first-difference models are estimated in addition:

$$\begin{aligned}\Delta w_{i,t} =& \Delta\beta_{0,t} + \beta_1 \Delta Exposure_{i,t} + \beta_2 \Delta Exposure_{i,t}^2 + \rho_1 \Delta D_{export,i,t} \\ &+ \beta_2 \Delta(Exposure_{i,t} \times USD_t) + \beta_3 \Delta(Exposure_{i,t}^2 \times USD_t) \\ &+ \beta_4 \Delta VAPC_{i,t} + \beta_5 \Delta(Exposure_{i,t} \times VAPC_{i,t}) \\ &+ \beta_6 \Delta(Exposure_{i,t}^2 \times VAPC_{i,t}) + a_{i,1} + \eta_{i,t} \end{aligned} \tag{4.5}$$

where $\eta_{i,t} = \Delta\epsilon_{i,t}$. The expected $a_{i,1}$ can be zero if there are no trended unobservables correlated with both independent variables and wages, or a fixed-effect trend. Industrial fixed-effect and firms' fixed-effect models are thus tested. In practice, other observed firms' characteristics are added to these models as control variables, e.g. state-owned capital, the age of firms, and assets, etc..

4.4 Empirical Results

As seen in Table 4.6, the coefficients and t-values of the OLS model, industry fixed effect model, and firm fixed-effect model of log real wages are presented. The first eight rows of numbers are coefficients and t-values for export exposure and its correlated factors, exchange rate and log net value-added per worker (as defined in the methodology).

It is clear that the results from different models are inconsistent with each other to some extent. Taking the OLS estimation as an example, the OLS model suggests that, if the export exposure increases by 10%, all other things remaining equal, the log wage will be lower by 0.439 log point (=55.1% lower real wages), which decreases as export exposure gets larger. When export exposure grows beyond 43.6%, its effect on the log real wage starts to mount. The exchange rate significantly affects the quadratic term of the export exposure effect, which is minute in magnitude. On the contrary, an increase in log net value-added per worker can increase the effect of export exposure on log wages. Other things being equal, 1 log point increase in the net value-added per worker will result in an additional 0.036 log points export exposure effect on wages. The coefficient of export dummy is 0.180, which implies that a non-exporter transforming into an exporter will increase the firms log wage by 0.180 log points (=19.7% increase in real wage).

When industrial fixed-effect is accounted for, the coefficients of export exposure become larger in magnitude, while the interactive effects of exchange rate and export exposure remain similar to those in the OLS model (Table 4.6). Moreover, the overall effect of exports (including export dummy and export exposure and its quadratic form) on log wages becomes negative. Firms that export between 8% and 99% of their total sales will pay workers less than non-exporting firms, other things being equal. That means, accounting for industrial time-invariant unobservables, e.g. technology and endowment, export lowers wages.

When firms' fixed-effect is considered, the overall negative effect of exports on wages does not change (Table 4.6). More specifically, although starting to export will have a one-off positive effect on wages, as the export ratio increases beyond 0.6%, the overall effect of exports on wages becomes negative until it reaches

95%. On the other hand, the interaction of log net value-added per worker with export exposure becomes negative, meaning that increasing log net value-added per worker will further decrease the negative export exposure effect on wages.

Table 4.6: OLS and FE Estimations of Log Wage on Exports

	OLS[a]	Industry FE	Firm FE
Exposure	-0.4394	-1.7156	-1.9749
	(0.0089)	(0.0086)	(0.0072)
Exposure^2	0.5031	1.5999	2.0467
	(0.0094)	(0.0091)	(0.0076)
Exposure × USD	0.0000	0.0017	0.0025
	(0.0000)	(0.0000)	(0.0000)
$\text{Exposure}^2 \times$ USD	-0.0001	-0.0016	-0.0026
	(0.0000)	(0.0000)	(0.0000)
VAPC	0.1490	0.1386	0.0989
	(0.0000)	(0.0000)	(0.0000)
Exposure × VAPC	0.0359	0.0352	-0.0273
	(0.0003)	(0.0003)	(0.0003)
$\text{Exposure}^2 \times$ VAPC	-0.0204	-0.0222	0.0167
	(0.0003)	(0.0003)	(0.0003)
Export Dummy	0.1796	0.1280	0.0125
	(0.0001)	(0.0018)	(0.0001)
Controls[d]	Y	Y	Y
Year Dummy	Y	Y	Y
Constant	1.3052	1.4512	1.5757
n	465347616	465347616	465347616
R^2	0.430	0.478	0.819

[a] *All estimations are a weighted average using numbers of workers. The coefficients are reported, and respective standard errors are in parentheses underneath. All coefficients are significant at 95% level apart from that for Exposure × USD in OLS estimation.*
[b] *Expo is short for exposure. USD is the Chinese Yuan per 100 US Dollar.*
[c] *VAPC is log net value-added per worker.*
[d] *Controls are firm characteristics including ownership, age of firm, and assets. Firms' age is calculated as the year of observation minus the year of the company founded, and then grouped into six categories: group 1 has an opening-year prior to 1900 or has observational error; group 2 has opened less than 5 years; group 3 opened between 5 and 10 (not inclusive) years; group 4 aged 10 to 20 (not inclusive) years; group 5 firms have operated for 20 to 50 (not inclusive) years; group 6 firms have existed for at least 50 years.*

Comparing the results of the three models, assuming a firm fixed-effect is more plausible. The unobserved variables are correlated with independent and dependent variables. As discussed in the methodology, unobservables can be trended, like skill-biased technology progress and adoption of computers and Internet.

First-difference model are now estimated. The coefficients of the first-difference terms in Table 4.7 can be interpreted as the percentage change in real wages as a result of one unit change in the respective explanatory variable. It is confirmed by all the estimations that a rise in export exposure will have a positive effect on wages, which decreases slightly as export exposure rises in the firm fixed-effect estimation. The RMB appreciation has a statistically significant positive effect on the export effect on wages in general, but is very minute in magnitude. When firm-specific unobservables' trends are accounted for (see Firm FE estimation in Table 4.7), a rise in the log net value-added per worker will also increase the real wage. Its effect on the export-wage relationship, however, is negative.

Together with the estimations in Table 4.6, it can be found that while high export exposure firms pay less to their workers, an increase in export exposure will increase wages after accounting for fixed-effect unobservable trends. This is consistent with the lock-in theory: that firms hire the most productive workers to enter and compete in the international market, but become doomed when their terms of trade worsen. As firms exporting more and more, with a sunk cost, they are "locked" into international trade.

Given that the assumption of the firm-level fixed-effect estimation of the first-difference model is the least strict assumption among those of all models, and coefficients are different between level regression and first-difference regression, the firm-level fixed-effect estimation of first-difference model is most reliable.

From the firm-level FE estimation on first-difference model, export exposure has a positive effect on wage growth. Such an effect decreases in line with export exposure change. It indicates that, other things being equal, exporting firms will converge in log wage.

There could be endogeneity problem in terms that through hiring more productive workers, the firms become more competitive in the international market, and export more. The effect of change in value-added per worker, however, has been controlled, as a measurement for productivity in addition to the effect of export exposure on wage. Moreover, the joint effect of value-added per worker and export exposure on the change in wage is negative, which does not support for the endogeneity that higher wage workers increases both productivity and export exposure.

Table 4.7: OLS and FE Estimations of Log Wage on Exports

	OLS[a]	Industry FE	Firm FE
Exposure	0.1309	0.3917	0.9580
	(0.0103)	(0.0104)	(0.0128)
Exposure^2	0.3817	0.1536	-0.2740
	(0.0109)	(0.0110)	(0.0136)
Exposure × USD	0.0000	-0.0004	-0.0011
	(0.0000)	(0.0000)	(0.0000)
Exposure^2× USD	-0.0006	-0.0003	0.0002
	(0.0000)	(0.0000)	(0.0000)
VAPC	0.0690	0.0682	0.0617
	(0.0000)	(0.0000)	(0.0000)
Exposure × VAPC	-0.0179	-0.0176	-0.0163
	(0.0003)	(0.0003)	(0.0003)
Exposure^2× VAPC	0.0212	0.0217	0.0209
	(0.0004)	(0.0004)	(0.0004)
Export Dummy	0.0005	0.0010	0.0000
	(0.0001)	(0.0001)	(0.0001)
Controls[d]	Y	Y	Y
Year Dummy	Y	Y	Y
Constant	0.0449	0.0405	0.0409
n	294175351	294175351	294175351
R^2	0.0338	0.0357	0.2537

[a] *All estimations are a weighted average using numbers of workers. The coefficients are reported, and respective standard errors are in parentheses underneath. All coefficients are significant at 95% level apart from that for Export Dummy in Firm FE estimation.*
[b] *Expo is short for exposure. USD is the Chinese Yuan per 100 US Dollar.*
[c] *VAPC is log net value-added per worker.*
[d] *Controls are firm characteristics including ownership, age of firm, and assets. Firms' age is calculated as the year of observation minus the year of the company founded, and then grouped into six categories: group 1 has an opening-year prior to 1900 or has observational error; group 2 has opened less than 5 years; group 3 opened between 5 and 10 (not inclusive) years; group 4 aged 10 to 20 (not inclusive) years; group 5 firms have operated for 20 to 50 (not inclusive) years; group 6 firms have existed for at least 50 years.*

Other concerns of the results include the serial correlation issue of the error term, which would undermine the significance of coefficients. Nevertheless, unbalanced data may bring sample biasness to the results. More research is needed to provide better solutions to these issues.

4.5 Conclusion

This chapter discusses the effect of changes in exports on industrial wage distribution. The results show that increases in export exposure have an positive effect on the growth rate of wages. Such an effect decreases in exposure change. It indicates that, other things being equal, exporting firms converge in wages, and that export exposure can reduce wage differentials.

Two channels of export increase are included: 1) exchange rates for changes in foreign demand for Chinese goods, and 2) net value-added per worker for productivity growth in China. Both channels are significant. Firm and 4-digit industrial fixed-effect models are estimated and compared, and show that there are industrial unobserved factors that disperse wages. Moreover, within the same industry, firm-level unobservable differences are also important to account for wage differentials.

From summary statistics, there seem to be conflicts between wages and value added. OLS and fixed-effect models of log real wage suggest that a higher export exposure will result in a lower wage. After accounting for firm-specific trended unobservables using firm-level fixed-effect estimation through a first-difference model, however, all other things being equal, both increases in export exposure and in value-added per worker are shown to have a positive effect on wages. These superficial conflicts are most likely “lock-in” symptoms.

Finally, the first order decomposition of changes in log wage standard deviation show that employment redistribution cannot explain much of the changes. On the other hand, the wage equilibrium effect has a much stronger explanatory power.

4.6 Appendix: Simple Prim's Algorithm

Define a graph G with two sets of vertices and a set of edges. Let any 4-digit industrial classification i in GB/T4754 ver.1994 be a vertex a_i in set $A = \{a_i\}$, and any 4-digit industrial classification j in GB/T4754 ver.2002 be a vertex b_j in set $B = \{b_j\}$. If, according to the correspondence table between GB/T4754 ver.1994 and ver. 2002, a_i corresponds to b_j, draw an edge $e_{i,j}$ with a value of 1 between the two vertices and put it into the edges' set $E = \{e_{i,j}\}$.

To bridge two versions of a classification it is necessary to find "independent" industry clusters with no correspondence edge drawn between the them, which is equivalent to finding the minimum connected graphs in graph G.

Thus, the algorithm is simply:

1. Mark all the vertices as "unselected";
2. Select a "unselected" vertex a_i from set A and put it into current cluster set X;
3. Search all edges E; if edge $e_{i,j} = 1$, and if $a_i \in X$ or $b_j \in X$, add a_i and b_j into X;
4. Repeat step 3 until there is no new vertex added to X;
5. Give X a new cluster name $c_p, p = 1, 2, ...$, mark vertices in c_p as "selected", and empty X;
6. Start again from step 2 until all vertices in A are marked "selected".

After completing the algorithm, all 4-digit industries are clustered under the new classification $newcode = \{c_p\}$. As a result, $newcode$ has 94 clusters.

Chapter 5

Summary

This thesis studies the effect of institutional changes on wage inequality in China. It focuses on the early twenty-first century, when China experienced public sector reform, expansion in higher education, reform in the public insurance system, minimum wage policy changes and joining World Trade Organization (WTO). Adopting parametric and semi-parametric methods to decompose the changes in wage dispersion, institutional changes are shown to account for a significant part of the change.

In Chapter 1, statistics about wages and institutional changes are provided. Since the 1990's, China has experienced high growth and real wages in China have also increased eight times from 1991 to 2007. Unlike in the US and many European countries, the growth rate of wages in China was not procyclical before 2006. This clearly indicates that there are other factors having a stronger influence on wage determination than the GDP growth. In addition, the variation in wages has changed since the late 1990's and early 2000's. Household survey data from the CHNS showed an increasing wage dispersion, while industrial firm data from the CIE showed an drop in wage variance between 2002 and 2005. Chapter 3 has shown that such differences arise from sectoral biased changes, like the minimum wage.

The expansion in higher education since 1999 increased the higher-educated labour force from 2003 onwards. In Chapter 2, it was shown that higher education expansion reduced wage dispersion between 2000 and 2004 in China because it allowed more people to enter the graduate labour market, where wages are higher and less dispersed.

Public health insurance has covered an increasing proportion of the population, weakening the traditional *hukou* barrier in the Chinese labour market. With less restriction in labour migration, wages have become more dispersed. The results in Chapter 2 also indicate a possibility that compulsory public insurance can increase the wage gaps between firms compared to optional insurance, since with optional insurance, firms with a disadvantaged status can offer better wages without insurance for productive workers with high discount rate in their utility function.

Reform of state-owned enterprises has reduced public sector employment, and these public firm reforms have also dispersed wages in China. The results from Chapters 2 and 3 consistently show that, when the previously dominant public sector in the Chinese economy shrank, wages become more dispersed because the sectoral employment share become more dispersed.

A minimum wage can have spillover, disemployment and lower tail eliminating effects on wage dispersion. In Chapter 3, all of these three effects have been discussed. With no-spillover, no-disemployment and minimum wage conditional lower tail as the initial primary assumptions, the minimum wage has shown a significant negative effect on the wage dispersion. The minimum wage effect remained significant even if the assumptions on disemployment and conditional lower wage tail were relaxed.

After joining the WTO, the workers exposed to international trade increased from 40.5% to 46.9% of the workforce between 2000 and 2004. In Chapter 3, with export firms offering higher wages, increases in export-based employment had an positive effect on the wage dispersion. In addition, Chapter 4 has shown that expansion in the export sector also increased the wage premiums of export firms. The results from a fixed-effect model and first-difference model also indicate that there is "lock-in" effect of international trade in China. After entering international trade, exports dampen the positive effect of productivity on wages, indicating a worsening payoff from export to workers.

A few issues can challenge the results of this thesis. To decompose institutional effects on wage dispersion, orthogonality was assumed between employment share changes and relative wage premium changes. It is possible, however, that employment share shifts the relative wage premiums as well. In that case, the results from Chapter 3 may be biased. Due to lack of employee-employer matched data, Chapter 2 has to assume that there are no demographic biased demand shocks that might cause sufficient labour supply and demand shifts to have an effect on the wage premium. Although an attempt was made to account for trended firm fixed-effects, Chapter 4 had to ignore non-trended unobservable changes. This may also introduce some degree of bias into the results.

In summary, this thesis has decomposed wage dispersion changes in China and found that expanding higher education and increasing the minimum wage can reduce wage dispersion, while privatization, increasing public insurance coverage and international trade liberalization can disperse wage distribution. Further research is needed to understand the changes in relative wage premiums, especially the effect of demographic-biased demand changes in Chinese labour market.

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