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Three Essays on the Discourse and Consequences of Rural-urban Migration in China

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Abstract

Rural-urban migration in China is the largest human movement in the history of the world in terms of quantity. Rural-urban migrants make great contributions to urban economy and rural development in China. Yet, they usually lack formal supports in both urban and rural areas. The thesis consists of three essays related to rural-urban migration, looking at the discourse and consequences of rural-urban migration in China. The thesis augments the study of migration, social network, and human capital.

The first essay in the Chapter 2 is about how job contact network affect rural-urban migrants' wages. In the nationally representative household data from the 2008 wave of Rural Urban Migration in China (RUMIC), nearly two thirds of rural-urban migrants found their employment through family members, relatives, friends or acquaintances. Using a switch regression approach, we find evidence of positive selection effects of the use of networks on wages. Users of networks tend to be older, to have migrated longer ago and to be less educated. In addition, married workers and those from villages with more out-migrants are more likely to use networks, while those without local residential registration status are less likely. Controlling for selectivity, we find a large negative impact of network use on wages. Using job contacts brings access to urban employment, but at the cost of markedly lower wages.

The second essay in the Chapter 3 provides a four dimensional job quality index for rural-urban migrants, looking at the effect of job contact network on job quality. The multidimensional job quality index has captured job reality, combining information on earnings, working time, job stability, and work-related social insurances in one index. By using data of RUMIC 2008 and employing the endogenous switching regression for ordered outcomes, we find unobserables that affect the use of network also impact the job quality of the non-users of network. The positive selectivity does not exist in users of network. We demonstrate that the use of social network brings low job quality for rural-urban migrants, especially for the users of network. The findings are robust to a range of alternate measures of the job quality index, and to different identification methods.

The third essay in the Chapter 4 explores the effects of the rural school consolidation on the living arrangement of rented accommodation for students and how rented accommodation affects students' academic performance in China. It is the first paper –to examine the effect of rented accommodation on children's academic performance and to use a double robust estimator with multivalued treatments on this topic. Using a survey of 9,071 Grades 4 and 5 students in 133 primary schools in Shaanxi Province in 2013, we find that one quarter of students are rented accommodation near their schools. Rented accommodation results from students living long distances from schools, the unavailability of local schools and the low quality of schools near their home villages. Overall, rented accommodation brings students better academic performance, especially for boys. The study indicates that rented accommodation might offer another way to avoid the negative effects of school merge policy and boarding schools.

I would like to dedicate this thesis to my loving wife Junxia and my baby girl
Bengbeng.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains about 48,435 words including appendices, bibliography, footnotes, tables and equations.

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Chapter 1 Overview

1.1 Background: rural-urban migration in China

1.1.1 Rural-urban migration and urbanisation in China

The reform and opening-up in China began in rural areas (Chen 2018). During the last forty years, rural people have made great scarifies in order to provide sufficient food, labour, and land to the development of industry and cities. By 2018, 44 % of China's labour force was still working in rural areas, while agriculture industry contributed only 7.2% of GDP ¹. This mis-match of labour in sectors has lead huge rural-urban disparity, which can be called “One Country, Two Society ” (Whyte 2010). Surplus labour in rural China and the increasing income gap between rural area and urban areas were the key factors pushing farmers to go to cities (Zhang and Song 2003; Zhao 2004). The rapid economic growth after open-up policy has attracted and absorbed a great number of rural-urban migrants.

According to the latest official reports ², the number of rural-urban migrants with more than 6 months outside their home towns is 172.66 million in 2018. Rural-urban migration in China is the largest human movement in the history of the world in terms of quantity (Knight and Song 2005), which makes rural-urban migrants studies in China important for both China and the rest of the world.

Moreover, studies have shown that rural-urban migrants contribute to both

¹Data are from National Bureau of Statistics of China:

http://www.stats.gov.cn/tjsj/zxfb/201902/t20190228_1651265.html

²Data are from National Bureau of Statistics of China:

http://www.stats.gov.cn/tjsj/zxfb/201904/t20190429_1662268.html

migrants sending and receiving areas, which has played a huge role in China's economic growth and poverty alleviation (Bai and Li 2008; Zhang et al. 2010; Cai 2018; Liu et al. 2018; Zhang et al. 2018b). For migration destinations, rural-urban migrants contribute to the local GDP and speed up the industrialization process. As an important channel of national economic accumulation, they facilitate the development of the labour market. For labour export areas, rural-urban migrants promote the resource allocation and become a new channel of income source.

Although rural-urban migrant are very important to the economy, they do not receive the protection they deserve in the city. They have to rely on social networks to find work and deal with risks. They also lack the corresponding support in the rural areas, including their children's education. Given the importance of rural-urban migration, research on the discourse and consequences of rural-urban migration is not only crucial to China's future but also to the rest of world.

1.1.2 The role of social network for rural-urban migrants in urban area

The urbanisation rate of resident population is 59.6 % in 2008, whereas the urbanisation rate of population with urban hukou is only 43.4 %. The gap between the two urbanisation rate is 16.2 %, which indicates that more than 226 million people are living in urban areas without urban hukou. Most of them are rural-urban migrants.

Rural-urban migrants fall behind urban residents in terms of earnings, contracting, and social insurance. They are usually working long hours, lacking off days and holidays. Although the wage is rising in China, the employment relationship is unfavourable to workers (Périsse and Séhier 2019). Rural-urban migrants are unable to enjoy the full protections according to laws and regulations, which reflects the lack of formal institution for rural-urban migrants.

For example, many studies show that rural-urban migrants are subject to wage discrimination after controlling their productivity characteristics (Zhao 2005;

Démurger et al. 2009; Lee 2012; Cheng et al. 2013; Wang et al. 2014; Zhang et al. 2016; Zhu 2016). According to the monitoring report on migrant workers issued by the National Bureau of Statistics of China (NBSC), in 2011, 43.8% of migrant employees have signed labour contracts with employers, and this ratio fell to 38.2% in 2016 ³.

When rural-urban migrants cannot get protections from formal institution, they often tend to use their social networks as the resource of social capital to find jobs and gain more monetary or non-monetary benefits, including health benefits (Meng and Xue 2019; Zhang and Centola 2019). Therefore, social network and social capital is crucial for rural-urban migrants in cities. To examine the effect of social network on rural-urban migrants labour market outcomes has significant implications for the rural-urban migrant study and the social network study.

1.1.3 Education problems for rural-urban migrants' children in rural area

When rural-urban migrants encounter various kinds of discrimination in the city, massive rural-urban migration leads many problems in the countryside unintentionally. Children's education is one of them.

The problem of children's education comes from three sides. First, migrant children cannot access public education equally as urban children in cities. Many migrant children have to study at private schools, of which the education quality is low and the cost is high. Between 2010 and 2017, according to the official statistics of the Ministry of Education, the number of migrant children in the junior high school is about 3 to 4 million per year, and the number of migrant children in primary school is roughly 9 to 10 million per year.

Second, since migrant children encounter difficulties to enjoy education in cities, many of them are left in rural areas and become left-behind children. The number

³Data are from National Bureau of Statistics of China:

http://www.stats.gov.cn/tjsj/zxfb/201704/t20170428_1489334.html

http://www.stats.gov.cn/ztjc/ztfx/fxbg/201204/t20120427_16154.html

of left-behind children is much larger than that of migrant children. A report from UNICEF ⁴ shows the number of left-behind children is nearly 41 million, which accounts for 29.4 % of rural children. Left-behind children usually lack parental supervisions, which is bad for their development. The effect of parental migration on children's academic performance, however, is mixed (Li et al. 2017b).

Third, given the large-scale outflows of population and the decline in the number of enrolments, local governments implement school consolidation policy in rural areas. Many schools are either shut down or merged into other schools. The distance from home to school becomes longer, especially for children in remote villages. Many children are forced to board at school because of the long distance or lack of guardians. Some students are more likely to drop out of school (Haepf and Lyu 2018).

Apart from boarding at school, some households choose to rent houses near school for their children. Much attention is paid to the study of boarding school student, whereas relatively little attention is put on the phenomenon of rented accommodation for rural children. To examine the relationship between rural school consolidation policy, rented accommodation, and students' academic performance can help us understand the education problem for migrant children as well as other rural children.

1.2 Research questions

The thesis consists of three topics. Each topic has one main research question.

The research question for the first topic is that what the impact of job contact network on wage for rural-urban migrants in China is.

The research question for the second topic is that what the impact of job contact network on job quality for rural-urban migrants in China is.

The research question for the third topic is that how rural school consolidation

⁴Please see:

<http://www.unicef.cn/cn/uploadfile/2017/1009/20171009112641471.pdf>

impacts students' rented accommodation and how rented accommodation impacts students' academic performance in rural China.

The first and second topic is going to use data of the 2008 wave of Rural Urban Migrants in China (RUMIC). RUMIC is the first national representative migrant dataset in China. It provides enough samples and information of social network and labour market involvement that needed for the first and second topic.

For the third topic, I will use a dataset from a survey which I was involved in questionnaire design. The survey covers more than nine thousand primary students in north-west rural China. It has much information on the level of students, households, teachers, and schools.

1.3 Research significance

The past forty years of development in China confirms the great values of labour mobility and education. However, rural-urban migrants still face obstacles of job search and settling down in cities (Wu et al. 2015). They cannot get the same quality of jobs as urban residents. Labour right issues even become a sensitive topic for the government. Rural students are lack of schools and are forced to pay more for their own education.

The three main research questions in the thesis are all related to the rural-urban migration in China. The first and second topics are about the impact of social network on labour market outcomes, which is directly related with the social network and social capital theory. The third topic is about rural education, which is directly related with the human capital theory. So I will show the detailed research significance from the perspectives of the migration study, the social network and social capital theory, and the human capital theory.

1.3.1 Migration study

There are two types of migration: domestic migration and international immigration. Most of domestic migration in developing countries are rural-urban migrants, as is the case with China's rural-urban migrants. Whether it is about domestic migration or international immigration, a large number of studies have shown the importance of social networks to migrants. But few people look at the role of social networks in the performance of migrants in the labour market from a multidimensional perspective, especially in developing countries.

Labour migration is always accompanying with left-behind children. Both rural left-behind children and international left-behind children face the same problem, that is, parents are not around and the left-behind children cannot get enough educational resources they deserve.

Moreover, different from rural-urban migrants in other countries, China's rural-urban migrants have many characteristics of international immigration. For example, the hukou system in China is kind like the green card system in other countries. In China, rural-urban migrants cannot access public health system or have local pension unless they have local urban hukou. In early years, migrant children cannot go to public school unless they get local urban hukou.

The three main research question in the thesis is not only important for rural-urban migrants, but also for international immigrants. The thesis will enrich the migration study by examining the impact of social network on wage and job quality, and by exploring the relationship among rural school consolidation, rented accommodation, and children's academic performance.

1.3.2 Social capital and social network

The concept of social capital has been world widely used and recognized by researchers (Bourdieu 1986; Coleman 1988; Burt 1992; Putnam 1995; Fukuyama 1997; Lin 1999) and practitioners (World Bank 2001; Harper 2002) for more

than two decades. Although the definition of social capital varies at collective and individual level, it is agreed that social capital can increase collective and individual productivity, just like physical capital and human capital. Thus, social capital is important for development (Fafchamps 2006).

Social capital can refer to social cohesion, social norm, trust, reciprocity, sanction, voluntary associations and organizations, civic engagement, group membership, and social network that fascinate individual or collective actions. Despite different aspects of social capital, the key idea is that social capital is the values of social networks (Portes 1998; Lin 2001). Social networks can be individuals or groups (Wellman and Wortley 1990; Burt 1992).

Social capital have been used to explain economic growth, poverty alleviation (Knack and Keefer 1997), public goods, civic engagement, democracy, physical and mental health, and educational achievement. Indeed, both positive and negative effects of social capital have been acknowledged and thereby studies of social capital are significant both theoretically and practically.

Social capital comes from social network. Researchers noticed that importance of social networks in the labour markets earlier before “The Strength of Weak Ties” published (Rees 1966; Granovetter 1973; Granovetter 1983). After that, more and more researchers were trying to explore the relationship among social network, job search, wage, and other labour market outcomes, especially for the poor (Smith 2017).

The role of social networks in the labour markets deserves our attention for at least two reasons: first, because of the central role networks play in disseminating information about job openings they place a critical role in determining whether labour markets function efficiently; and second, because network structure ends up having implications for things like human capital investment as well as inequality (Jackson 2010; Nicodemo and García 2015) and poverty (Zhang et al. 2017).

1.3.3 Human capital and rural education

The major explanation for increases in national output can be explained by investment in human capital (Schultz 1961), which indicates the importance of human capital for the society. Investment in human capital is from consumption like expenditures on education, health, and internal migration, or by opportunity costs that come from education and training (Schultz 1961). Investing in human capital can provide more choices for people and is one way to raise people's welfare, especially for low income people (Becker 1962). Education and individual labour market performance are so connected that even both education attainment and school quality can affect earnings in labour market (Guo 2018).

Education is the most important way to accumulate human capital. Human capital investment has a strong positive effect not only on individuals but also on the development of society as a whole (Krueger and Lindahl 2001). The increase in enrolment and education investment in rural free compulsory education reform can be transformed into the long-term income of human capital (Xiao et al. 2017). The birth rate in 2018 is only 10.94 ‰. In the case of ageing and reduced birth rate, rural children are more important to China. Just like Rozelle and Johnson (2019) claim that China's future lies in the countryside, where over two-thirds of Chinese children are growing up. If rural education cannot be improved, it may become China's invisible crisis.

Education development is a key element that promotes China's economic growth in the past forty years (Garnaut et al. 2018). For rural education, the central and local government play two different roles. Local governments selectively adapt education policy by the central government (Wang 2016). For migrant children, they cannot get equitable compulsory education like urban children. For children in rural areas, they are far behind urban children in terms of academic achievement. Difference in teacher quality between the rural and the urban can explain the rural-urban gap in education (Zhang et al. 2018a). Studies have shown that students

living with family tend to do better in education (Huang et al. 2018).

The rural school consolidation policy in China provides an excellent case to look at the education problem for rural-urban migrant children, which can enrich the study of rural education policy and the human capital theory.

1.4 Research outline and structure of thesis

The structure of thesis is as follows:

The Chapter 1, “Overview”, presents the big picture of rural-urban migration in China, gives the motivation and research questions in thesis, highlights the research significance from the perspectives of the migration study, the social capital and social network theory, and the human capital and education theory.

The Chapter 2, “The Impact of Job Contact Networks on Wages of Rural-Urban Migrants in China”, explains how rural-urban migrants use social network to find jobs and how social network affects their wages. Using a national representative migrant data, this chapter puts much effect on dealing with the bias from selection of network use and unobservables, which is ignored by previous studies. This chapter contributes to the economics of network and social capital theory in migrant study.

The Chapter 3, “The Impact of Job Contact Networks on the Job Quality of Rural-Urban Migrants in China”, provides a four dimensional job quality index for rural-urban migrants, looking at the impact of job contact networks on the job quality. Chapter 3 is much based on Chapter 2, as both chapters have to deal with the bias from selection bias of network use and unobservables. The difference is that Chapter 3 takes a further step to examine the job quality rather than just one dimension of the job quality, like wage. The concept of job quality provides a new angle and weapon to understand the whole performance of migrants in the labour market.

The Chapter 4, “School Consolidation, Rented Accommodation and Children’s

Academic Performance in Rural China”, examines about how rural school consolidation affects students’ rented accommodation and how rented accommodation affects students’ academic performance. Chapter 4 shows how government education policy impact rural-urban children’s education. This chapters has strong policy implications for the education in the migrant sending areas.

The Chapter 5, “Concluding Remarks”, discusses the main findings, contributions, and limitations of the thesis, following a reflection on potential areas for future work. This chapter summaries critical review of existing arguments and their distinction from new arguments developed by the thesis.

Chapter 2 The Impact of Job Contact Networks on Wages of Rural-Urban Migrants in China

2.1 Introduction

There has been increased interest in the role of social networks and its relation to the economic outcomes. Following Coleman (1988), ‘social capital’ has been hypothesised as a determinant of productivity, much as human capital was earlier added to the conventional factors of production like land, labour and capital. Social capital has variously been understood as norms of behaviour such as ‘trust’ that may underpin economic relations or as ‘networks’ of contacts that may provide valuable economic gains. Early empirical studies often found large economic benefits to social capital, for example, for household income in rural Tanzania (Narayan and Pritchett 1999); for manufacturing productivity in Ghana (Barr 2000); or agricultural traders in Madagascar (Fafchamps and Minten 2002). The significant role of job contacts in obtaining employment has long been recognised, although what is less well understood are the possible effects on subsequent wages or labour productivity of using such networks. In this paper, we estimate the effect of using social networks on the wages of migrants in China.

Much as the general literature on social capital focussed on productivity benefits, theoretical models of labour markets often predict beneficial effects on wages from

using job contacts. In line with the ‘social capital as networks’ interpretation, using job contacts may give job searchers more information about opportunities and ensure a better matching of workers to jobs, translating into higher wages for users of networks (Montgomery 1991; Mortensen and Vishwanath 1994). Additionally, following the ‘social capital as trust’ approach, those who find jobs by using contacts may feel additional peer pressure to perform and thus attain higher productivity and wages (Kandel and Lazear 1992). However, while positive wage effects from using job contacts are sometimes found, this is far from universal and has led to consideration being given as to why using job contacts may appear to lower wages (Delattre and Sabatier 2007). One explanation centres on training costs (Pellizzari 2010). Firms may only be able to expend extra effort in using formal means of filling posts (for example, advertising or using recruitment agencies), rather than informal means (using social networks). Consequently, the use of formal means of filling posts will be more common where the costs of the posts remaining unfilled are high, as is likely to be the case with posts with high training costs (and consequent high wages). A second explanation centres on job seeker impatience: those keen to find employment quickly may use job contacts, sacrificing potentially higher wages from better matched posts for quicker entry into work (Bentolila et al. 2010). They cannot take advantage of their specialities because of mismatched jobs (Matsuda and Nomura 2017).

Given the ambiguous theoretical predictions about the impact of using job contacts on subsequent wages, it is interesting to try to estimate the impact empirically. However, while it is straightforward to measure the correlation between using of job contacts and subsequent wages, one must be cautious about drawing causal inferences from this due to unobservables that may affect both uses of social networks and labour market outcomes (Mouw 2006). Users of job contacts to find employment typically differ from non-users in various observed characteristics - for example, they may be often older. If they are found to have higher (or lower) wages than non-users, the suspicion arises that this may simply reflect higher (or

lower) unobserved productivity. In order to control for the possible selectivity of use of job contacts, we employ a switching regressions model for wages.

We focus on the impact of using social network on labour market outcomes for rural-urban migrants in China. This is an interesting case to study, not only because rural-urban migration in China is the largest human movement in the history of the world in terms of quantity, but also because rural-urban migrants in China cannot access institutional assistance from governments at their destinations. They are often forced to rely on using their social contacts to find work but the effect of this on labour market outcomes in China is not yet well understood.

Our intention in this study is therefore to answer three main questions. First, what are the determinants of migrants using contacts finding employment? Second, is the use of job contacts endogenous to wages: that is to say, are the unobservables which influence job search methods correlated to those which determine wages? Third, what is the causal effect of using job contacts on subsequent wages: do users of networks enjoy higher or lower wages than non-users, *ceteris paribus*? These questions may have implications for policy - for example, people would question the existence of public employment agencies if social networks have positive impacts on job search and wages (Delattre and Sabatier 2007). Conversely, in the Chinese context, if using networks appears to incur a wage penalty, it may spur policy-makers to find ways to increase rural people's access to formal means of finding urban jobs.

The remainder of the paper is structured as follows. Section 2 reviews the literature, focusing on the measures of social networks and the methods to identify their effects on labour market outcomes. Section 3 describes the data and the switching regressions model to be estimated. Section 4 reports descriptive statistics and Section 5 presents the econometric results. Section 6 concludes.

2.2 Literature review

There are a great number of studies on the relationship between social networks and labour market outcomes (Chua 2011; Krug 2012; Picard and Zenou 2018). Studies may disagree because they analyse different contexts or use different datasets. They may also disagree for two methodological reasons. First, studies use different proxies to measure social networks. Second, studies employ different econometric models to estimate the relation between social networks and labour market outcomes. Consequently, in this section, we will first talk about social networks and labour market in China, then discuss alternative measures of social network and the econometric methods commonly used in the existing literature.

2.2.1 Social network and labour market in China

China is so called a “relational society”, as relation or *guanxi* is deeply ingrained in Chinese society. Fei (1939) uses “the structure of grade” to illustrating interpersonal relationship of the traditional society in China. He finds Chinese society was built on “graded interpersonal relationships” that governed how people treated others. People take themselves as centres and different relationships formulate various circles, just like putting a stone into water and thus create wave circles. Everyone has his/her own relational circles and everyone belongs to others’ relational circles. The structure of grade depends on the distance between centre and circle. Thus social relations work through social networks of personal relations with the self at the centre and decreasing closeness as one moves out. Marital and family relation, kinship are closest relations. Acquaintances in same village or region are just next to blood relationships. However, the factors determining the closeness of relation may differ while network in employment might have an increasing influence on people’s relation (Wang et al. 1997).

In China, a good network is a very powerful asset as it could help to accomplish many things, almost including every aspects of life (marriage, employment,

education, etc.). Therefore, a man who has built an elaborate network is called “a person in the society” (Yan 1996). China is a model of “network capitalism” (Bian et al. 2015).

Bian and Huang (2015) distinguished two types of network resources. The first one is called network-transmitted information that could reduce uncertainties of job seekers and prospective employers and thus increases entry-level wage for users of information ties. Information from social network is always closely related to weak ties. The second one is network-mobilized favouritism that refers to the influence of powerful social contacts through whom users of favor-exchange ties receive preferential treatment with a higher starting wage. Favouritism from social network is always connected with strong ties.

Migrant’s social network

Social network is partially important in finding jobs for immigrants (Beine 2016; Lancee 2016; Elsner et al. 2018; Goel and Lang 2019) and internal migrants (Berardi 2013; Swee 2017; Sharma and Das 2018). For example, a survey in Swedish shows immigrants are more likely to rely on informal search through friends and relatives (Carlsson et al. 2018). But jobs from informal search tend to be low paid. In India, informal job search channel is more effective in large cities (Sharma and Das 2018).

As to China, the availability of a range of social ties is important for rural-urban migrants, for such social relationship enable migrants to cope with uncertainties and risks (Chen and Deng 2018). The largest proportion of migrants’ social network is so called kinship network like family member and relatives (Li and Wu 2010). Migrants’ social ties can be categorized into three groups based on kinship and geo-relationship. Family members and relatives are the first tie and this is the central and strongest ties for migrants; friends and village fellows are the second tie, like Laoxiang network (Wu 2018); employers, colleagues and neighbours are the third tie. These social ties are potential helpers when migrants face crisis.

Many studies suggest that most rural-urban migrants seek jobs through their

own social networks, such as their family members, relatives and friends in the same village (Ying and Nansheng 1997; Zhao 2003; Shen and Kogan 2017; Giuliatti et al. 2018). Yueh (2008) shows that social networks rise the elasticities of labour supplies for migrant workers. Social networks could be used in job search and thus increases the mobility rate for urban residents, especially if it is voluntary (Knight et al. 1999).

However, people argue whether or not rural-urban migrant could benefit from their social network, as we do not know what exactly social network they have and how social network affects their economic well-being or subjective well-being (Zhang and Lu 2009)

The effect of social network on wages is still unclear. Giuliatti et al. (2010) test the sensitivity of the results to the definition of social network and found that size and quality of rural-urban migrants' network are positively correlated with their wages. The positive effect is proved by Knight and Yueh (2008). But some researchers argue that the effect is very small (Zhang and Lu 2009). The social network size is not a determinant of labour market outcomes once locality characteristics and the endogeneity of the network measure are controlled (Giuliatti et al. 2010).

Many empirical results need more robust examination (Obukhova and Zhang 2017). Liu (2017) shows individual social capital has positive effects on wages. But social network can also bring wage penalty for rural-migrants who use informal channels in job search (Chen et al. 2018). One possible reason for the wage penalty is that informal job search represents a negative signal for the quality of job seekers. Guanxi is more actively used by those who are not able to meet employers' requirements (Weng and Xu 2018), especially for women (Xiong et al. 2017). Another reason comes from the trade-off between earnings and job search efficiency.

Li and Wu (2010) argues that social network could bring adverse effect on migrants' health. They suggest that migrants tend to suffer from poor psychological

health problem because of the relatively closed social circle and limited social network. For the same reason, migrants may be hard to get useful information or information source in time. Sometimes the closed social network may delay migrants from getting help in time and subsequently become a barrier to health-care access. So in their view, the closed and limited social network causes the adverse effect on migrants' health. Apart from the negative effect of social network on migrants' health, Li and Wu (2010) find migrants could benefit from financial and emotional support from their social network. So social network is a double-edged sword to rural-urban migrants with regard to health-care access.

2.2.2 Defining and measuring social networks

Recent literature has largely focused on econometric methods and tended to neglect the issue of the measurement of social networks. Obtaining agreement on suitable econometric methods only but ignoring the definition of social network may lead to incomparable estimates. Our intention therefore is to pay attention to the measurement of social networks to avoid contradictory estimates resulting from different measures of social network when examining the relationship between social networks and their labour market outcomes.

Guanxi (social relations in Chinese) has been largely equated to social networks by many scholars. Zhang and Li (2003) categorise three types of *guanxi* for migrants: receiving help from relatives or family members during the process of finding a job; having contacts outside the dwelling region or receiving remittances transactions from non-family members; and having family member who are cadres. Some researchers use more direct measurements of social network. For example, Giulietti et al. (2010) measure social network by including both the quality and quantity of contacts. To them, the size of the social network is calculated by the total number of people living in cities whom they had sent greeting cards to during the last Spring Festival, traditionally the most celebrated holiday for rural Chinese. The quality of social network is proxied by a dummy variable which equals to 1

if the closest supporter is currently employed. Mouw (2010) uses the number of relatives in the U.S. to measure Hispanic workers' social capital. Wahba and Zenou (2005) use population density as a proxy for the size of social network and use the unemployment rate as a proxy for the quality of social network. Brady (2015) defines weak ties by participation in social groups.

The most relevant measurement to this study is in Chen (2011), who reviews three kinds of social network: 1) the treatment effects of using contacts or social networks on individual's labour market outcomes; 2) the quantity and quality of public and social resources already mobilized from a given helper; 3) the quantity and quality of the public and social resources to which an individual has access to.

This study measures social network adopting the first of Chen's three definitions: relying on personal contacts to find jobs in the labour market. This is the most common measure of social networks used in labour market studies and so places us within the mainstream of work on this issue.

2.2.3 Econometric methods for exploring the relationship between social networks and wages

The most common method to explore the relationship between social network and wages is to run an OLS wage equation with a variable that measures social networks. Previous studies include Granovetter (1973); Granovetter (1983); Montgomery (1991); Bian (1997); Zhang and Li (2003); Aguilera (2005). For example, we can estimate a Mincer wage equation and include a dummy variable that equal to 1 when people use their social network to find a job. The coefficient of this dummy variable captures the level effect of social network. An assumption of this method is the restriction of the coefficient to being the same between users of social network and non-users of social network, which might be wrong in reality.

Another problem with OLS is that there might be sample-selection bias on unobserved abilities in choosing job search methods. For example, migrants with high skills may be more likely to choose market-methods. A simultaneity bias

may be raised if the use of social network to find a job is correlated with the expectation of labour market outcomes (Giulietti et al. 2010). Omitted variables that are positively correlated with both social network and earnings may lead to overestimation of the coefficient of networks. Therefore, endogeneity must be addressed and several methods have been applied to do this.

Random assignment including social and natural experiments is the best way to correct self-selection bias (Mouw 2006; Chandrasekhar et al. 2018). For example, Beaman and Magruder (2012) create short-term jobs in a laboratory to investigate who gets job referrals. They ask every participant to refer a friend who is most suitable for the job. Thus the type of referral contract and amount offered is randomised and selection bias is avoided. Khan and Lehrer (2013) try to identify the effects of changes of social networks on employment by using the random assignment method. Beaman et al. (2018) apply a field experiment and find that women are disadvantaged in referral-based hiring.

Using panel data is another way to eliminate unobserved fixed effects (Yakubovich 2005; Battu et al. 2011; McDonald 2015; Krug and Fuchs 2019). However, the use of panel data may depend on the definition of social network. For example, Knight and Yueh (2008) use Chinese Communist Party membership and the number of close contacts of the respondent as measures of social capital. They admit that panel data might fail to explore the effect of social capital on the labour market as CCP membership and the number of close contacts does not vary much over time or may even be time-invariant for many observations.

A third approach to estimating the effect of networks on labour market outcomes is to model the selection process and build a model of labour market outcomes that controls for the selectivity. Instrumental variable methods (IV) (Chen et al. 2018), treatment effect model, Heckman's Selection model, endogenous switching regression model, propensity score matching (Ye et al. 2012), and structural equation models (SEM) are typical methods to discover the selection process under restricted data.

With IV and related econometric methods, the practical problem is finding an appropriate instrumental variable. Distance from home village to destination might be a potential instrumental variable for social networks. However, Zhang and Zhao (2013) prove that rural-urban migrant incomes are correlated with the distance from home village to destination as migrants face an income-distance trade-off. Knight and Yueh (2008) admit that even with the use of the best instruments available in the dataset they cannot deny that social network and CCP membership may be correlated with unobserved factors. The endogeneity still needed to be addressed.

Both treatment effects model and Heckman selection models are two-stage processes. A two-step strategy involves first using a probit model on the complete data. They then calculate an inverse Mills ratio (non-selection hazard rate) for selected samples and selection hazard rate for unselected samples. The hazard rate variable is then used as an additional regressor in the second stage OLS model. They can be estimated by either the maximum likelihood method or a two stage least squares method. The difference between Heckman selection model and treatment effects model is that the former only uses the samples which are observed and does not include a dummy variable in wage equation, whereas, the latter uses the full sample and includes a dummy variable in wage equation Guo and Fraser (2009). The Heckman selection model is used in Amuedo-Dorantes and Mundra (2007) and Yueh (2008).

The switching regression approach uses the Heckman two-stage procedure twice, one for selected sample and another for unselected sample. Studies using switching regressions can be found in Delattre and Sabatier (2007) and Liang (2010). Dutoit (2007) suggests that Hackman's selection model should be more appropriate when one regime is missing, whereas, switching regression model is more appropriate when both regimes are observed. Specifically, the endogenous switching regression is used to address issues of self-selection and the estimation of treatment effects when the self-selection is not random and the control group is observed.

In this chapter, we use the switching regression approach as the data provides information of both users and non-users of social networks, and we need to address issues of self-selection bias in investigating the effect of social networks on wages.

2.3 Data and methodology

2.3.1 Data

The empirical analysis is based on the first wave of the Rural to Urban Migration in China survey (RUMIC 2008). This survey was conducted in 2008 and includes approximately 5,000 rural-urban migrant households. Samples were randomly chosen in the fifteen migrant destination cities nationally. The dataset includes detailed information about social-demographic characteristics, labour market outcomes, health conditions, major life events and social network information. Our analysis is based on 5453 employed migrant workers, aged 16-60 years old.

Our focus in this paper is on real wages, defined to include bonuses, allowances and income in-kind. Results from the survey are reported in Dmurger and Li (2012), Qu and Zhao (2011) and Meng et al. (2010).

Granovetter (1974) notes that individuals may use several methods to find a job and only one method leads to success. But the dataset we use only ask the main source of job finding, i.e., the one leads to retaining the job. The dataset does not have variables about information flows between employers, contacts, and employees, so we are limited in what we can analyse about the process of job search.

2.3.2 Methods

An endogenous switching regression is used to estimate the relation between using of social network and wages, controlling for self-selection bias. The endogenous switching regression can be used to predict expected wages for users of social networks if they switched to not using networks and vice versa for non-users

(Lokshin and Sajaia 2004; Dutoit 2007; Powers 2007). This method has proved to be useful in dealing with endogeneity from self-selection by Adamchik and Bedi (2000) and Heitmueller (2006). Different decomposition methods can be used after calculating consistent estimates. OLS regression and treatment effects models will also be estimated to give comparisons and gauge robustness.

Endogenous Switching Regression Model

Let Z^* denote a latent variable for the propensity to use social networks with the following index function:

$$\begin{aligned} Z^* &= W\gamma + v, \quad v \sim N(0, \sigma_v^2) \\ Z &= 1 \quad \text{if } Z^* > 0, \quad Z = 0 \text{ otherwise} \end{aligned}$$

where $Z = 1$ if the individual chooses social networks to find a job and $Z = 0$ otherwise. Z^* can be estimated using models for binary data.

Let Y_1 be the earnings for users of social networks and let Y_0 be the earnings for non-users of social networks.

$$Y_1 = X_1\beta_1 + \mu_1, \quad \mu_1 \sim N(0, \sigma_1^2) \quad \text{if } Z = 1$$

and

$$Y_0 = X_0\beta_0 + \mu_0, \quad \mu_0 \sim N(0, \sigma_0^2) \quad \text{if } Z = 0$$

In practice, we observe sample respondents in only one state $Z = 1$ or $Z = 0$. That is, we observe Y_1 when $Z = 1$, in which case Y_0 is unobserved. Similarly, we observe Y_0 when $Z = 0$, in which case Y_1 is unobserved.

Assume that v, μ_1, μ_0 have a trivariate normal distribution with mean vector zero and covariance matrix:

$$\Omega = \begin{bmatrix} \sigma_v^2 & \sigma_{1v} & \sigma_{0v} \\ \sigma_{1v} & \sigma_1^2 & . \\ \sigma_{0v} & . & \sigma_0^2 \end{bmatrix}$$

where σ_v^2 is a variance of the error term in the selection equation, Normalising with $\sigma_v^2 = 1$. σ_1^2 and σ_0^2 are variances of the error terms in the wage equations. σ_{1v} is a covariance of μ_1 and v , and σ_{0v} is a covariance of μ_0 and v . The covariance between μ_1 and μ_0 is not defined, as Y_1 and Y_0 are never observed simultaneously.

Using direct maximum likelihood methods, the log-likelihood function associated with our model is written as

$$\begin{aligned} \log L = & \sum_{Z=1} [\log \Phi(\eta_1) - \frac{1}{2} \{ \log(2\pi\sigma_{1v}) - (\frac{Y - X\beta_1}{\sigma_1})^2 \}] \\ & + \sum_{Z=0} [\log \Phi(\eta_0) - \frac{1}{2} \{ \log(2\pi\sigma_{0v}) - (\frac{Y - X\beta_0}{\sigma_0})^2 \}] \end{aligned}$$

where

$$\eta_1 = \frac{W\gamma + (Y - X\beta_1)\sigma_{1v}/\sigma_1^2}{\sqrt{1 - \rho_{1v}^2}}$$

and

$$\eta_0 = \frac{W\gamma + (Y - X\beta_0)\sigma_{0v}/\sigma_0^2}{\sqrt{1 - \rho_{0v}^2}}$$

Note: $\rho_{0v} = \frac{\sigma_{0v}^2}{\sigma_0\sigma_v} = \frac{\sigma_{0v}}{\sigma_0}$ is the correlation coefficient between μ_0 and v .

$\rho_{1v} = \frac{\sigma_{1v}^2}{\sigma_1\sigma_v} = \frac{\sigma_{1v}}{\sigma_1}$ is the correlation coefficient between μ_1 and v .

$\Phi(\cdot)$ is the standard normal density function.

$\Phi(\cdot)$ is the standard normal cumulative distribution function.

After estimating the model's parameters, the following unconditional expectations could be calculated:

$$E(Y_1|Z = 1) = X_1\beta_1 \tag{2.1}$$

$$E(Y_0|Z = 0) = X_0\beta_0 \tag{2.2}$$

Because of the selection problem (the failure to observe Y_0 when $Z = 1$ and the failure to observe Y_1 when $Z = 0$), we need to write these outcomes in a selection-equation format. Taking expectations of the outcome equations, we can

find the conditional expected earnings for a user of social networks who self-selected into user of social networks as follows:

$$\begin{aligned}
 E(Y_1|Z = 1, X_1) &= E(Y_1|Z^* > 0) \\
 &= E(Y_1|W\gamma + v > 0) \\
 &= X_1\beta_1 + E(\mu_1|v < W\gamma) \\
 &= X_1\beta_1 + \sigma_1\rho_{1v}\frac{\Phi(W\gamma)}{\Phi(W\gamma)} \tag{2.3}
 \end{aligned}$$

Where $\frac{\Phi(W\gamma)}{\Phi(W\gamma)}$ is referred to as non-selection hazard rate or the inverse Mills ratio.

Similarly, the conditional expected earnings for a non-user of social networks who self-selected into non-user of social networks is:

$$\begin{aligned}
 E(Y_0|Z = 0, X_0) &= E(Y_0|Z^* < 0) \\
 &= E(Y_0|W\gamma + v < 0) \\
 &= X_0\beta_0 + E(\mu_0|v > W\gamma) \\
 &= X_0\beta_0 - \sigma_0\rho_{0v}\frac{\Phi(W\gamma)}{1 - \Phi(W\gamma)} \tag{2.4}
 \end{aligned}$$

Where $\frac{\Phi(W\gamma)}{1 - \Phi(W\gamma)}$ is referred to as the selection hazard rate.

In experimental studies, those assigned to status 1 differ only randomly from those assigned to status 0, so that there is an interchangeability across statuses. However, in non-experimental studies one must adjust for selectivity when evaluating expected earnings if individuals were assigned to statuses other than the ones they in fact entered. The expected outcome for users of social networks if they

were non-users is:

$$\begin{aligned}
E(Y_1|Z = 0, X_1) &= E(Y_1|Z^* < 0) \\
&= E(Y_1|W\gamma + v < 0) \\
&= X_1\beta_1 + E(\mu_1|v > W\gamma) \\
&= X_1\beta_1 - \sigma_1\rho_{1v}\frac{\Phi(W\gamma)}{1 - \Phi(W\gamma)}
\end{aligned} \tag{2.5}$$

Similarly, the expected outcome for non-users of social networks, had they been users, is:

$$\begin{aligned}
E(Y_0|Z = 1, X_0) &= E(Y_0|Z^* > 0) \\
&= E(Y_0|W\gamma + v > 0) \\
&= X_0\beta_0 + E(\mu_0|v < W\gamma) \\
&= X_0\beta_0 + \sigma_0\rho_{0v}\frac{\Phi(W\gamma)}{\Phi(W\gamma)}
\end{aligned} \tag{2.6}$$

We can use Stata command **movestay** to estimate this endogenous switching regression with consistent standard errors by using the full-information maximum likelihood method (Lokshin and Sajaia 2004).

2.4 Descriptions

2.4.1 Job Search Methods

Employed individuals in the survey were asked about the way through which they obtained the current (main) jobs. The survey provides an extensive list of job search methods as listed in Table 2.1.

The job search methods in Table 2.1 can be grouped into four types. Group One is through the government, including: 1) assigned by the government, 2) through an employment agent run by government, 3) through a community employment service station; Group Two is through the market, including: 1) through a commercial

employment agent run by private (including job fair), 2) applied for advertised job, 3) applied directly, 4) employer recruitment. Group Three is through social networks, including: 1) introduced by family members, 2) introduced by relatives, 3) introduced by friends, 4) introduced by acquaintances. Group four is through any other method not categorised ¹.

Table 2.1: Composition of job search methods

Job search methods	Frequency	Percent
Assigned by the government	30	0.55
Through employment agent run by government	52	0.95
Through community employment service station	37	0.68
Through commercial Employment agent run by private	316	5.79
Applied for advertised job	395	7.24
Applied directly	613	11.24
Introduced by family members	413	7.57
Introduced by relatives	1145	21.00
Introduced by friends	1696	31.10
Introduced by acquaintance	159	2.92
Employer recruitment	447	8.20
Other (please specify)	150	2.75
Total	5453	100

Source: RUMIC 2008.

Details from Table 2.1 reveal that the dominant method of obtaining jobs is via migrants' social network. 31.1 percent of the respondents obtained the current jobs through friends, the most frequent means of getting jobs. The second most common job search method is through relatives, which accounts for 21 percent. 7.57 percent of them used family members and 2.92 percent used acquaintances.

When aggregating all sources of job search into the four main categories (in Table 2.2), we find 63% of migrants obtained their current jobs through social networks, followed by 32% through market mechanisms and only 2% through government means.

To simplify the analysis but highlight on social networks, we merge those who got jobs by using government, market and others methods into one group to contrast the other group using social networks for job obtaining. This is to say, in further analysis, we only deal with two categories - the users of networks

Table 2.2: Regrouped composition of job search methods

Job search methods	Frequency	Percent
Through the government	119	2.18
Through the market	1771	32.48
Through social network	3413	62.59
Other methods	150	2.75
Total	5453	100

Source: RUMIC 2008.

and others. Shen and Bian (2018) identify an additional job search methods called mixed method. Unfortunately, we are not able to do this because of data constraints. Table 2.3 shows the details of grouping. 63 percent of rural-urban migrant use social network to find jobs, while 37 percent of them do not.

Table 2.3: Users of network and non-users of network

Job search methods	Frequency	Percent
Users of network	3413	62.59
Non-users of network	2040	37.41
Total	5453	100

Source: RUMIC 2008.

2.4.2 Homophily

The descriptive data in Tables 2.1, 2.2 and 2.3 reveal an observed tendency of homophily - ‘like to associate with like’ in job seeking for rural-urban migrants. Contrasted with 63% of migrants getting jobs through social networks and 33% from market mechanism, only 2% utilised the government job recruitment services. The difference among the recruitment methods cannot be further explored by this research, as we do not have information on whether migrant who use social networks to get jobs also assist fellow migrants to find jobs. To be more specific, we have no information on the composition of migrants’ job contact network apart from the relationship between the job-seekers and the helpers; therefore we cannot pair the users and those who offer the help. With this, we rely on the fact that a migrant’s family members, relatives or friends are more likely to share similar

status.

Homophily does matter in this research if we regard the government recruitment service as a public good yet find that it hardly serves rural-urban migrants, the big group of Chinese labour force. We further learn from Table 2.4 that it is the old and less educated are more likely to use social networks for job obtaining, and less so for the young and educated (Table 2.4). Does this reveal a restriction for them to get efficient information on jobs or simply a lack of market demand of them?

Due to data limitations, we cannot detect whether the large migrant cohort has taken action of such is based on economic rationality or just a series of individual events due to the lack of information or resources. However, we can test how their earnings are affected by different job-search methods. Thus, we employ a rigorous econometric approach to establish the relationship between the earnings and job-obtaining methods.

Table 2.4: Frequency of use of social networks by individual attributes

	Non-users of network	Users of network	Total
Female	42.25	42.43	42.36
Male	57.75	57.57	57.64
Married	52.99	60.01	57.38
Unmarried	47.01	39.99	42.62
Age 16-25	45.54	40.2	42.2
Age 26-35	28.53	28.77	28.68
Age 36-45	20.05	22.21	21.4
Age 46 and above	5.88	8.82	7.72
Elementary school or below	10.1	14.7	12.98
Junior middle school	48.77	58.16	54.64
Senior middle school	20.83	16.87	18.36
Specialized secondary or above	20.29	10.27	14.02

Source: RUMIC 2008.

Table 2.4 highlights the extent to which age and education are correlated with the use of social networks. Older and less educated people are more likely to use social networks to find jobs while young and educated people tend to find jobs through the market, the government and other channels. This shows that the use

of social networks is not randomly distributed across individual characteristics and thus may be endogenous to wages. Gender differences between the users and non-users of network are small. Married people are more likely to use social network than unmarried people. All these variables are included in our further tests.

2.4.3 Job Search Methods and Wages

Migrants who use social networks receive lower wages than those who do not. Table 2.5 reports mean hourly wages for users and non-users of social networks. The gap in hourly wages is 0.64 yuan or 11.7%. This suggests that there is wage cost to using social networks, although further analysis is required to establish a causal impact.

Table 2.5: Wages for users of network and non-users of network

	N	Hourly wage		log hourly wage	
		Mean	SD	Mean	SD
Non-users of network	2030	6.02	3.96	1.73	0.54
Users of network	3389	5.39	3.39	1.63	0.50
Total	5419	5.63	3.62	1.67	0.52

Source: RUMIC 2008.

We plot the logged hourly wage using the kernel density graph (Figure 2.1) to show how the distribution of earnings differs between the two types of job-seekers. We see that plot of the log hourly wage for the users of networks is slightly to the left of that for non-users, showing a gap across the distribution.

2.5 Models for Job Search Methods and Wages

2.5.1 OLS regressions

Our estimations start with OLS regressions on wage rate. The explanatory variables we control for are divided into personal characteristics, job related characteristics and a set of dummy variables for provinces. Personal characteristics include gender,

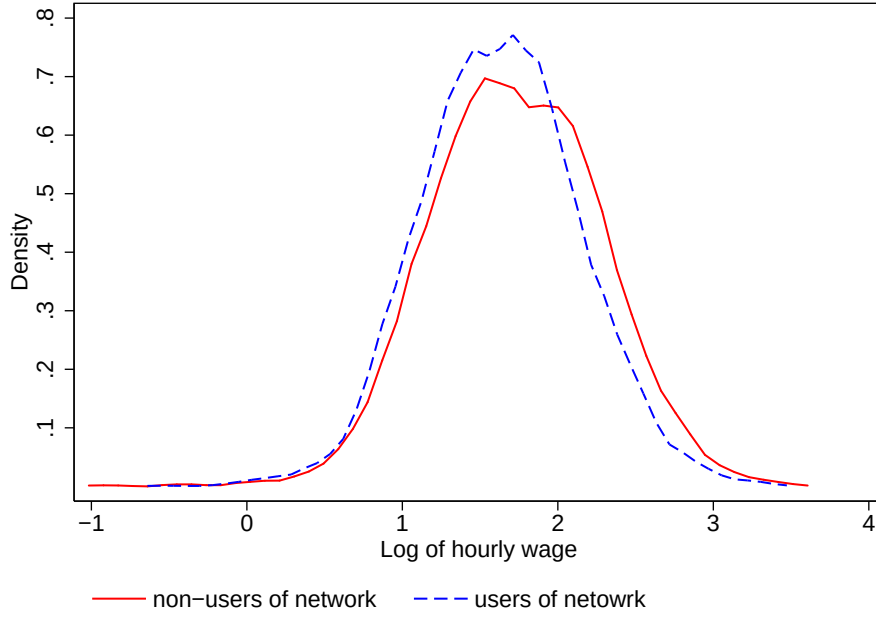


Figure 2.1: Kernel density graph of log of hourly wage

age, age squared, years of migration, years of migration squared, and years of schooling. Job related characteristics include occupation, industry, ownership sector and firm size. Our focus is on whether using networks to find jobs has an impact on the wages subsequently earned on that job. From the OLS regressions in Table 2.6, the magnitude of the coefficient is small, implying the use of social networks is associated with 1% lower wages, *ceteris paribus*. Moreover, the coefficient is not statistically significant; using OLS, we cannot reject the null hypothesis that network use has no effect on wages.

2.5.2 Switching regression

Since OLS estimates may be biased due to self-selection over the use of social networks, we run a switching regression instead. The key issue in controlling for the endogeneity of social networks is identification: finding instrumental variables that could be included in the selection model and excluded from the wage equation. Delattre and Sabatier (2007) use parental occupation and ease of access to public employment agencies to identify the effect of using social networks on wages in France ².

Table 2.6: Wage equations: OLS regressions

	All Sample		Non-users of network		Users of network	
	Coef.	SE	Coef.	SE	Coef.	SE
Users of network	-0.0091	0.0135				
Age	0.0417***	0.0047	0.0294***	0.0085	0.0477***	0.0057
Age squared	-0.0647***	0.0068	-0.0481***	0.0124	-0.0729***	0.0081
Years of migration	0.0218***	0.0035	0.0316***	0.0055	0.0174***	0.0042
Years of migration squared	-0.0478***	0.0126	-0.0823***	0.0181	-0.0322**	0.0153
Male	0.1096***	0.0130	0.0841***	0.0223	0.1283***	0.0160
Years of schooling	0.0424***	0.0027	0.0500***	0.0048	0.0372***	0.0034
<i>Occupation: Base group=White collar</i>						
Blue collar	-0.1953***	0.0247	-0.2360***	0.0360	-0.1470***	0.0342
Other occupation	-0.1643	0.1012	-0.0748	0.1460	-0.1961	0.1330
<i>Industry: Base group=Manufactory</i>						
Construction	0.1204***	0.0240	0.1506***	0.0465	0.1141***	0.0281
Electricity, gas, water, transportation and IT	0.0217	0.0331	-0.0073	0.0544	0.0476	0.0418
Commerce and trade	0.0091	0.0228	0.0191	0.0413	0.0112	0.0271
Restaurant and catering	-0.1232***	0.0210	-0.1361***	0.0340	-0.1046***	0.0266
Finance, estate, health, education	-0.0374	0.0236	-0.0158	0.0395	-0.0421	0.0293
Services	-0.0626**	0.0266	-0.0636	0.0445	-0.0490	0.0331
<i>Ownership: Base group=State and collective</i>						
Private enterprises	-0.0477**	0.0223	-0.0724*	0.0410	-0.0367	0.0263
Self-employed Individuals	-0.0790***	0.0256	-0.0807*	0.0468	-0.0848***	0.0303
Foreign, joint venture	0.0368	0.0277	0.0240	0.0477	0.0328	0.0345
Shared company	0.0340	0.0283	0.0565	0.0495	0.0006	0.0342
Other enterprises	-0.2063	0.1403	-0.4682***	0.1528	0.1451	0.1379
<i>Firm size: Base group= Below 8</i>						
8-50	0.0921***	0.0192	0.0870**	0.0341	0.0925***	0.0234
Above 50	0.1347***	0.0200	0.1619***	0.0354	0.1216***	0.0241
Constant	0.7124***	0.0870	0.7912***	0.1478	0.6458***	0.1065
Adjust R^2	0.3330		0.3384		0.3283	
N	4845		1819		3026	

Note: Dependent variable=log of hourly wage; SE refers to robust standard error; Provinces controlled.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: RUMIC 2008.

From the variables we have in the dataset, we use marriage status, ratio of migrants in the home village and *hukou* status as identifying variables. Married workers may have access to a wider network of contacts, via their spouses, encouraging the use of networks. Ye and Zhou (2010) suggest that marriage does not affect migrant earnings directly because most migrants are working on less skilled jobs. Where there is a large proportion of rural-urban migrants being sent from the worker's home village, workers in that village are likely to have more contacts who can help them find urban jobs. Hence we follow Chen (2009) and Chen et al. (2010) in using the proportion of labour migrants in the home village as an indicator of the village social network. When the household registration (*hukou*) of the worker is not local, they may have fewer contacts with local people and thus less chance of using their networks to find employment. We assume that these identifying variables influence the selection choice to use social networks but not impact wages directly (assumptions that we test empirically).

The selection model from Table 2.7 shows that each of three hypothesised identifying variables have significant effects on the likelihood of using social networks to find employment, with the predicted signs. Amongst the other control variables, the use of social networks declines with education level and increases with age and with years of migration. Older workers are likely to have accumulated more acquaintances and thus have access to a wider social network. Educated workers may have less need to use social networks to find jobs, as their qualifications give them an edge in job competition. Age, age squared, years of migration, years of migration squared, and educational level are included in selection model.

Table 2.8 shows the results of wage equations from the switching regressions. The rho values in Table 2.8, which measure the correlation coefficients between the error terms in the selection model and the wage equation, are both statistically significant. This implies that the use of social network is endogenous to wage determination. Thus the switching regression is more appropriate than the OLS regression. The rho term of non-users of networks, corresponds to ρ_{0v} discussed

Table 2.7: Switching regression: selection model

	Coefficient	SE
Unmarried	−0.1572***	0.0524
Non-local rural hukou	−0.1193***	0.0436
Ratio of labour migrants in home village	0.0044***	0.0008
Age	−0.0382**	0.0158
Age squared	0.0528**	0.0218
Years of migration	−0.0139	0.0113
Years of migration squared	0.0848**	0.0426
Male	0.0288	0.0395
<i>Education:base group=Junior middle school</i>		
Elementary school or blow	0.1265**	0.0593
Senior middle school	−0.1854***	0.0443
Specialized secondary school	−0.4888***	0.0519
Constant	0.9628***	0.2633
<i>N</i>	4723	

Note: Dependent variable: dummy=1 if user of network.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: RUMIC 2008.

earlier: its positive value implies that unobserved factors v which increase the likelihood of using social networks are positive correlated with the unobserved determinants μ_0 of the wages of those not using networks. Similarly, the positive value of the rho term for users of networks, corresponds to ρ_{1v} and implies v is positively correlated with the unobserved determinants μ_1 of the wages of those using networks.

There is thus positive selection in network use - those who use social networks are likely to be paid more due to unobservable factors. Note that this positive selectivity is present in both regimes - users of networks have unobservables that would imply higher wages conditional on using networks, but also conditional on not using networks. This implies that users of networks tend to have unobserved characteristics ('ability') that raise wages, or perhaps to work in jobs with unobserved characteristics that are associated with higher pay. Not controlling for this, for example in the OLS models, will bias upwards estimates of the impact of network usage on wages. Delattre and Sabatier (2007) obtained the same finding when analysing data from France in 1995.

Table 2.8: Switching regression: wage equation

	non-users of network		users of network	
	Coefficient	SE	Coefficient	SE
Age	0.0255***	0.0091	0.0463***	0.0059
Age squared	−0.0412***	0.0133	−0.0700***	0.0084
Years of migration	0.0284***	0.0070	0.0150***	0.0045
Years of migration squared	−0.0615**	0.0269	−0.0174	0.0161
Male	0.0923***	0.0244	0.1278***	0.0176
Years of schooling	0.0346***	0.0052	0.0288***	0.0036
<i>Occupation: Base group=White collar</i>				
Blue collar	−0.2137***	0.0345	−0.1376***	0.0315
Other occupation	−0.0708	0.1655	−0.1754	0.1231
<i>Industry: Base group=Manufactory</i>				
Construction	0.1572***	0.0425	0.1066***	0.0281
Electricity, gas, water, transportation and IT	−0.0054	0.0572	0.0506	0.0414
Commerce and trade	0.0254	0.0383	0.0076	0.0280
Restaurants and catering	−0.1379***	0.0348	−0.1109***	0.0268
Finance, estate, health, education, science	−0.0250	0.0378	−0.0437	0.0295
Services	−0.0599	0.0393	−0.0588*	0.0310
<i>Ownership: base group=state and collective</i>				
Private enterprises	−0.0501	0.0399	−0.0411	0.0261
Self-employed Individuals	−0.0595	0.0454	−0.0902***	0.0297
Foreign, joint venture	0.0411	0.0454	0.0248	0.0349
Shared company	0.0721	0.0475	0.0024	0.0350
Other enterprises	−0.4367**	0.1797	0.1040	0.2394
<i>Firm size: Base group=Below 8</i>				
8-50	0.0846***	0.0321	0.0987***	0.0223
Above 50	0.1512***	0.0325	0.1235***	0.0235
Constant	1.2765***	0.1733	0.5617***	0.1073
Rho	0.6613***	0.0662	0.6227***	0.0647
Sigma	0.5107	0.0239	0.4604	0.0144
R^2	0.3614		0.3366	
N	1765		2958	

Note: Dependent variable=log of hourly wage; Province controlled.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: RUMIC 2008.

The switching regression model differs from an endogenous dummy variable model in allowing explanatory variables to impact wages differently between users of network and non-users of network. However, comparing the wage equations for users of networks and for non-users, few differences are apparent. Generally, speaking the determinants of wages appear similar in the two sub-samples. Wald tests for differences in the individual coefficients reveal no differences in the explanatory variables that are statistically significant at the 5% level. The coefficients on age and age squared are each significantly different in the two samples at the 10% level. Plotting the joint effects of the age quadratics, it is apparent that wages fall with age at a faster rate for users of networks than for non-users. The constant terms in the two wage equations are significantly different from each other at the 1% level, implying wage differences between the two sub-samples.

2.5.3 Wage difference

Table 2.9 compares the predicted log wages from the wage equations in Table 2.7 with the observed values. Unconditional log wages are predicted from the switching model using Equation 2.1 and 2.2. Conditional log wages are predicted from the switching model using Equation 2.3, 2.4, 2.5 and 2.6. The predicted unconditional log wages are the most useful for calculating the effect of using social networks on wages, since they are not subject to any selectivity bias.

Table 2.9: Observed and predicted log hourly wages

		Mean	SD
Users of network	Observed	1.6285	0.5015
	Unconditional	1.4608	0.2784
	Conditional on users of network	1.6286	0.2897
	Conditional on non-users of network	2.1705	0.3014
Non-users of network	Observed	1.7181	0.5317
	Unconditional	2.0490	0.2971
	Conditional on users of network	1.2349	0.2915
	Conditional on non-users of network	1.7176	0.3166

Source: RUMIC 2008.

Non-users of networks have somewhat higher observed mean log wages than

users, implying a wage differential of around 9%. However, the gap in unconditional predicted mean wages is much greater, consistent with a wage differential of around 59%. This reflects the positive selectivity of network use - network users have unobservable factors that raise their wages and thus the observed wage gaps masks the extent of the negative effect of using networks to find jobs on wages.

It is not uncommon in the literature to find wage discounts from using social networks. However, what is striking about our results is the magnitude of the effect. For example, Delattre and Sabatier (2007) find a 7% wage discount in France in 1995. Bentolila et al. (2010) report discounts of at least 2.5% in the EU and US. While of the same sign, the wage differentials we estimate for rural-urban migrants in China are of an order of magnitude higher than those found in industrialised countries. We can only speculate on why the wage discount from using social networks is so much higher in China, but one factor is likely to be the large rural-urban gap in labour productivity in China. Potential rural-urban migrants may be faced with a choice between staying in low return agriculture and finding a much more remunerative non-agricultural job if they migrate. It is not uncommon to find estimates of labour productivity outside of agriculture being ten times as high as in agriculture (Knight and Song 2003). In such a situation, it is quite plausible that rural workers will accept a sizeable urban wage discount from using networks, if that gives them access to urban jobs.

2.5.4 Robustness tests

OID test

In our selection model, we use three instrument variables: marriage status, ratio of labour migrants in home village and *hukou* status. We assume that the instrumental variables only effect wages through network use. We test this assumption by an over-identifying test for instrumental variables in Table 2.10. The dependent variable is the residual of wage equation from the switching regressions. The independent variables are all the exogenous regressors in the wage equations together with

the three instrumental variables. This auxiliary regression shows that all the instrumental variables do not affect the residuals of the wage equations, so we cannot reject our assumption that they can be excluded from the wage equations.

Table 2.10: Over-identifying test

	Coefficient	SE
Unmarried	−0.0103	0.0200
Non-local rural hukou	−0.0066	0.0184
Ratio of labour migrants in home village	−0.0004	0.0003
Constant	0.0237	0.0267
Adjust R^2	−0.0062	
N	4723	

Note: Dependent variable: residual of wage equation from switching regression.

All variables used in wage equation are controlled.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: RUMIC 2008.

In preliminary work, we explored various other potential instruments for network usage, including family political background, parental education, parental occupation, number of siblings, number of friends living in urban areas and the distance from home province to working province. However, these were rejected as instruments either because they were not correlated with network user or because they were correlated with wage residuals from the switching regressions. Specifically, although family political background is a good IV in Zhang and Lu (2009), it is not correlated with the use of networks in our data. Likewise, parents' education and occupation are not significantly correlated with the use of network. The number of siblings, the number of friends living in city and the distance from the home province to the workplace province are correlated with the use of network, but fail the OID test.

Treatment effects models

An alternative to the switching regressions approach is to use a treatment effects model, in which use of social networks in job search is included as an endogenous dummy variable in a wage equation. Both Maximum Likelihood (ML) and Two Step estimators imply the dummy variable has a large, significant negative impacts

on wages. The coefficient implies use of networks would lower log wages by 0.438 points. This is of a similar order of magnitude to that implied by a comparison of the predicted unconditional mean log wages from the switching regression models.

Table 2.11: Wage equations from Treatment effect models: ML and two-steps

	ML		Two-steps	
	Coefficient	SE	Coefficient	SE
Users of network	−0.4380***	0.0558	−0.5303***	0.1131
Rho	0.5705***		0.6631***	
Sigma	0.4662		0.4871	
Lambda	0.2660		0.3230	
<i>N</i>	4723		4723	

Note: Dependent variable=log of hourly wage.

Personal characteristics, job characteristics and Province dummies controlled.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: RUMIC 2008.

Job change

There might be a difference in the selectivity of network use between migrants who still hold their first jobs and those who changed their jobs. Migrants who rely more on social network to find their first migrant jobs may be totally unfamiliar with the environment when they come to cities. So we divide all sample into two groups: those who still hold their first jobs and those who changed their jobs. We run the same switching regression for both of them. Table 2.12 reveals that selectivity bias between network use and wage equation exists for both first job holders and for migrants who changed their jobs. This indicates the contingency of the effect of social network on wages. However, the selectivity bias for non-network users is much lower in people changed jobs than for first job holders. Thus the unconditional wage gap between users of network and non-users of network is smaller for migrants changed jobs than that for first job holders.

Table 2.12: Observed and predicted log hourly wages

		First Jobs holders N=2056		People changed Jobs N=2658	
		Mean	SD	Mean	SD
users of network	rho	0.5418***		0.6721***	
	sigma	0.4329		0.4707	
	observed	1.6269	0.5106	1.6293	0.4937
	unconditional	1.4993	0.3116	1.4358	0.2667
non-users of network	rho	0.8838***		0.3047*	
	sigma	0.6388		0.4268	
	observed	1.7607	0.5633	1.6898	0.5086
	unconditional	2.3477	0.3275	1.8105	0.2892

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: RUMIC 2008.

2.6 Chapter conclusions

It is well understood that social networks play an important role in labour markets, with many people finding jobs through their friends, acquaintances and relatives. In our survey of rural-urban migrants in China in 2008, nearly two thirds found their employment by such job contacts. However, what is less clear is the impact of such job search mechanisms on subsequent wages. Addressing this issue in a convincing manner requires explicit consideration of the selection process which determines whether or not workers use social networks to find their jobs and whether this causes any selectivity bias for wages.

In this paper, we modelled the selection of job search methods. We found that users of networks to find jobs tended to be older, to have been migrants for longer and to be less educated. In addition, married workers and those from villages which sent out many migrants were more likely to use networks, while those with non-local household registration were less likely. The last three effects - marital status, migration rates in home village and household registration - were used as instrumental variables to identify the impact of network use on wages.

We found evidence of positive selection effects between use of networks and wages. Those using networks to find their jobs appear to have unobservables that

are associated with higher pay - this could be unobserved personal characteristics such as ability or perhaps remunerative job characteristics. Thus, although users of networks are less educated than non-users, they appear to have other, unobserved advantages for pay determination. This implies that simple estimations of the impact of network use on migration that do not control for selectivity are upwards biased - benefits would be ascribed to networks that more properly reflect the favourable unobserved characteristics of network users.

Controlling for selectivity, we find a large negative impact of network use on wages. Using job contacts brings benefits in terms of giving people from rural China access to urban employment. However, it also imposes a substantial cost - those urban jobs found using job contacts pay markedly less than those found by impersonal means. This negative effect of using employment has been found before, using comparable methods, in industrialised countries. However, what is striking about our results is the magnitude of the effect. This may be explicable given the greater segmentation of labour in China and the consequent large gap in labour productivity between agriculture and the employment of rural-urban migrants. At first look it appears a puzzle, why so many rural-urban migrants use friends and relatives to find jobs if they face a wage penalty as a result. However, such migrants may have less chance of finding jobs if they rely on formal means of job search. Given the large gap in labour productivity rural and urban areas, it may well be worth accepting a wage discount by using social networks if it is the means by which the migrants can escape low return farming and find more remunerative work in urban areas.

We did not examine the inter-groups heterogeneity for users of network. Social contact may differ from gender, race, strength of relationship, and influence (Smith 2000). As shown in Antoninis (2006), people cannot get a higher starting wage when they get recommendations from relatives and friends, while people can enjoy a higher starting wage when referrals have knowledge of their productivity. Kramarz and Skans (2014) shows that, however, strong ties are more important in

job search and wages for young graduates. Future research can explore inter-groups heterogeneity by different directions, including the types of network, different sectors, and different job skills.

Appendices of Chapter 2

Table A.1: Data descriptions (mean or frequencies)

	Non-network	Network	Total
Age (years)	29.16	30.60	30.06
Years of migration	7.73	8.34	8.11
Years of schooling	9.46	8.68	8.97
Ratio of labour migrants in home village (%)	56.46	59.38	58.28
Male (%)	57.75	57.57	57.64
Unmarried (%)	47.01	39.99	42.62
Local rural hukou (%)	16.72	20.77	19.26
<i>Occupation (%)</i>			
White collar	10.87	6.25	7.98
Blue collar	83.82	89.11	87.13
Other occupation	5.31	4.64	4.89
<i>Industry (%)</i>			
Manufactory	26.71	20.95	23.10
Construction	8.44	14.41	12.18
Electricity, gas, water, transportation and IT	3.58	4.20	3.97
Commerce and trade	17.18	19.31	18.51
Restaurants and catering	20.23	19.04	19.49
Finance, estate, health, education, science	12.86	11.53	12.03
Services	11.00	10.56	10.73
<i>Ownership (%)</i>			
State and collective	8.38	10.17	9.50
Private enterprises	40.65	43.61	42.50
Self-employed Individuals	24.39	28.73	27.10
Foreign, joint venture	15.31	9.15	11.46
Shared company	10.97	8.22	9.25
Other enterprises	0.30	0.12	0.19
<i>Firm size (%)</i>			
Below 8	23.93	27.31	26.05
8-50	25.11	30.16	28.27
Above 50	50.96	42.53	45.69

Source: RUMIC 2008.

Table A.2: Switching regression: selection model

	Marginal Effect	SE
Unmarried	−0.0547	0.0236
Non-local rural hukou	−0.0594	0.0183
Ratio of labour migrants in home village	0.0013	0.0004
Age	−0.0019	0.0016
Years of migration	−0.0009	0.0021
Male	0.0099	0.0154
<i>Education: Base group=Junior middle school</i>		
Elementary school or below	0.0404	0.0237
Senior middle school	−0.0890	0.0194
Specialized secondary school	−0.2046	0.0218
<i>N</i>	4723	

Note: Dependent variable: dummy=1 if user of network

Source: RUMIC 2008.

Table A.3: Wage equations from Treatment effect models: ML and two-steps

	ML		Two-steps	
	Coefficient	SE	Coefficient	SE
Users of network	−0.4380***	0.0558	−0.5303***	0.1131
Age	0.0403***	0.0051	0.0401***	0.0054
Age squared	−0.0619***	0.0074	−0.0615***	0.0077
Years of migration	0.0185***	0.0039	0.0183***	0.0041
Years of migration squared	−0.0291**	0.0143	−0.0271*	0.0150
Male	0.1113***	0.0147	0.1118***	0.0153
Years of schooling	0.0328***	0.0031	0.0303***	0.0039
<i>Occupation: Base group=White collar</i>				
Blue collar	−0.1781***	0.0230	−0.1759***	0.0231
Other occupation	−0.1389	0.0985	−0.1389	0.0991
<i>Industry: Base group=Manufactory</i>				
Construction	0.1156***	0.0233	0.1131***	0.0234
Electricity, gas, water, transportation and IT	0.0250	0.0337	0.0250	0.0337
Commerce and trade	0.0082	0.0227	0.0065	0.0227
Restaurants and catering	−0.1281***	0.0213	−0.1281***	0.0213
Finance, estate, health, education, science	−0.0438*	0.0232	−0.0467**	0.0232
Services	−0.0665***	0.0243	−0.0657***	0.0242
<i>Ownership: Base group=State and collective</i>				
Private enterprises	−0.0450**	0.0221	−0.0456**	0.0221
Self-employed Individuals	−0.0770***	0.0251	−0.0762***	0.0251
Foreign, joint venture	0.0376	0.0274	0.0357	0.0274
Shared company	0.0367	0.0280	0.0342	0.0281
Other enterprises	−0.2643*	0.1430	−0.2612*	0.1402
<i>Firm size: base group=Below 8</i>				
8-50	0.0957***	0.0184	0.0951***	0.0184
Above 50	0.1330***	0.0191	0.1316***	0.0192
Constant	1.0695***	0.1014	1.1502***	0.1333
Rho	0.5705		0.6631	
Sigma	0.4662		0.4871	
Lambda	0.2660		0.3230	
N	4723		4723	

Note: Dependent variable=log of hourly wage; Province controlled

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: RUMIC 2008.

Chapter 3 The Impact of Job Contact Networks on the Job Quality of Rural-Urban Migrants in China

In the Chapter 2, I have examined the impact of job contact networks on the wage rate of rural-urban migrants in China. The wage rate stems from wage and working hours. Although the wage and working hours are two key components of job quality, job quality has more dimensions other than just wage and working hours. This chapter measures the job quality index based on the wage, working hours, the job stability, and social insurances. I intend to explore the impact of job contact networks on the job quality of rural-urban migrants in China. The analysis will extend the literature of social network and job quality.

3.1 Introduction

Jobs are a critical concern for individual and society across the world, for jobs contribute to broader goals for personal benefits, productivity, and social well-being (World Bank 2012; Salvator et al. 2018). Policy on jobs is not only about the quantity of jobs, but also about the quality of jobs (UNDP 2015). Job quality¹ or decent work is a timely issue (Findlay et al. 2013) and has been addressed in

¹Job quality, quality of work, quality of work life, and quality of employment are interchangeably in this study.

many development goals, such MDG ² and SDGs³. To improve job quality is an essential social agenda and policy goal in many developed countries, like US, UK, Germany (Dahl et al. 2009), and in many international organizations, like European Commission, OECD, and ILO (European Commission 2008; ILO 2013; OECD 2016).

Previous studies have demonstrated the role of social network on job search (Wahba and Zenou 2005) and employment outcomes (Frijters et al. 2005). But they usually examine one dimension of job quality only and treat this single dimension as the whole job quality unintentionally. For example, Meurs and Valat (2019) use the educational requirement for a given occupation to measure job quality. The impact of job contact network on the whole job quality has been rarely examined.

Although research about the measurement of job quality have not reached a consensus, most studies employ a multi-dimension approach. This approach treats job quality as a multi-dimensional phenomenon related to individual job characteristics, ranging from earnings, working time, the job stability, social insurances, etc. If the research focuses only on single dimension, like wage, we risk ignoring other key elements related to job quality (Clark 2015). As shown in Green et al. (2013), non-monetary aspects of job quality distributed unequally among different countries and periods.

As to China, the distinguished feature of job is its segmentation, often distinguishing between formal employment and informal employment (Liang et al. 2016), or by education (Maurer-Fazio and Dinh 2004), or by ownership of firm (Dong and Bowles 2002; Zang 2002), or by industries (Ma 2018), or by types of workers (Fan 2002), or by occupations (Meng and Zhang 2001). Previous studies on the Chinese labour market tend to focus on earnings, social insurance, or other indicators (Knight and Song 2005; Zhao 2005; Li and Wan 2014; Zhao 2019). Yet

²Millennium Development Goal 1, Target 1.B: “To achieve full and productive employment, as well as decent work for all, including young people and women”, <http://www.un.org/millenniumgoals/poverty.shtml>

³One of SDGs 8 targets is “By 2030, achieve full and productive employment and decent work for all women and men, including for young people and persons with disabilities, and equal pay for work of equal value”, <https://www.un.org/sustainabledevelopment/economic-growth/>

a more comprehensive indicator to measure job quality has not been systematically investigated.

This chapter is going to create a job quality index for rural-urban migrants in China and to explore the impact of job contact networks on the job quality of rural-urban migrants. We define the job quality index as a combination of the wage, working hours, the job stability, and social insurances. Using the nationally representative survey data from Rural to Urban Migration in China Survey (RUMIC 2008), we compare the difference of job quality between network users and non-network users. We find that the use of network is related with low job quality, especially for the users of network.

The novelty of this chapter is threefold:

First, this chapter offers a new angle to understand job realities for rural-urban migrants in China, viewing job quality through the lens of objective job characteristics. As argued by Combarrous (2016), the concept of job quality offer a new instrument for labour market analysis. Most of job quality frameworks are created by developed counties. Those frameworks are not easily transferable to China with data constraints and local contexts. This chapter will use a multi-dimensional approach designed for China, combing the monetary and non-monetary indicators.

Second, this chapter augments the traditional studies to studying the relationship between social network and labour market performance. Unlike most studies that focus on the impact of social network on separate dimensions of job quality, this chapter creates a single job quality index, divides migrants into different job quality groups by their job quality index, and then examines the impact of job contact network on job quality groups. As far as we know, no attempt has been made to investigate the impact of job contact network on job quality for rural-urban migrants in China.

Third, this chapter employs the endogenous ordered switching regression with the latent-factor approach. This method can take count of selectivity of unobserv-

ables for ordered comes and dummy treatment. The latent-factor approach allows a more flexible error distribution.

This chapter is structured as follows. Section 2.2 reviews job quality related literature in general and particular in China. Section 2.3 introduces the data and econometric methods for analysis. Section 2.4 presents the main empirical result and uses different methods to run robust test for our main findings. Section 2.5 summaries main findings of this chapter and discusses contributions and shortcomings.

3.2 Literature review of job quality

This section first focuses on indicators of job quality and methods to create job quality index, then discusses the relationship between social network and job quality, and moves to the job quality in China in last.

3.2.1 Measurement of job quality

There are two main approaches to measure job quality. One is to use objective job characteristics. The other is to use job satisfaction as a proxy to job quality.

Objective indicators of job quality: job characteristics

Many international organizations have established indicators to measure job quality.

United Nations Economic Commission for Europe (UNECE) defines seven dimensions of quality of employment, including safety and ethics of employment, income and benefits from employment, working time and work -life balance, security of employment and social protection, social dialogue, skills development and training, employment-related relationships and work motivation. For each dimension, there are several employment-related relationships and work motivation suggested indicators (UNECE 2015).

European Trade Union Institute (ETUI) creates an European Job Quality

Index. It includes six dimensions: wage, non-standard forms of employment, working time and work-life balance, working conditions and job stability, skills and career development, and collective interest representation (Leschke et al. 2012; Leschke and Watt 2014).

International Labour Organization (ILO) measures decent work based on ten elements, including employment opportunities; adequate earnings and productive work; decent working time; decent working time combining work, family and personal life; work that should be abolished; stability and security of work; equal opportunity and treatment in employment; safe work environment; social security; social dialogue, employers' and workers' representation (ILO 2013). They also call to recognise workplace safety and health as a fundamental principle and right at work (ILO 2019a; ILO 2019b). The framework of decent work has been applied in analysis of many countries. For example, Moktan (2019) employs this framework to evaluate employment opportunities, social security, and social dialogue in India. The framework of decent work also can be applied in micro level analysis, like studies in Switzerland (Masdonati et al. 2019), UK (Dodd et al. 2019), Turkey (Buyukgoze-Kavas and Autin 2019), Italy (Fabio and Kenny 2019), Portugal (Ferreira et al. 2019), and Brazil (Ribeiro et al. 2019).

OECD develops a Job Quality Framework that has three dimensions: earnings quality, labour market security and the quality of the working environment (OECD 2015).

Apart from indicators created by international originations, there are many other research of job quality within specific country or countries.

In US, Kalleberg et al. (2000) define bad jobs to those with low wages (below 20th percentile) and without health insurance and pension. By employing this three-dimension-measurement, they find that one-seventh workers are bad on all three dimensions in 1995. They run a logit regression for each dimension and run a negative binomial regression to explore the determinants of bad jobs. This approach can be applied to job quality analysis for different non-standard employment

(Kalleberg 2000).

In Germany, the German Confederation of Trade Unions (DGB) has established the DGB Good Work Index since 2007. The DGB Good Work Index is composed of three dimensions called resources, demands/strains, and income/security (Kraemer 2016). The three dimensions include eleven sub-dimensions, which are all subjective indicators that have an impact on the worker's well-being. The index is scored from 1 to 100. The score is further used to divide four different groups: good work, upper medium level, lower medium level, and poor work. Jones et al. (2014) employ the framework of the DGB Good Work Index to study job quality of bus drivers in UK.

In Britain, McGovern et al. (2004) emphasizes the role of promotion in job quality. They list four dimensions to conceptualize bad jobs: low pay, no sick pay, no pension scheme besides governmental scheme, and not being part of a recognized career or promotion ladder. They get a scale valued 0 to 4 and use it as dependent variable to measure bad jobs in a Poisson model.

In Canadian, CIBC-World Markets Canadian Employment Quality Index has drawn much public attention when the report said it reached a lowest level in the year of 2015 since 1988 (Tal 2015). The CIBC index uses three dimensions: the distribution of part-time and full-time work, the pay of any given job, and job stability. People criticize that job quality should be measured by more than three dimensions and the CIBC index should not use the average pay by industry as the actual pay (Cross 2015). Chen and Mehdi (2018) from Statistics Canada assess six dimensions of job quality, including income and benefits, career prospects, work intensity, working-time quality, skills and discretion, and social environment.

Other important indicators include autonomy and control (Addabbo and Solinas 2012), employment relationship (Lowe and Schellenberg 2001), physical well-being (Jackson and Kumar 1998), training opportunities and task discretion (Gallie 2007). Some studies try to compare job quality between the standard and nonstandard employment (McGovern et al. 2004).

Job quality can be distinguished by intrinsic and extrinsic aspects of job quality (Peña-Casas et al. 2018). Intrinsic aspects of job quality include working environment, safety and health, working time, skill and training, etc. Extrinsic aspects of job quality include earnings, job security, contracts, social protections, workers' rights, etc. Job quality can also be evaluated by monetary and non-monetary aspects. Among the monetary aspects of job quality, gross wage is the centre for workers (Gebel 2009). Piasna et al. (2017) provide a model with five levels of analysis to measure job quality, including workers, jobs, legal framework, welfare policy, and structural features.

Most of studies consider job quality at a certain point in time, whereas Berloff et al. (2019) give a new definition of job quality by the changes of employment conditions over a period of time. The changes include three parts: employment security, earning quality (income security and economic success), and educational-occupational match.

Subjective indicator of job quality: Job satisfaction

The choice of dimensions of job quality is to some extent arbitrary and so is weights and priorities of each dimensions (Osterman 2013). Even for the same dimension, there are disagreement about the measurement (Hauff and Kirchner 2014). Some indicators of job quality are more of a subjective and qualitative nature, thus raising the importance of subjective indicators. The subjective approach usually asks directly how people assess their jobs. The most frequent way is to ask questions of job satisfaction in general or by dimensions.

There are two main reasons that why job satisfaction can be used to measure job quality. First, job satisfaction can capture aspects that are not reflected by objective indicators (Freeman 1978). Job satisfaction represents labour market participants' own values about their own jobs, instead of researchers or policy-makers (Ritter and Anker 2002). Second, Job satisfaction is a good predictor for objective indicators. However, different job quality dimensions affect subjective

well-being in different ways (Horowitz 2016).

Clark (2005) considers job satisfaction as one kind of job outcomes. Using a 1-7 scale, he explores the change of overall satisfaction and four sub kinds of satisfaction (with pay, security, work itself, and working hours). He also examines inequality of job satisfaction by county, age, education and union membership. European Commission (2001) studies job satisfaction and its relationship with other job characteristics. They admit that job satisfaction at individual level is related with personal selection and attitude, so job satisfaction is not equivalent to job quality.

However, Muñoz de Bustillo et al. (2011) argue that there are some other factors that affect job satisfaction but are not related with job quality. Workers in poor job quality sectors can be satisfied with their jobs too (Deery et al. 2019). Job satisfaction, therefore, cannot catch all characteristics of job quality. For example, in France, employees in the cleaning sector are considered having poor quality jobs, but they report higher job satisfaction than other employees despite of the poor job quality (Léné 2019). In China, rural-urban migrants who use job contact network tend to have higher job satisfaction because of the good social network relationship in workplace (Zhou and Hu 2019). But they are more likely to have higher quitting intentions, which is a signal of lower job quality. Therefore, job satisfaction is not be equivalent to job quality.

The objective approach and the subjective approach to measure job quality can be mixed in practice (Stier and Yaish 2014). For example, job satisfaction can be treated as one part of job quality (Saks and Ashforth 2002; Brisbois 2003; Deguilhem et al. 2019). Gallie et al. (2016) use both intrinsic job quality and job satisfaction for female part-time work.

Methods to form job quality index

There are two ways to use different dimensions of job quality. One is to examine each dimension separately. For example, Stecy-Hildebrandt et al. (2019) compare the

difference of employment security, leave benefits and earning trajectories between permanent and temporary employees in public sector.

The other is to form a job quality index. The most popular way is to standardize each indicator, then add standardized-score together with weights, as shown in Crespo et al. (2017). Most studies use equal weight (Leschke et al. 2012). This approach is similar to the construction of Human Development Index (UNDP 2018)⁴. Other methods to create a sing index can be the principal component analysis, the cluster analysis, or the factor analysis (European Commission 2008; Ferreira et al. 2019), the latent class analysis (van Aerden et al. 2014; Chen and Mehdi 2018), the multiple correspondence analysis (MCA) (Combarnous 2016; Deguilhem et al. 2019), the structural equation modelling (SEM) (Díaz-Chao et al. 2016; Ficapal-Cusí et al. 2018), the fuzzy logic (McGovern et al. 2004; Addabbo et al. 2007), the qualitative comparative analyses (Kalleberg and Vaisey 2005), and the Alkire and Foster method (Huneus et al. 2012; Brummund et al. 2018).

The job quality index can be used as the dependent variable in models or divided into several groups. For example, Lowe and Schellenberg (2001) add all dimension scale into a single one, rank them by new scale, then cut them into three groups of equal size. Vanroelen (2019) identifies five employment types based on the employment quality.

3.2.2 Social network and job quality

Social network is widely used by firms and workers because of lower search costs, reduced informational asymmetry, and positive peer effects (Beaman 2016). The literature on the effect of social network on labour market performance is voluminous, growing and somewhat sobering. Conditions of job search is closed related to job quality afterwards (Gaure et al. 2012). Here we narrow down social network

⁴HDI has three dimensions: long and healthy life (life expectancy at birth), knowledge (expected years of schooling, mean years of schooling), and standard of living (gross national income per capita in PPP). The weight for each of the three dimensions is the same. The weight for two indicators for education is also the same. The formula to calculate each dimension index is: Dimension index = (actual value – minimum value)/(maximum value – minimum value). The geometric mean of the three indices is called HDI.

to the scope of job search and job contact network.

Social network and objective job stability

In many European countries, finding jobs by social contacts can lead both wage premium and wage penalty, depending upon the efficiency of formal job search ways (Pellizzari 2010). Social contacts reduce the duration of unemployment (Cingano and Rosolia 2012), but are related with occupation mismatch and wage discount (Bentolila et al. 2010).

People with fixed-term contracts are paid significantly less compared to those with permanent jobs, especially for the first job holders (Gebel 2009). The effect of job contact network on job search are different between sectors. In China, social network is more influential in state sector than non-state sector, as the procedures to hire employees is more transparent and standardised in non-state sector (Huang 2008).

Dang (2019) observes that rural-urban migrant with more social network tend to change wage employment to self-employment. Social capital in the workplace is positively associated with satisfaction and quality of life in the workplace (Requena 2003).

Using a nationally representative immigrant survey data in Korea, Kim (2019) finds that finding jobs through personal contacts is associated with low monthly income for men only, especially for those using bonding (co-ethnic) ties. There is no significant difference of monthly income between informal job search and formal job search for women.

Social network and job satisfaction

As to the relationship between social network and job satisfaction, Hurlbert (1991) shows that co-worker social circles and kin-centred networks are positively related with job satisfaction through social support. Winstead et al. (1995) also find that the quality of friendship at work is a good predictor of job satisfaction.

Flap and Völker (2001) view social network as social capital, arguing that the effect of social network on job satisfaction depends on the structure of network and the content of ties. For example, closed networks of identity-based solidarity ties can increase job quality, while bow-tie structure is negatively related with job quality. But we should be cautious to interpret the close relationship between social network at work and job satisfaction because of the different measures of social network. This chapter uses job contact network rather than the friendship or other networks at work. One study about college graduates examines the difference of job search methods and job satisfaction between different race and gender, but it does not go further to explore the effect of job search methods on job satisfaction (Mau and Kopischke 2001).

3.2.3 Job quality in China

During recent years, China comes to a point that need to address its job quality when increasing quantity of jobs. The number and structure of labour force in urban China have changed, partly because of the new Labour Contract Law effected in 2008⁵. The 2008 new labour contract law gives workers more employment rights and security (Gallagher et al. 2015; Akee et al. 2019). There are many heated debates around the new Labour Contract Law in 2008 (Gallagher et al. 2015; Wang et al. 2016; Wang et al. 2019)

As suggested by Li (2008), quality jobs or decent work for rural-urban migrants face a major challenge. One unexpected phenomenon is the pace of rural-urban migration has slowed down since 2012, especially for rural-urban migrants outside local township⁶. In large cities⁷, there was almost no increase in rural-urban migrant between 2014 and 2017 (Gregory and Meng 2018). Relative scarcity of rural-urban migrants leads massive debate about whether China has reached or

⁵Details can be found in: http://www.gov.cn/flfg/2007-06/29/content_669394.htm

⁶Data from the monitor report of rural-urban migrants survey 2016 by China National Bureau of Statistics: http://www.stats.gov.cn/tjsj/zxfb/201704/t20170428_1489334.html

⁷Some cities, deliberately or not, is trying to kick out low-level industries and so-called low-level population (mostly rural-urban migrants) (Qian 2018; Chan and O'Brien 2019).

passed Lewis turn point (Cai and Du 2011; Knight et al. 2011; Dong et al. 2018; Kwan et al. 2018). While the number and the age structure of urban labour force are transforming, wages of rural-urban migrants are growing. The government has allocated more and more resources on rural areas, which makes rural area more attractive to migrants. As to the coverage of rural-urban migrants' "Five Insurance and One Fund", the National Bureau of Statistics of China (NBSC) has publicly reported it from 2009 to 2014, but stopped after 2014. Given the high labour cost and potential shortage of labour force, job quality in urban China deserves more attention. Plus, rural-urban migrants with bad jobs may fall into new urban poor group (Liu and Guo 2008). The second generation of rural-urban migrants are more eager to demand decent work (Hannan 2009).

Comparing with urban residents, rural-urban migrants tend to work on non-standard employment with fewer benefits (Stainback and Tang 2019). Those non-standard jobs are usually considered as bad jobs. There are some distinguished features when coming to job quality: first, most of them have the rural health care insurance and do not care much about pension. In addition, for rural-urban migrants, health care insurance and pension are hard to be transferred across provinces and between cities and rural areas. Plus, they cannot get the fully benefit after the transfer. So the health insurance and pension provided by employment are less useful in the rural-urban migrants' context. However, the urban health care and the urban pension are critical if rural-urban migrant wish to settle down in cities.

Second, work-life balance means different for rural-urban migrants and urban residents. For migrants, many of them cannot join with their parents, spouses, and children. The most severe problem is separation of family members. For urban residents, separation of family members is not a big problem.

Thirdly, most of rural-urban migrants did not join any union or professional association. Even if they do, membership is like a puppet and does not increase migrants' resources or bargaining power.

Most studies on job quality of China focus on job satisfaction, treating job satisfaction as a dependent variable and running regressions with other job characteristics variables (Chan and Wyatt 2007).

Yang and Shao (2018) identify ten multi-component variables to measure employment quality. They study the effect of industrialization process on employment quality between 1990 and 2014 in China. However, the data of study is at macro level and collected from yearbooks.

Zhao and Zhang (2010) claim that since the new Labour Contract Law (2008) tend to raise the labour cost, the enterprises may increase recruiting standards. Most of rural-urban migrants, however, are with low education and do not have good skills. They would be in worse situation, especially for small and medium enterprises.

Using the 2016 China Urban Labour Survey (CULS) and the 2010 Social Status of Women in China Survey (SSWCS), ILO (2019c) discuss workers' physical environment, work intensity, working time quality, social environment, skills and discretion, prospects, earnings, self-reported health, mental health status, and work-life balance. But they talked about each dimension separately and did not put all dimensions together.

A similar study to this chapter is by Xue et al. (2019). They examine the impact of social network size and heterogeneity on job quality for part-time peasants. A feature of this study is that they use a six dimensional job quality index, including wage, working time, employment stability, employment conditions, career development, and social security. This study, however, has several limitations. First, the sample of this study is only 194, which is a big problem for models and analysis. Second, they did not consider the endogeneity of social network, which will cause bias of results.

3.2.4 Summary

Although the existing studies have provided profound insights into job related characteristics in China, less attention is paid to job quality from a multi-dimensional angle. Previous studies have no consensus on a single composite indicator of job quality. Objective indicators are more straightforward and easier to be monitored, so this chapter will objective indicators to explore job quality. Just like said in Felstead et al. (2019), a shorter set of measures of job quality is more appeal and practicable because of the financial and timing constrains of new data. Given the different culture and institutional elements underlying the use of social network and labour market (Sharone 2014), indicators that measure job quality should be suitable in local social context.

3.3 Data, variables, and descriptions

3.3.1 Data: RUMIC 2008

This chapter will use migrant samples data from the first wave of the Rural to Urban Migration in China survey (RUMIC 2008⁸). We restrict our analysis on employees aged between 16 and 60. We exclude those holding part-time jobs and internships. RUMIC 2008 migrant survey has 5000 households in nine provinces. After excluding the sample with missing variables, we have 4385 individuals for analysis.

Unlike Muñoz de Bustillo et al. (2011) , we did not include the self-employed migrants in the analysis, mainly because it is difficult to find a comparable and objectively way to measure job quality for both the self-employed and employees. The self-employed have a different motivation for earnings, working hours, the job stability, and social insurances. It might be not appropriate to compare job quality between the self-employed and employees directly. For example, although

⁸RUMIC 2008 is also called the Chinese Household Income Project Survey (CHIP) 2007 migrant survey.

the job stability is an important aspect of job quality (Green 2003) and vital for both paid-employees and self-employed (McManus 2000), the measurement of job stability is difficult objectively for self-employed, as self-employed do not have contracts for themselves. Some studies tend to use subjective views to scale job security (Clark 2005).

A related study using RUMIC 2008 is by Cheng et al. (2015). They examine differences of the effect of contract on wage, working hours, social insurance and subjective well-being between urban and migrant workers.

3.3.2 The construction of job quality index for rural-urban migrants

This chapter uses earnings, working time, the job stability, and work-related social insurances to measure job quality of rural-urban migrants.

The idea of aggregating an index is simplicity and feasibility. There are some important dimensions that are not listed in cons, including job safety, career development, and work autonomy. Unfortunately, RUMIC 2008 has no information about those dimensions. RUMIC 2008 did not include job satisfaction in the questionnaires, so we will not use objective measure of job quality in this chapter. We also did not include work-family balance because we cannot find any appropriate indicators in our dataset. We believe the dimension of working time can partly represent the nature of employment related work-family balance.

Wage

RUMIC 2008 asked total income of all kinds, wage-related income, and operating-income. Since we focus on employees only, we use wage-related income including all wages, bonuses and subsidies after individual income tax. Unlike studies using starting wage (Antoninis 2006; Hensvik and Skans 2016) which is not reported in RUMIC 2008, the wage-related income used in this chapter is the average monthly income from current jobs.

Working time

By the Labour Law in China ⁹, workers work no more than 8 hours per day and 44 hours per week. For rural-urban migrants, they usually work much more than the standard. There is not, however, a consistent relationship between working hours and job quality. Long working hours may reduce time for leisure and family, causing low quality of life. Short working hours might be the results of part-time job, which is always considered with low quality. To overcome the dilemma of the relationship between working hours and job quality, we exclude those working less than thirty hours per week. Those migrants only account for 1.3 percent. So it would not cause bias if we drop those samples.

Job stability

Job stability is similar with job security or job insecurity. It is related with employees' health and productivities (Erlinghagen 2007). In this chapter, we use types of contract to measure job stability. In RUMIC 2008, there are four types of contract: no contract, short term contract, long term contract, and permanent contract. We create a dummy variable for those with long term contract or permanent contract, who are considered as having good job stability.

Although contract is one dimension of job quality, it can be used to measure employment status and further to examine the relationship between employment status and job quality (Loughlin and Murray 2013; Eurofound 2018; Moortel et al. 2018).

Work-related social insurances

Since social insurance can improve the ability to deal with risks and make the distribution of income more equal, social insurance is crucial for social cohesion (Levy 2019). In China, there is a large segmentation between urban residents that enjoy many social insurance and rural-urban migrants that do not (Song and Appleton

⁹Details can be found in: http://www.gov.cn/banshi/2005-05/25/content_905.htm

2008). The expansion of social benefits for rural people reduced the growing income inequality between rural and urban area (Gao et al. 2019). This makes social insurance more important for rural-urban migrants in terms of their welfare and social cohesion.

Here we only consider work-related social insurances. The reason are as follows:

First, work-related social insurances contribute a lot in personal earnings. According to the law, employers need to pay all five types of work-related social insurances for employees, including the medical insurance, the pension, the work-related injury insurance, the unemployment insurance, and the maternity insurance. Some working units provide the housing fund for their employees. Together, those work-related social insurances and housing fund can account for more than forty percentage of wages. The major three one is the medical insurance, the pension, and the housing fund. The payment rate is 28 percent for the medical insurance, 12 percent for the pension, and 10-24 percent for the housing fund.

Second, work-related social insurances are directly related with employment. There are other kinds of social insurances in China, like governmental insurances and commercial insurances. It is not reasonable to use those non-work-related insurance when examining job quality.

Third, work-related social insurance has special policy meaning: employment units provide social insurance as a main form of social welfare. Beside personal social welfare, work-related social insurances are particularly important for migrants. Many cities in China issued policies that connect public service to work-related social insurances. For example, Beijing city government forbids migrants to buy cars unless they have paid pension and income tax for at least five years. Migrants' children cannot access local schools unless their parents have paid pension or income tax. Work-related social insurances are key elements that contribute local points-based Hukou system.

One may argue that work-related social insurance is a heavy burden for employees. But the coverage and the paid level of work-related social are two different

subjects. High coverage and low paid level can be met at the same time. In China, individual wage includes the employee-paid part of social insurances, but not the employer-paid part of social insurances. Since employees paid most of social insurances, entitlement of social insurances is another way for employees to get work-related benefits.

Job quality index

We use the Principal Component Analysis (PCA) as the reduction technique to construct the job quality index. In this chapter, we assume there is a latent job quality index that can be constructed by four dimensions. PCA can extract linear combination of several variables into a single index. We can use PCA to get the latent job quality index. Before performing PCA, we normalise all dimensions and indicators within dimensions through the max-min method .

Job quality index groups

The job quality index is a continuous variable that can be used in regressions. However, there are two limitations of the job quality index. One is that the index might not be normally distributed and be highly sensitive to extra values, especially for continuous dimensions like wages and working hours. Another limitation is that since the job quality index is composed of multiple dimensions, it is hard to explain the index in a meaningful way besides its magnitude.

To overcome those two limitations, we can use job quality ranks other than the index. Specifically, we divide all samples into three groups by the job quality index: the high level of the job quality index, the middle level of the job quality index, and the low level of the job quality index. People in the high level of job quality index is treated as good jobs holders. People in the middle level of the job quality index is treated as fair jobs holders. People in the low level of the job quality index is treated as bad jobs holder.

We realise that there is no agreement on what good jobs are and it is hard to

define a good job or a bad job by objective indicators. Good jobs can go bad and dirty jobs can be considered as good one in difference contexts (Adamson and Roper 2019). Measures of job quality at national level and individual level are different because individuals benchmark their job quality against their peers (Felstead et al. 2019). This chapter, however, takes a step back. We did not seek to give a clear definition of good jobs. We only try to distinguish good jobs and bad jobs among rural-urban migrants by their job quality index rank.

We measure job quality from employers' perspectives. Measurement of job quality highly depend on the perspective adopted (Piasna et al. 2019). Different social actors have different interpretation and agenda of job quality (Burchell et al. 2014), which creates difficulties for the comparison of job quality between different social actors and countries. For example, higher earning and more job security are good for employees, while they are not so welcome by employers.

3.3.3 Descriptions of job quality for rural-urban migrants

Job search methods

The proportion of network users is 62% in 2007¹⁰. Non-users of network only account for 37 %. Most of migrants have found jobs through their social networks.

Table 3.1: Job search methods for rural-urban migrants in 2007

	N	%
Non-network users	1637	37.33
Network users	2748	62.67
Total	4385	100.00

Source: RUMIC 2008.

¹⁰The numbers in Table 3.1 is a bit different than that in Table 2.3 on page 27 because of different sample sizes. But results of these two tables are nearly the same.

Job search methods and dimensions of job quality

Table 3.2 shows that non-users of network enjoy high wage, work less hours, and have more coverage of long contract and social insurance. The difference of those indicators of job quality between users of network and non-users of network are been tested by T-test or Chi-2 test. All the differences are statistically significant. So users of network are in disadvantage with all indicators of job quality.

Table 3.2: Job search and dimensions of job quality for rural-urban migrants

	Non-network	Network	Diff
Earnings (yuan)	1452	1375	77***
Working hours	57.3	59.1	-1.8***
Long contract (%)	0.6042	0.4894	0.1147***
Pension (%)	0.2889	0.2020	0.0870***
Urban medical insurance (%)	0.2303	0.1132	0.1171***
Unemployment insurance (%)	0.1875	0.1368	0.0507***
Work-related injury insurance (%)	0.2700	0.2067	0.0633***
Housing fund (%)	0.1350	0.0637	0.0713***

Source: RUMIC 2008.

Job quality index: PCA

Before using PCA, we first normalise the four dimensions. The formula of normalisation is: $Z = (Real - Min)/(Max - Min)$. The range after normalisation is between 0 and 1. To get a more clear view of the number, we multiply 100 for each value after normalisation. Then we get Table 3.3. The differences of four dimensions between users of network and non-users of network are still statistically significant.

Table 3.3: Normalisation of dimensions of job quality for rural-urban migrants

	Non-network	Network	Difference
Earnings	16.90	15.93	0.97***
Working hours	71.54	69.65	1.89***
Job stability	60.42	48.94	11.47***
Social insurance	22.24	14.45	7.79***

Source: RUMIC 2008.

We use the Principal Component Analysis (PCA) to predict the job quality index, as in Table 3.4. The mean of job quality index is 0.1841 for non-users of network and -0.1097 for users of network. The gap of job quality index is 0.2937, which is statistically significant.

Table 3.4: The job quality index for users of network and non-users of network

	Non-network	Network	T-test
Job quality index	0.1841	-0.1097	0.2937***

Source: RUMIC 2008.

Figure 3.1 shows the distributions of the job quality index for users of network and non-users of network. First, the distribution of the job quality index is not a typical normal one for both users of network and non-users of network, which means OLS might be inappropriate. Second, the distribution line for non-users of network is above that for users of network when the job quality index is relative high, while the distribution line of non-users of network is under that for users of network when the job quality index is relative low. This suggests that non-users of network tend to have higher job quality index than users of network.

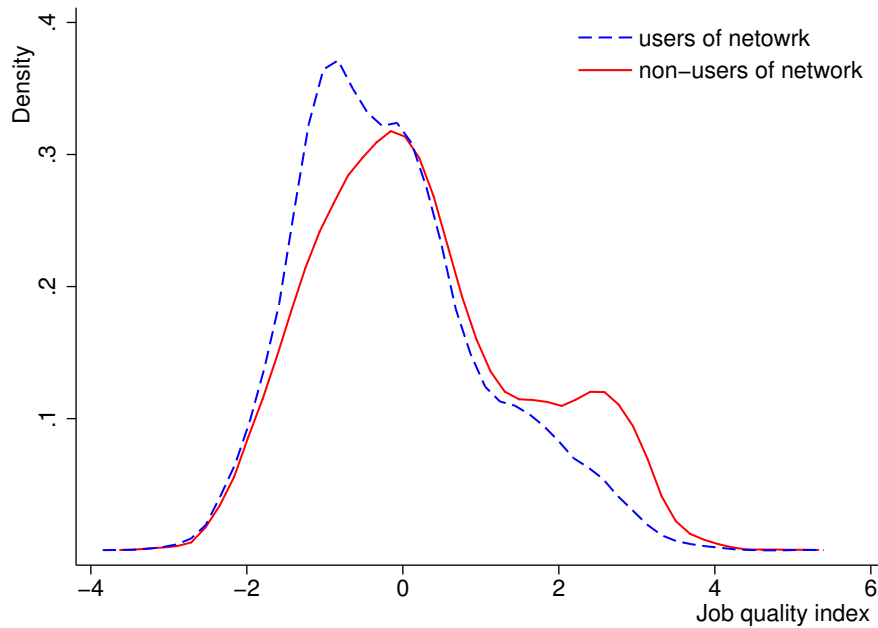


Figure 3.1: Kernel density graph of job quality index (PCA) for rural-urban migrants in 2007

Job quality groups

To better capture the difference of job quality between users of network and non-users of network, we divide all migrants into three groups based on their job quality index rank. We treat the groups as an ordered variable: 1=Low job quality; 2=Fair job quality; 3=High job quality.

For no-users of network, 41% of them fall into high job quality group; 32% fall into fair job quality group; only 27% are in low job quality group.

For users of network, 30% of them fall into high job quality group; 34% fall into fair job quality group; more than 36% are in low job quality group.

Table 3.5 tells that users of network have nearly 10 percentage point higher proportion of having low job quality than non-users of network. In contrast, non-users of network have more than 10 percentage point higher proportion of having high job quality than users of network. The difference of the proportion of having fair job quality less than 1 percentage point, which is very small. So users of network tend to have low job quality, while non-users of network are more likely to have good job quality.

Table 3.5: Job search methods for rural-urban migrants (%)

	Non-network users	Network users	Total
Low	27.06	37.05	33.32
Fair	32.86	33.62	33.34
High	40.07	29.33	33.34
Total	100.00	100.00	100.00

Source: RUMIC 2008

3.4 Models for job quality and job contact networks

Since the outcome variable in this chapter is ordinal, we will first use the ordered probit model to examine the relationship between job contact networks and job

quality. The ordered probit model, however, might be biased. There might be observables that affect both the use of network and job quality. Like the Chapter 2, the use of network is endogenous. So we will use the endogenous switching model for ordered outcomes to solve potential selection bias and endogeneity.

This chapter uses the job quality groups as the dependent variable. The independent variable is job search methods. Control variables include personal characteristics, job characteristics, and region characteristics. Personal characteristics include age, gender, marriage status, hukou, and education. Job characteristics include occupation, ownership, industry and firm size. Province dummies are used to control regional fixed effects. The ratio of labour migrant in home village is used in the selection part of the endogenous switching regression. Table B.1 in the appendix of this chapter gives a description of those variables.

3.4.1 Endogenous switching model for ordered outcomes

Endogenous switching model involves a selection model and an outcome model. In this chapter, we assume that the selection model is:

$$T_i = \begin{cases} 1 & \text{if } T_i^* = Z_i\gamma + v_i > 0 \\ 0 & \text{if } T_i^* = Z_i\gamma + v_i \leq 0 \end{cases}$$

For non-users of network, the outcome model is:

$$Y_{0i} = \begin{cases} 1 & \text{if } Y_{0i}^* \leq \mu_{01} \\ 2 & \text{if } \mu_{01} < Y_{0i}^* \leq \mu_{02} \\ \dots & \\ J-1 & \text{if } \mu_{0J-1} < Y_{0i}^* \leq \mu_{0J} \\ J & \text{if } Y_{0i}^* > \mu_{0J} \end{cases}$$

Where $j = 1, \dots, J$ are ordered outcomes and $Y_{0i}^* = X_{0i}\beta_0 + \epsilon_{0i}$.

For users of network, the outcome model is:

$$Y_{1i} = \begin{cases} 1 & \text{if } Y_{1i}^* \leq \mu_{11} \\ 2 & \text{if } \mu_{11} < Y_{1i}^* \leq \mu_{12} \\ \dots & \\ J-1 & \text{if } \mu_{1J-1} < Y_{1i}^* \leq \mu_{1J} \\ J & \text{if } Y_{1i}^* > \mu_{1J} \end{cases}$$

Where $j = 1, \dots, J$ are ordered outcomes and $Y_{1i}^* = X_{1i}\beta_1 + \epsilon_{1i}$.

Unlike to assume that v and ϵ follow a bivariate normal distribution (Miranda and Rabe-Hesketh 2006), we let:

$$v_i = \lambda_T \eta_i + \zeta_i$$

$$\epsilon_i = \lambda_Y \eta_i + \iota_i$$

Where supposing that η need not be normal, while ζ and ι are normal.

As suggested by Aakvik et al. (2005), Deb and Trivedi (2006b), and Gregory (2015), the likelihood function can be:

$$L_i = \frac{1}{S} \prod_{i=1}^N \sum_{s=1}^S \sum_{\ell=0}^{\ell=1} \{I \times (T_i = \ell)\} \times \Phi \{\tau \times (Z_i \gamma + \lambda_{\ell T} \eta_i)\} \times \sum_{\ell=0}^{\ell=1} \{I \times (T_i = \ell)\} \\ \times \sum_{k=1}^K \{I \times (Y_i = k)\} \{\Phi(\mu_{\ell k} - X_{\ell i} \beta_{\ell} + \lambda_{\ell Y} \eta_{\ell i}) - \Phi(\mu_{\ell k-1} - X_{\ell i} \beta_{\ell} + \lambda_{\ell Y} \eta_{\ell i})\}$$

Where S is the number of simulation draws, λ s are loading factors that represent the dependence between the unobservables in outcome and treatment model, Φ is the standard normal distribution, I is an indicator function, $\tau = 2 \times T_i - 1$, $K = J + 1$, $\mu_0 = -\infty$, $\mu_K = \infty$, and $\ell \in (0, 1)$.

ATE can be calculated as:

$$ATE_k^S = \frac{1}{N} \frac{1}{S} \sum_{i=1}^N \sum_{s=1}^S [\Phi \{\mu_{1k} - (X_{1i} \beta_1 + \lambda_1 \eta_{is})\} - \Phi \{\mu_{1k-1} - (X_{1i} \beta_1 + \lambda_1 \eta_{is})\}] \\ - [\Phi \{\mu_{0k} - (X_{0i} \beta_0 + \lambda_0 \eta_{is})\} - \Phi \{\mu_{0k-1} - (X_{0i} \beta_0 + \lambda_0 \eta_{is})\}]$$

ATT can be calculated as:

We can use Stata command *switchoprobitsim* to estimate the endogenous switching regression for ordered outcomes by the latent-factor approach (Gregory 2015). We use 1000 simulations to calculate the standard error of ATE and ATT.

3.4.2 Ordered Probit model

Table 3.6 gives coefficients of the ordered Probit model. Our focus is on whether using networks to find jobs has an impact on job quality groups. For the dummy variable “Users of network”, the sign of the coefficient is negative. This suggests that users of network tend to be lower job quality groups than non-users of network. The threshold parameters (Cut1 constant, Cut2 constant) appear to be statistically significantly different from each other, so the three types of job quality groups should not be collapsed into two categories. We also run two separate regressions for users of network and non-users of network. The coefficients are slightly different between the two regressions, so are the significant levels. This suggests that independent variables may have different effects between users of network and non-users of network.

Table 3.7 reports the marginal effects of network on each job quality group. There is no significant difference of the probability of having fair job quality group between users of network and non-users of network. Non-users of network have higher probability into the high job quality group than users of network. The gap is about 3 percentage points. Users of network have higher probability into the low job quality group than non-users of network. The gap is about 3 percentage points.

3.4.3 Endogenous switching model for ordered outcomes

Ordered probit model is biased when there are unobservables that affect both the selection and the outcomes, in which case endogenous switching model is more appropriate. Table 3.8 is the results of the selection part from the endogenous switching model for ordered outcomes. The dependent variable is the use of

Table 3.6: Ordered Probit models for job quality groups

	All		Non-users of network		Users of network	
	Coef.	SE	Coef.	SE	Coef.	SE
Users of network	-0.1074***	0.0384				
Age	0.0917***	0.0130	0.0730***	0.0236	0.0942***	0.0158
Age ²	-0.0014***	0.0002	-0.0011***	0.0003	-0.0015***	0.0002
Years of migration	0.0226***	0.0038	0.0251***	0.0072	0.0205***	0.0045
Male	0.1453***	0.0387	0.1242*	0.0656	0.1718***	0.0482
Years of schooling	0.0940***	0.0083	0.1092***	0.0147	0.0835***	0.0102
<i>Occupation: Base group=White collar</i>						
Blue collar	-0.2976***	0.0712	-0.3411***	0.1004	-0.1936**	0.0971
Other occupation	0.0802	0.2187	0.3412	0.2605	0.0280	0.3434
<i>Industry: Base group=Manufactory</i>						
Construction	-0.4787***	0.0674	-0.4180***	0.1199	-0.4547***	0.0835
Electricity, gas, water, transportation and IT	-0.2143**	0.1028	-0.2211	0.1774	-0.1722	0.1231
Commerce and trade	-0.1662**	0.0666	-0.1079	0.1130	-0.1859**	0.0819
Restaurant and catering	-0.3817***	0.0628	-0.3407***	0.1013	-0.3603***	0.0793
Finance, estate, health, education	-0.1486**	0.0697	-0.1654	0.1182	-0.0861	0.0886
Services	-0.2159***	0.0728	-0.3275***	0.1162	-0.1469	0.0906
<i>Ownership: Base group=State and collective</i>						
Private enterprises	-0.3145***	0.0656	-0.4006***	0.1187	-0.2823***	0.0769
Self-employed Individuals	-0.4881***	0.0747	-0.4683***	0.1336	-0.4865***	0.0884
Foreign, joint venture	0.1901**	0.0835	0.2658*	0.1418	0.1879*	0.1054
Shared company	-0.0567	0.0849	0.0634	0.1482	-0.1394	0.1077
<i>Firm size: Base group= Below 8</i>						
8-50	0.3249***	0.0541	0.4333***	0.0936	0.2316***	0.0664
Above 50	0.5989***	0.0567	0.7661***	0.0980	0.5141***	0.0702
Cut1 constant	1.3559***	0.2524	1.3493***	0.4448	1.3688***	0.3066
Cut2 constant	2.4359***	0.2536	2.4523***	0.4467	2.4367***	0.3079
Province dummies	Yes		Yes		Yes	
Observations	4384		1636		2748	
Log pseudolikelihood	-4075.24		-1459.97		-2596.81	
Pseudo R ²	0.1539		0.1760		0.1376	
AIC	8210.47		2977.94		5251.61	
BIC	8402.04		3134.54		5423.25	

Source: RUMIC 2008

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Marginal effects of network from ordered probit model

	Marginal effect	SE
Low	0.0311***	0.0111
Fair	0.0005	0.0005
High	−0.0316***	0.0114
Source: RUMIC 2008		

network. Two variables used in the selection model but not in the outcome models are marriage and the ratio of labour migrants in home village. These two variables are believed to be related with the use of network, but not affect job quality. Table 3.8 shows that married migrants and local migrants tend to use network to find jobs. Higher ratio of labour migrants in home village is associated with higher probability of using network.

Table 3.8: Probit model for the use of network

	Coefficient	SE
Unmarried	−0.1667**	0.0836
Ratio of labour migrants in home village	0.0057***	0.0013
Non-local rural hukou	−0.1655**	0.0733
Age	−0.0379*	0.0225
Age ²	0.0563*	0.0306
Years of migration	0.0081	0.0060
Male	0.0178	0.0578
<i>Education:base group=Junior middle school</i>		
Elementary school or below	0.1649*	0.0924
Senior middle school	−0.4164***	0.0606
College or above	−0.9078***	0.1337
Constant	0.9866**	0.3982
<i>N</i>	4385	

Source: RUMIC 2008

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9 is the results of the outcomes parts from the endogenous switching model for ordered outcomes. The dependent variable is the three ordered job quality groups. The value of Λ in the bottom of Table 3.9, which measures the correlation coefficients between the error terms in the selection model and the outcome model, is statistically significant for non-users of network only. This implies that the use of social network is endogenous to job quality for non-users

of network. So the endogenous switching regression is more appropriate than the ordered probit model. The positive value of Λ for non-users of network indicates that unobserved factors which increase the likelihood of using social networks are positive correlated with the unobserved determinants of job quality for those not using networks.

In the outcome model for users of network, the value of Λ is very small and is not statistically significant. Thus we did not find any unobserved factors that affect the use of network and job quality for users of network. The positive selectivity is only present in non-users of network, which means non-users of network have unobservables that would increase their job quality conditional on not using networks.

Table 3.10 reports the average treatment effects (ATE) and the average treatment effects on the treated (ATT) from the endogenous switching model. The output reveals that ATE is statistically significant for the low and the high job quality group, but is not statistically significant for the fair job quality group. The probability of having low job quality would increase by 0.2986 if the entire migrants had used social network to find jobs. In contrast, the probability of having high job quality would decrease by 0.2605 if the entire migrants had used social network to find jobs. For users of network, the probability of having low job quality would increase by 0.2759 if they had used social network, while the probability of having high job quality would decrease by 0.3825 if they had used social network.

In summary, from the endogenous switching regression for ordered outcome, we find large job quality discounts from using social networks, especially for the users of network.

3.4.4 Robustness analysis

The results in Table 3.10 may be sensitive to the methods that constructs job quality index and job quality groups. Here we try to use other ways to measure the job quality index, to create job quality groups, and to calculate ATE and ATT.

Table 3.9: Ordered switching regression: job quality groups

	Non-users of network		Users of network	
	Coefficient	SE	Coefficient	SE
Age	0.1496**	0.0606	0.1089***	0.0162
Age ²	-0.2234**	0.0879	-0.1673***	0.0236
Years of migration	0.0720***	0.0197	0.0223***	0.0046
Male	0.2681	0.1743	0.1709***	0.0492
Years of schooling	0.1837***	0.0381	0.0820***	0.0182
<i>Occupation: Base group=White collar</i>				
Blue collar	-1.0524***	0.2756	-0.1657*	0.0950
Other occupation	0.7631	1.1521	0.0759	0.3439
<i>Industry: Base group=Manufactory</i>				
Construction	-0.8343***	0.3160	-0.5452***	0.0844
Electricity, gas, water, transportation and IT	-0.2898	0.4218	-0.2436*	0.1246
Commerce and trade	-0.1260	0.2814	-0.2331***	0.0828
Restaurant and catering	-0.7231***	0.2611	-0.4220***	0.0795
Finance, estate, health, education	-0.2692	0.2798	-0.1579*	0.0863
Services	-0.6584**	0.2907	-0.1686*	0.0916
<i>Ownership: base group=state and collective</i>				
Private enterprises	-1.3931***	0.3316	-0.2181***	0.0774
Self-employed Individuals	-1.5954***	0.3726	-0.4682***	0.0903
Foreign, joint venture	0.2240	0.3545	0.1972*	0.1066
Shared company	-0.0451	0.3707	-0.1477	0.1046
<i>Firm size: Base group=Below 8</i>				
8-50	1.1888***	0.2519	0.2470***	0.0672
Above 50	1.8529***	0.2861	0.5276***	0.0724
Cut1 constant	-0.1512	1.0977	1.6080***	0.3071
Cut2 constant	2.6566**	1.1140	2.6874***	0.3034
<i>Lambda</i>	2.8352***	0.2997	-0.0800	0.5365
<i>N</i>	1637		2748	

Note: Dependent variable=job quality groups; Province controlled.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: RUMIC 2008.

Table 3.10: ATE and ATT from endogenous switching model: PCA

	ATE	SE	ATT	SE
Low	0.2986***	0.0582	0.2759***	0.0370
Fair	-0.0381	0.0574	0.1066***	0.0319
High	-0.2605***	0.0735	-0.3825***	0.0475

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

SE is calculated with 1000 simulations.

Source: RUMIC 2008.

The robustness analysis also find large job quality discounts from using social network.

Treatment effect model for ordered outcomes

The switching regression model assumes that the effects of each independent variable on the dependent variable are different between the treated group and the untreated groups. The treatment effect model assumes those effects are the same between the treated group and the untreated group. Therefore, we can use the treatment effect model as an alternative method for switching regression model. Specifically, we use Stata command ***treatoprobitsim*** to estimate the treatment effect model for ordered outcomes by the latent-factor approach (Deb and Trivedi 2006a).

Comparing with Table 3.10, the results in Table 3.11 is quite similar.

Table 3.11: ATE and ATT from treatment effect model: PCA

	ATE	SE	ATT	SE
Low	0.2482***	0.0799	0.2319***	0.0720
Fair	0.0201	0.0594	0.0579	0.0651
High	-0.2684***	0.0929	-0.2898***	0.0976

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

SE is calculated with 1000 simulations.

Source: RUMIC 2008.

Principal Component Factor Analysis

In the main analysis, we use PCA to get the job quality index. An alternative way is to use the Principal Component Factor Analysis (PCF). The pattern of the distribution of job quality in Figure 3.1 and Figure 3.2 are nearly the same. The ATT and ATE in Table 3.12 are identical to Table 3.10. Therefore, PCF method yields the same results as PCA method.

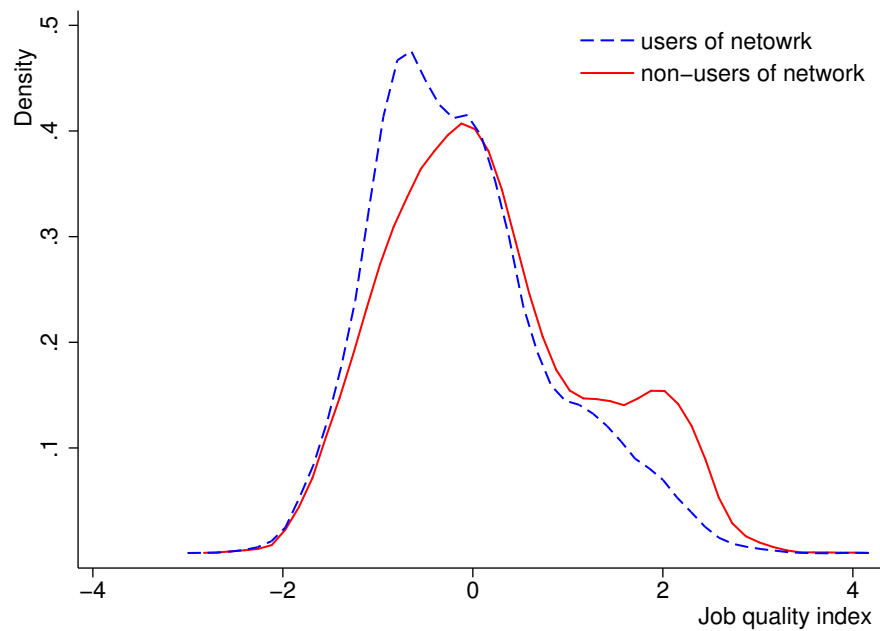


Figure 3.2: Kernel density graph of job quality index (PCF) for rural-urban migrants in 2007

Table 3.12: ATE and ATT from endogenous switching model: PCF

	ATE	SE	ATT	SE
Low	0.2986***	0.0604	0.2759***	0.0365
Fair	-0.0381	0.0575	0.1066***	0.0324
High	-0.2605***	0.0748	-0.3825***	0.0475

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

SE is calculated with 1000 simulations.

Source: RUMIC 2008.

More job quality groups

In the main analysis, we create three job quality groups. We have shown that the division into three groups is appropriate and useful in the analysis. Using the same method, here we try to create four and five job quality groups to see whether the main finding from three job quality groups still hold. Both Table 3.13 and Table 3.14 confirm that the use of network is related to lower job quality, especially for the top and the bottom job quality groups.

Table 3.13: ATE and ATT from endogenous switching model: Four job quality groups

	ATE	SE	ATT	SE
Very low	0.2533***	0.0504	0.2190***	0.0313
Low	0.0613	0.0404	0.1469***	0.0234
High	-0.1364**	0.0639	0.0124	0.0255
Very high	-0.1782***	0.0665	-0.3782***	0.0476

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

SE is calculated with 1000 simulations.

Source: RUMIC 2008.

Table 3.14: ATE and ATT from endogenous switching model: Five job quality groups

	ATE	SE	ATT	SE
Very low	0.2168***	0.0854	0.1789***	0.0393
Low	0.0781**	0.0400	0.1387***	0.0272
Fair	-0.0390	0.0509	0.0599**	0.0279
High	-0.1357**	0.0669	-0.0191	0.0277
Very high	-0.1201*	0.0637	-0.3584***	0.0527

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

SE is calculated with 1000 simulations.

Source: RUMIC 2008.

Different dimensions of job stability and social insurances

In the main analysis, the dimension of job stability is measured by a dummy variable to indicate whether migrants have long contract. The dimension of social insurance covers five types of social insurance. Here we can make some changes to

those two dimensions. Specifically, contract can be divided into three groups: no contract, short contract, and long contract. Five types of social insurance can be narrowed to three types: medical insurance, pension, and housing fund. The sign and significant levels of ATE and ATT are the same between Table 3.15 and Table 3.10. The magnitude of ATE and ATT in Table 3.15 is a little bit higher than those in Table 3.10. So by using different dimensions of job stability and social insurances, we also find that the use of social network is associated with low job quality, especially for the users of network.

Table 3.15: ATE and ATT from endogenous switching model: PCA with different contracts and social insurances

	ATE	SE	ATT	SE
Low	0.3292***	0.0524	0.2737***	0.0374
Fair	-0.0234	0.0564	0.1170***	0.0341
High	-0.3058***	0.0760	-0.3907***	0.0482

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

SE is calculated with 1000 simulations.

Source: RUMIC 2008.

Different dimensions: PCA

In the main analysis, we use four dimensions to measure job quality index. In particular, dimensions of the wage, working time and the job stability are measured by single indicator. The only exception is the dimension of social insurance, which involves five types of social insurances. Here we use six dimensions, including earnings, working time, the contract, the medical insurance, the pension, and the housing fund. Table 3.10 also shows that the results from six dimensions are nearly the same as that from four dimensions. Users of network are also more likely to have lower job quality.

Equal weights for different dimensions

In the main analysis, we let PCA method to set the weights for each dimension and get the final job quality index. Here we use manual weights for each dimension.

Table 3.16: ATE and ATT from endogenous switching model: PCA with different dimensions

	ATE	SE	ATT	SE
Low	0.3236***	0.0519	0.2737***	0.0354
Fair	-0.0404	0.0594	0.1154***	0.0306
High	-0.2832***	0.0737	-0.3891***	0.0470

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
SE is calculated with 1000 simulations.
Source: RUMIC 2008.

The weight for each dimension is set to 0.25. So all four dimension have the same weight.

The results from each weight method show a different picture of the impact of job contact network on job quality groups. First, all the values of ATE are not statistically significant, which means there is no significant effect of the use of network on job quality groups. For the users of network, however, the values of ATT for the high and the low job quality groups are statistically significant. This suggests that for the users of network, there is still job quality penalty of using network.

Table 3.17: ATE and ATT from endogenous switching model: Equal weights

	ATE	SE	ATT	SE
Low	0.0937	0.0739	0.0931**	0.0474
Fair	0.0053	0.0390	0.0028	0.0320
High	-0.0990	0.0825	-0.0959**	0.0497

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
SE is calculated with 1000 simulations.
Source: RUMIC 2008.

3.5 Chapter conclusions

Job quality is a development goal for individuals and policy makers. It is not only about earnings or other single indicator, but rather multidimensional. However, much attention has been paid to the impact of social network on separate dimensions of job quality, while the impact of social network on job quality as a whole have

remained neglected. There is still no consensus of the measurement of job quality, especially for developing countries.

This chapter offers a novel perspective to interpret and analyse the effect of social network on the performance of labour market. We reveal job quality penalty of the use of network for rural-urban migrants in China. This chapter provides a basic measurement of job quality with four dimensions for rural-urban migrants China, looking at the impact of job contact network on job quality. The multidimensional job quality index has captured job reality, combining information on earnings, working time, the job stability, and work-related social insurances in just one index. Using the migrants survey data from RUMIC 2008, we show that comparing with non-network users, network users have lower monthly wage, longer working hours, less job stability, and low coverage of social insurance. By employing the endogenous switching regression for ordered outcomes, we find unobservables that affect the use of network also impact the job quality of the non-users of network. The positive selectivity does not exist in users of network. We demonstrate that the use of social network brings low job quality for rural-urban migrants. The findings are robust to a range of alternate measures of the job quality index, and to using other identification methods.

Although the nature of work is changing (World Bank 2018), the pursue for high quality jobs never changes. Future research can be improved in three ways.

First, we admit that the four-dimensional job quality index is still at primary level and can be improved. For example, one shortage of this chapter is the exclusion of workplace safety in job quality index because of data availability. We can add more dimensions of job quality when data is available.

Second, we did not look at the inter-groups heterogeneity. As shown in Deguilhem et al. (2019), the effect of network on job quality are different between vulnerable workers and protected workers.

Third, we did not explore the dynamic changes of the effect of social network on job quality, mainly due to data availability. The relationship between job contact

network and labour market outcomes might be different in the cross-sectional data and the longitudinal data (Mouw 2002). Dynamic analysis is crucial for accurately assessing the effect of social network on labour market outcomes (Beaman 2012). Future studies can use different cross-sectional data or panel data to examine the changes of the effect of social network on job quality during different periods or years.

Appendices of Chapter 3

Table B.1: Distribution of job quality groups for rural-urban migrants

	Low	Fair	High	All
Age (years)	29.70	29.26	29.79	29.58
Years of migration	7.38	8.19	8.47	8.01
Years of schooling	8.45	8.95	9.92	9.11
Male(%)	55.03	60.60	63.61	59.75
Unmarried(%)	47.23	46.92	42.75	45.63
Ratio of labour migrants in home village(%)	59.13	58.76	56.58	58.16
Non-local hukou(%)	73.44	82.76	86.94	81.05
<i>Occupation(%)</i>				
Professional technicians or Clerk staff	5.48	6.63	13.06	8.39
Worker	94.39	92.61	86.59	91.20
Other occupations	0.14	0.75	0.34	0.41
<i>Industry(%)</i>				
Manufacturing	13.89	20.18	41.75	25.27
Construction	14.31	16.21	7.39	12.64
Electricity,gas, water, transportation and IT	3.83	3.49	4.65	3.99
Commerce and trade	19.58	16.14	11.36	15.69
Restaurants & catering	26.01	19.97	11.70	19.23
Finance, estate, health, education	11.64	12.31	13.00	12.32
Services	10.75	11.70	10.13	10.86
<i>Ownership(%)</i>				
State and collective	7.26	8.76	13.68	9.90
Private enterprises	46.82	51.57	37.76	45.38
Self-employed Individuals	34.77	22.64	10.67	22.69
Foreign,joint venture	4.79	8.55	24.97	12.77
Shared company	6.37	8.48	12.93	9.26
<i>Firm size(%)</i>				
Less than 50	66.19	53.63	31.60	50.47
From 50 to 1000	29.57	39.26	46.17	38.34
More than 1000	4.24	7.11	22.23	11.20

Source: RUMIC 2008.

Chapter 4 School Consolidation, Rented Accommodation and Children's Academic Performance in Rural China

The Chapter 2 and Chapter 3 explore the impact of social network on wage and job quality for rural-urban migrants. The two chapters show that rural-urban migrants use social network to get jobs with the cost of wage penalty and job quality penalty. This chapter turns to the third research question mentioned in the Chapter 1. The chapter is going to explore the relationship among school consolidation, rented accommodation, and children's academic performance. This topic reflects the education problem for rural-urban migrant children.

4.1 Introduction

School consolidation is a common phenomenon when a county is being transformed from agricultural society to industrial society. For example, in US, the school consolidation began as early as the mid 1800's and the industrial revolution had accelerated this process (Bard et al. 2006); in Michigan, many schools were closed in the past decade (Brummet 2014). Rural school consolidation is driven by depopulation, out-migration, and financial savings. Given declining enrolments and limited financial resources in rural areas today, many counties (especially developing counties) still have to deal with challenges associated with possible rural school consolidations. China is one of them.

For China, rural school consolidation is not a new phenomenon. Back to 1978 when the Culture Revolution was ended, the governments started to shut down or relocate many rural schools. According to the data in Zhang and Song (2003), the number of rural primary schools has been dropped 19.3%, from 949 thousand in 1978 to 766 thousand in 1985. Meanwhile, the number of urban primary schools has been raised 26.3%, from 33 thousand in 1978 to 57 thousand in 1985. This is the first time that such large-scale school consolidation happened in China. However, we do not know much about the consequence of rural school consolidation during this period because of the lack of information and research.

From 2000 to 2012, Chinese governments launched another large-scale rural school consolidation. According to the National Bureau of Statistics of China (2001; 2013), the number of total enrolments in rural primary schools has declined by 57.0%, from 85.0 million in 2000 to 36.5 million in 2012. The decline of enrolments in rural primary schools is closely related to demographic changes—a low birth rate alongside increasing migrations from rural to urban areas. Some local governments shut down schools in remote villages and merged them into “central” schools at town or county level in the late 1990s. This action became national policy in 2001.

The number of rural primary schools nationwide has fallen by 64.8%, from 440,284 in 2000 to 155,008 in 2012 (National Bureau of Statistics of China 2001; National Bureau of Statistics of China 2013). More than half of rural primary schools disappeared during this period and this trend continues. Given the longer distances from home to school as a result of school mergers, students from remote villages have to take more time to travel and face more safety risks on their journeys (Zhao and Barakat 2015). Schools have become less accessible to students living in remote villages (Chan and Harrell 2009). School completion rate is decreased, especially for girls (Haepf and Lyu 2018).

Boarding schools¹ offer a solution to the problem of distance between home and school. According to the Minister of Education of China (cited in Dong

¹In rural China, students at boarding school may be not boarding at school. Boarding school can have both boarding students and day students.

(2013)), the number of boarding students in rural primary school was 9.88 million nationwide by 2011, accounting for 13.5 percent of total enrolments in rural primary schools. In Western areas, the rate of boarding students in rural primary schools is much higher than in central and eastern areas, from 16.0% in 2009 to 19.7% in 2011. In 2004 central and local government started to subsidise boarding students in poor areas. Tuition fees and textbook fees were waived for all rural students. From 2004 to 2007, the boarding and canteen facilities in 7651 schools' in middle and western areas were - upgraded to accommodate more students as boarders (China Development Research Foundation 2012).

Evidence in the US suggests that urban boarding school for the poor is an effective way to narrow the racial achievement gaps (Curto and Fryer Jr 2014). Moving from one school to another would negatively affect students' academic performance (Schwartz et al. 2017). School closure may lead socio-geographic inequality in access to education (Lee and Lubienski 2017). One study from France shows that only stronger students can benefit from boarding school because of their quick adjustment (Behaghel et al. 2017) .

In China, the rationale for boarding schools is different and conditions may be too. Luo et al. (2009) show that in China, boarding students suffered from poor dormitory and canteen facilities lacking good quality food and daily care. This was partly caused by poor trained life teacher (Yue et al. 2014). Mo et al. (2012) find that boarding has negative effects on students' mathematics scores. Chen et al. (2014) conclude that students did not benefit from boarding and their academic performance even deteriorated. Zhao (2011) argue that children's physical and psychological well-being, the cultural rights of ethnic minority students and other human rights are ignored by the authorities. He concluded that the boarding school policy in China has increased the urban-rural educational gap and extended social injustice. Wang et al. (2017) find that boarding on campus has negative effects on students' social-emotional competence, partly resulting from low food quality and poor caregivers' service. Wang and Mao (2018) also find that boarding

at school is negatively with left-behind children's sense of school belonging and academic achievement.

It seems that the boarding school policy in China has failed to reach its original goal of providing adequate resource for the development of rural students, especially those from poor remote villages. However previous findings are based on data collected before 2010 and government policies, have changed greatly since 2010.

In January 2010, the Minister of Education asked that local governments should meet the educational needs of young students and suspend the merger programme in the areas where the requirements were not yet fully reached. In September 2012, the State Council stopped the school merger policy nationwide. From 2010, the government increased the subsidy for poor boarding students (750 yuan per year for primary school students and 1000 yuan per year for junior middle school students). In 2011, some counties launched pilot nutrition projects. And in 2012 these were spread over 680 poor counties, covering 26 million primary school and junior middle school students. The new policies indicated that national and local government realised the negative effects of school merger policy and were trying to remedy it. The effect of new policies on children's academic development is not yet clear.

Beside new government policies a new phenomenon arose, families rented accommodation near school as an alternative to travelling the long distance from home to school and to avoid the negative effects of boarding school. We must admit that reasons for rented accommodation may be various. Not all the students rented accommodation were influenced by school merger program. Some students may just follow their parents who migrated to town or city. But in our survey, we find most of guardians who rented accommodation for their children did not have jobs in town or city. They were pure caregivers who had no other work to do.

To our knowledge, there is so far no published empirical study that examines the effect of rented accommodation on children's development. There is only one paper by Chen et al. (2014) mentioned the effect of rented accommodation. They

admitted that the negative effect of boarding schools on educational performance in their results might be challenged by the selection bias from students whose parents rented rooms near school and lived with their children. But they do not control the possible bias from rented accommodation because they do not include such data in their survey whereas in our survey, we found that rented accommodation near school is a common practice.

People may question that rented accommodation might not be a choice of the parents, but rather an unwilling arrangement of parents because of the unavailability of boarding school. It is not a serious problem in our survey because of the development of boarding school. Most of students can be allowed to board at school if their parents wish to do so. Rented accommodation may not be the first choice of parents in enabling their children to attend school, but it may be the best option available to them, given the unsatisfactory condition of boarding schools.

Given the increasing numbers of students who board at school or live in rented rooms, a significant question is whether either of these is of benefit to students. The negative effects of the school merger policy might be partly -offset if students got some physical, academic or psychological benefit from boarding school or rented rooms. How then do these living arrangements affect student achievement?

The overall goal of this paper is to evaluate the effects of living arrangement on primary age children's academic performance. The key questions we are going to address are: (a) What living arrangements are students making? (b) Does the school merger policy influence students' living arrangements? (c) How is students' academic performance affected by their living arrangements? (d) Do the effects of living arrangements differ between boys and girls?

In order to answer these questions, we use a dataset collected from our survey, designed specifically to examine students' living arrangements and educational performance. We begin by identifying types of living arrangement among students in the sample counties. We then explore the determinants of living arrangements for students. After that we compare standardized mathematics scores with living

arrangement. We use a double robust estimator with multivalued treatments to examine the effects of boarding school and rented accommodation on students' mathematics scores. Double robust estimators can correct for the self-selection bias and control important variables for both the treatment and outcome models. Moreover, double robust estimators are more insensitive when the conditional independence and overlap assumptions are violated. Finally, we discuss the possible relationship among the school merger policy, boarding school policy and children's academic achievement in poor rural areas.

4.2 Data

Our data came from a survey of 9,071 Grades 4 and 5 students in 133 primary schools in Yulin Prefecture, Shaanxi Province. Two waves of surveys were conducted during the autumn semester 2012 and spring semester 2013. The surveys were conducted by a team of scholars from Shaanxi Normal University, Stanford University, Chinese Academy of Sciences, and Renmin University of China. We put some questions about living arrangement in the second wave survey. So we use the maths score from the second wave survey because some specific living arrangement questions were not included in the first wave. Time-unvarying variables are derived from the first wave survey.

Yulin Prefecture has 12 counties and the survey was carried out in 11 of these (one was omitted because of its small population). We obtained a list of all primary school from each county's bureau of education, then selected schools at township level with more than 50 students in Grades 4-5. We randomly selected one school from each township in the 11 counties. If there were two or more classes in each grade, we randomly chose only one. This gave us a sample of 133 schools in total.

The questionnaire collected information on the sample of students and their families. It included items on age, gender, grade, living arrangements, time and mode of transportation from home to school, parental age and education, parental

migration status, household size, and household assets.

We used a standardised maths examination to test students' achievement. The questions were developed by the Trends in International Mathematics and Science Study (TIMSS) testing service. The larger the maths score, the higher the student's level of achievement and education performance.

Questionnaires for maths teachers and head teachers produced data on teachers (age, gender, educational level). Information about schools (size, type and boarding facilities) was obtained through questionnaires for school principals.

Compared with other datasets, ours has a bigger survey sample and contains more information on children's living arrangements and development information. Much of the existing research has its limitations. For example, academic performance is not studied in Luo et al. (2009) and in Mo et al. (2012), the sample size is too small for a multivariate analysis 284 boarders and 1223 non-boarders. Previous studies also ignore the distance variable, an important factor in decision-making about living arrangements. In our survey, we asked the time (in minutes) and mode of transportation for travel from home to school and measure distance.

It is important to isolate the transfer path effect as suggested by Liu et al. (2010), Mo et al. (2012), and Chen et al. (2014). Transferred students may enjoy better facilities and teachers, but they may have difficulties in adapting new environment and new relationship with teachers and classmates. So we included a variable indicating the type of school students went to before they transferred to their current school. This variable is a proxy for teachers' quality because of the increasing inequality of standards between teachers in communities near the county centre and those far away from it (Han 2013).

We take a gender perspective. Gender difference in academic performance is a hot topic (Gevrek et al. 2018). As to China, gender difference in education tends to be ignored in most studies except Wang et al. (2012). They suggest that boys tend to find transition to boarding school life tougher than girls because traditionally in the home, boys often receive preferential treatment but this is not

so in schools. Since the adaptation and learning mechanism between boys and girls may be different and parents may treat boys and girls differently, we have paid attention to gender difference in students' living arrangements and its effect on their academic performance.

4.3 Description of students' living arrangements and math score

4.3.1 Living arrangements

Table 4.1 shows there are three types of living arrangement according to our survey: living at home, boarding at school, and rented accommodation. Nearly one- third of students lived at home, more than two-fifths were boarding. And about a quarter lived in rented accommodation near school.

Living arrangements differed little between boys and girls. The percentages of girls living at home and rented accommodation are larger than those of boys, whereas the percentages of girls boarding at school is less than that of boys.

Table 4.1: Living arrangements

	Girls	Boys	Total
Home	33.29	32.29	32.75
School	40.58	43.49	42.13
Rent	26.14	24.22	25.11
Total	100	100	100

4.3.2 Reasons for not living at homes

Over half of students said they did not live at home because there was no school in their home villages. About a fifth of students said they lacked family members who could take care of them and just over a quarter said that their village school was of poor quality.

Nearly a quarter of boarding students (23.7 percent) lacked family members to look after them. But for students rented accommodation, only 14.8 percent of them are lack of family members who can take care of them. This is because family members are always living at the rented accommodation as same as these students rented accommodation.

Table 4.2: Why students do not live at home?

	Boarding students	Student living at rent house only	Total
No school in village	52.66	52.83	52.72
No family member can look after them	23.70	14.80	20.39
Poor quality of the school in village	23.64	32.37	26.89
Total	100	100	100

4.3.3 Time and transportation from home at village to school

The time from home at village to school is longest among students rented accommodation. Students with rented accommodation take more than one hour from their homes to school. Students living at home only need to spend 13 minutes from home to school. The time for students boarding at school is in the middle, nearly 41 minutes (see Table 4.3).

Table 4.3: Time from home to school (minutes)

	Girls		Boys		Total	
	Mean	SD	Mean	SD	Mean	SD
Home	12.70	9.31	12.78	9.95	12.74	9.65
School	38.97	40.38	40.64	42.35	39.89	41.48
Rent	64.67	70.85	69.03	76.53	66.91	73.83
Total	36.50	48.51	38.01	51.09	37.31	49.91

The time from home to school is related to the distance from home to school and to mode of transport. More than three-quarters of students living at home travelled to school on foot. For students boarding at school or rented accommodation, cars,

buses and other vehicles were the main form of transport between their school and home (see Table 4.4).

Table 4.4: Mode of transportation from home to school

		By foot	Bicycle, tricycle, motorcycle	Vehicle and others	Total
Girls	Home	77.35	11.40	11.25	100
	School	27.24	32.67	40.09	100
	Rent	26.16	23.07	50.77	100
	Total	43.64	23.08	33.28	100
Boys	Home	74.10	12.95	12.95	100
	School	26.73	31.39	41.88	100
	Rent	24.30	21.65	54.05	100
	Total	41.41	23.08	35.50	100
All	Home	75.64	12.21	12.15	100
	School	26.96	31.96	41.08	100
	Rent	25.20	22.34	52.46	100
	Total	42.45	23.08	34.47	100

4.3.4 School transfer

Table 4.5 shows that the percent of students who have never transferred school is highest for those who living at home. Nearly two third of student who living at home have never transferred school. The percent of students who have transferred school is highest for those who boarding at school. Nearly two third of students who boarding at school have transferred from teaching points, village schools, township schools and other schools. The percent of students who rented accommodation and have never transferred school is 45.22, which is higher than that for students boarding at school.

School transfer is mostly driven by the school merge policy. So most of transferred students are directly influenced by the school merge policy. However, we cannot generalise that students who did not transfer are not influenced by the school merge policy. In our survey, some students who were affected by school merger program may not transfer school because their parents sent them to other schools when they started grade one. In this case, the school merge policy has more

Table 4.5: Mode of school transfer

		No transfer	Teaching point	Village school	Township school	Other school ²	Total
Girls	Home	64.58	7.47	5.33	9.82	12.80	100
	School	34.01	22.64	12.14	16.98	14.24	100
	Rent	43.93	16.21	9.78	14.49	15.58	100
	Total	46.78	15.91	9.26	13.94	14.11	100
Boys	Home	65.11	6.20	4.54	11.63	12.52	100
	School	32.92	23.20	11.34	18.55	13.99	100
	Rent	46.42	15.67	7.33	14.74	15.84	100
	Total	46.59	15.89	8.17	15.39	13.97	100
All	Home	64.86	6.80	4.91	10.77	12.66	100
	School	33.41	22.95	11.70	17.84	14.10	100
	Rent	45.22	15.94	8.52	14.62	15.72	100
	Total	46.68	15.90	8.68	14.72	14.03	100

effects on those students who reported in our survey as non-transferred students.

4.3.5 Math score

As Table 4.6 shows, students living in rented accommodation have the highest average standardised scores in mathematics, boarding school students the lowest.

Table 4.6: Description of math scores

		Math score		Standardized math score	
		Mean	SD	Mean	SD
Girls	Home	17.68	5.51	0.03	1.00
	School	17.37	5.45	-0.04	0.97
	Rent	18.05	5.47	0.10	0.98
	Total	17.65	5.48	0.02	0.99
Boys	Home	17.46	5.60	0.01	1.02
	School	17.03	5.71	-0.11	1.03
	Rent	18.03	5.32	0.10	0.95
	Total	17.41	5.59	-0.02	1.01
All	Home	17.57	5.56	0.02	1.01
	School	17.18	5.59	-0.08	1.01
	Rent	18.04	5.39	0.10	0.97
	Total	17.52	5.54	0.00	1.00

4.4 Methods: The Inverse-probability-weighted regression adjustment (IPWRA) estimator with multivalued treatments

Most previous analysis rely on OLS (see Luo et al. (2009) and Wang et al. (2012)) or matching methods with binary treatments (see Mo et al. (2012)) and Chen et al. (2014)). OLS can be biased because of self-selection or unobservables. However, students who board at school or rent accommodations are not a random sample. Boarding school or rented accommodations might be a self-selecting process therefore self-selection bias must be addressed. As for matching methods, the propensity score matching (PSM) and covariate matching are typical. For PSM, its estimators cannot control variables that only affect outcome variables. For example, the age and education of mathematics teachers influence students' math scores, but do not affect students' boarding status. We will omit these two important variables because they cannot predict the propensity score of boarding. For covariate matching, it is hard to ensure that students with different living arrangement would have similar characteristics.

Moreover, our study requires multivalued treatments methods because we have two treatment groups: students living in boarding school and students living in rented accommodation. The control group is students living at home. A typical way to analyse multivalued treatment effects is to collapse multivalued treatments into different binary indicators. Examples can be found in Liu et al. (2010), Mo et al. (2012), and Chen et al. (2014). By doing this, however, we would have lost considerable information and efficiency because multiple differential effects with and across treatment groups is more appropriate. Therefore we allow joint inferences between and across living arrangements by using a multivalued treatment effect model.

Specifically, we employ the inverse-probability-weighted regression adjustment

(IPWRA) estimator with multivalued treatments³. The IPWRA estimator is derived in Wooldridge (2007) and discussed at length in Wooldridge (2010). The IPWRA estimator enjoys a so-called “double robust” property because it combines the regression adjustment (RA) and the inverse probability weighting (IPW) estimators (Wooldridge 2010; Derya Uysal 2015; StataCorp 2015; Słoczyński and Wooldridge 2018). The RA estimator runs separate regression for each treatment level and use averages of predicted outcomes from each regression. An RA estimator depends on the correctly specified outcome model. The IPW estimator derives the inverse probability from the treatment model and uses the weighted means of the observed outcome variable. The IPW estimator needs the correctly specified treatment model. For the IPWRA estimator, we still need to model the outcome and the treatment but we are only required to specify one of the two models correctly. This is the main advantage of the IPWRA estimator.

The IPWRA estimator needs three assumptions: the conditional mean independence assumptions, the overlap assumption and the independent and identically distributed sampling assumption. So the IPWRA estimator still may have risks, for example, unbalanced covariates between the treatment groups, or unstable inverse probability weights or misspecified models for both the outcome model and the treatment model (Kreif et al. 2013). Results from Glynn and Quinn (2010) and Derya Uysal (2015) show that the IPWRA estimator outperforms regression adjustment and propensity score matching (PSM) estimator when either the outcome model or the treatment model is misspecified, or when the inverse propensity is unstable. Kreif et al. (2013) find the IPWRA estimator also do better when both outcome model and treatment model are misspecified.

A further reason for using the IPWRA estimator in our study is that we did not have panel datasets. A few other studies have used panel data but have some limitations. Three papers in particular have used difference in difference (DID) estimator with panel data. Liu et al. (2010) employ semi-panel data (recall

³We use the official *Stata* command `teffects ipwra` in *Stata* 14.2 to imply the IPWRA estimator. Standard errors are calculated by using the bootstrap method with 1000 replications.

data from a one-year survey) and used DID and DID matching estimator. They examined the changes in Chinese and Math scores between the second semesters in the first and fifth grades. But they did not examine the boarding status of students. Li and Luo (2011) use DID with a subset experimental data from Guianxi province before and after 2007. However, among 719 students, the number of boarding students is 651. Given the small sample size of students living at home, they cannot compare the difference between boarding students and students living at home. Moreover, all sample only covers three schools and we do not know how they selected these three schools. A third paper by Qi and Zhao (2012) also focuses on the effect of nutrition intervention on students in boarding schools but they do not make a comparison between boarding students and non-boarding students. We believe the IPWRA estimator, a double robust estimator, is the most appropriate method for this study.

Suppose Y is the math score, T is the living arrangement, and Y_{ti} is the math score for student i with the living arrangement t . Then function $F(Y)$ would be the outcome model and $F(T)$ would be the treatment model. Let T_0 to be the control group, then we have:

1. If all students choose the living arrangement t , their average math score can be defined as $Y_t = E(Y_t)$.
2. If all students choose the living arrangements t instead of 0, the change of their average math score can be defined as $ATE_t = E(Y_t - Y_0)$. This is known as the average treatment effect (ATE).
3. For students with the living arrangement $\hat{t}$, if they choose the living arrangement $\tilde{t}$ instead of 0, the change of their average math score can be defined as $ATT_{\tilde{t},\hat{t}} = E\{(Y_{\tilde{t}} - Y_0) | t = \hat{t}\}$. This is known as the average treatment on the treated (ATT).

We use the IPWRA estimator to get Y_t , ATE_t and $ATT_{\tilde{t},\hat{t}}$ by following three steps: firstly, using multinomial logit model, it estimates the parameters of the

treatment model $F(T)$ and calculates inverse probability weights. Secondly, using the inverse probability from the first step as weights, it estimates separate weighted regression models $F(Y_t)$ of the outcome variable for each treatment level and computes the treatment-specific predicted outcomes for each subject. Thirdly, it obtains the averages of the treatment-specific predicted outcomes (Y_t) from the second step. The contrasts of these means for different groups provide the estimates of ATE_t and $ATT_{\hat{t},\hat{t}}$. To get the correct standard errors, we use the bootstrap methods with 1000 replications.

4.5 Results of multivariate analysis

4.5.1 Determinants of living arrangements from multinomial logit model

In our study, the dependent variables are three types of living arrangements. Students boarding at home are set to be the control group. The results of multinomial logit regression can be seen in Appendix Table C.3. In order to explore the effects of different elements on students' living arrangements, we calculate the marginal effects of each variable on living arrangements. Since we are particularly interested in the impact of school merging on students' living arrangement, we show marginal effects of the variables relating to school merger policy, as shown in Table 4.7.

Travel time from home at village to school is negative with living at home and positive with boarding at school and rented accommodation. With a travel time of one more minute from home to school, the probability of students living at home decreased 0.0094; the probability of students boarding at school increased 0.0048; the probability of students rented accommodation increased 0.0046. The effect of travel time on living arrangement is pretty small, after controlling the transportation from home at village to school.

The effect of transportations is both statistically and practically significant.

The probability of boarding at school for students who went to school by bicycle and motorcycle was 0.2171 more than that for students who went to school on foot. The probability of boarding at school for students who went to school by vehicle and others is 0.2340 more than that for students who went to school on foot. The probability of renting accommodation for students who went to school by bicycle and motorcycle was 0.0688 more than that for students who went to school on foot. The probability of boarding at school for students who went school by vehicle and others was 0.1440 more than that for students who went to school on foot. So compared to students who went to school on foot, students who went by bicycle, motorcycle, vehicle, and others, were less likely to live at home, but more likely to board at school and live in rented accommodation.

Table 4.7: Marginal effects from multinomial logit model for all students

	Home	School	Rent
Time from home to school (minutes)	−0.0094***	0.0048***	0.0046***
<i>Transport: basic group=on foot</i>			
Bicycle, motorcycle	−0.2839***	0.2171***	0.0668***
Vehicle and others	−0.3779***	0.2340***	0.1440***
<i>Type of school transfer: basic group=no transfer</i>			
Teaching point	−0.1276***	0.1670***	−0.0394**
Village school	−0.0947***	0.1430***	−0.0483**
Township school	−0.0691***	0.1383***	−0.0692***
Other schools	−0.0551***	0.1039***	−0.0488***
<i>N</i>	7766	7766	7766

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As to types of school transfer, compared with students who have never transferred, students who have transferred schools are less likely to live at home and more likely to board at school, as might be expected. Since school transfer is a consequence of the school merger policy, decisions to board at school is largely related to the school merger policy. Those transferring from teaching points were most affected by the school merger policy. The probability of boarding at school for those who transferred from teaching points is 0.1670 higher than those who had not transferred.

The effect of school transfer on rented accommodation is trick. Students

who transferred were less likely live in rented accommodation than students who did not transfer. The reason is that many students may have started to rent accommodations when they began first grade and remained at the one school, hence they would report they had never transferred. This group of students may be affected much more by the school merger policy than other students. As shown in Table 4.8, the differences of the percentage of students rented accommodation among different types of school transfer is small, ranging from 0.32% to 3.79%. Table 4.7 also shows the small differences of predicted probabilities of rented accommodation among different types of school transfer, ranging from 0.0394 to 0.0692.

Table 4.8: Type of schools transfer from (%)

	No transfer	Teaching point	Village school	Township school	Other school
Home	45.51	14.01	18.55	23.97	29.54
School	30.16	60.82	56.80	51.09	42.34
Rent	24.33	25.17	24.65	24.94	28.12
Total	100	100	100	100	100

The direction and attitude of the effects of time and transportation from home to school are similar between boys and girls. Boys are more affected by types of school transfer than girls.

Table 4.9: Marginal effects from multinomial logit model for boys and girls

	Girls			Boys		
	Home	School	Rent	Home	School	Rent
Time from home to school (minutes)	-0.0090***	0.0047***	0.0043***	-0.0099***	0.0047***	0.0052***
<i>Transport: basic group=on foot</i>						
Bicycle, motorcycle	-0.2128***	0.1679***	0.0449*	-0.2378***	0.1852***	0.0525**
Vehicle and others	-0.3173***	0.2000***	0.1173***	-0.3187***	0.2048***	0.1139***
<i>Type of school transfer: basic group=no transfer</i>						
Teaching point	-0.1253***	0.1713***	-0.0460**	-0.1231***	0.1446***	-0.0216
Village school	-0.0871***	0.1714***	-0.0843***	-0.0935***	0.1080***	-0.0145
Township school	-0.0631***	0.1389***	-0.0759***	-0.0623***	0.1259***	-0.0636***
Other school	-0.0432***	0.1036***	-0.0604***	-0.0608***	0.0953***	-0.0345
N	4098	4098	4098	3663	3663	3663

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5.2 The effects of living arrangements on math score

Boarding school may cause homesickness, stress, lack of positive parental support and input, loss of identity, lack of parental supervision, failure to develop independent decision-making ability, and increased likelihood of substance abuse (Curto and Fryer Jr 2014; Martin et al. 2014). Boarding school also have some potential benefits: safer, less volatile, and less stressful environments; less negative interactions with parents and community; positive adult role models; nutritious foods; less time being idle; more scholastic and social capital; tight schedule of students' daily routines (Curto and Fryer Jr 2014; Martin et al. 2014).

With regard to boarding schools in rural Shaanxi province, boarding schools may well cause homesickness. But homesickness is less of a problem because boarding students return home on weekends. Boarding students are under teachers' supervision all day and may get more supervision or attention from their teachers than from their parents. They will have more time to study and can get more effective academic support from their teachers and classmates. Boarding school is a safer physical environment. Students do not have to spend their time on the long way from their home to school. It can be very dangerous to travel from home to school when the weather is bad.

If a boarding environment is more conducive to achievement than the home environment, it could have positive effect on children's academic performance and psychological well-being. If it is less conducive to achievement than the home environment, it can yield negative effects. If the negative effects and positive effects are balanced, we predicted we would find no net effect of boarding school on children's academic and psychological well-being.

In order to compare math score for students in each type of living arrangements, we run outcome models using the IPWRA estimator. We provide the predicted math score in Table 4.10 and compare them in Table 4.11.

Table 4.10 shows that students in rented accommodation have the highest

Table 4.10: The predicted standardized math score

	All		Boys		Girls	
Home	-0.0418	0.0353	-0.0413	0.0504	-0.0684	0.0446
School	-0.0480	0.0274	-0.1343	0.0364	0.0454	0.0376
Rent	0.0261	0.0411	0.0335	0.0557	0.0472	0.0532

Note: Bootstrap standard error in the second row.

predicted standardized math scores regardless of gender. For boys, those who boarding at school have the lowest predicted standardized math score. For girls, those who living at home have the lowest predicted standardized math score.

Table 4.11: ATE of living arrangements on the standardized math score

	All		Boys		Girls	
School VS Home	-0.0062	0.0462	-0.0930	0.0639	0.1139*	0.0564
Rent Vs Home	0.0679	0.0535	0.0748	0.0763	0.1156*	0.0649
Rent VS School	0.0741	0.0516	0.1678**	0.0667	0.0018	0.0586

Note: SE are calculated by using the bootstrap method with 1000 replications..

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.11 reports the ATE of living arrangements on the standardized math score. For all students, there is no statistically significant difference of the predicted standardized math score if they change one type of living arrangement to another. For boys, if all boys change their living arrangement from boarding at school to rented accommodation, their standardized math score would increase 0.1678. For girls, if all girls change their living arrangement from living at home to boarding at school or rented accommodation, their standardized math score would increase 0.1139 or 0.1156 respectively.

4.5.3 The average treatment effect on the treated (ATT)

We are mostly interested in the ATT of living arrangement on the standardized math score.

For student living at home, if they choose to board at school instead of living at home, their standardized math score would drop 0.1046 with significant level on 0.1. For students boarding at school, their standardized math score would

not change too much if they choose living at home or rented accommodations instead of boarding at school. For students living at rented recommendations, their standardized math score would drop 0.1757 or 0.1021 if they turn to live at home or to board at school.

Table 4.12: ATT of living arrangements on math score

		All	Boys	Girls
Home	from home to school	-0.1046*	-0.2345***	0.0233
	from home to rent	-0.0842	0.0205	-0.0858
Schol	from school to home	-0.0320	0.0170	-0.1494*
	from school to rent	0.0819	0.1683**	0.0292
Rent	from rented to home	-0.1757***	-0.2502***	-0.1286*
	from rented to school	-0.1021***	-0.1719***	-0.0128

Note: SE are calculated by using the bootstrap method with 1000 replications..

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

For boys living at home, they would have 0.2345 decline of standardized math score if they choose to boarding at school instead of to living at home. For boys boarding at school, their standardized math score would increase 0.1683 if they turn to rent accommodations. For boys rented accommodations, their standardized math score would drop 0.2502 or 0.1719 if they turn to live at home or to board at school.

For girls living at home, their standardized math score would not change too much if they choose boarding at school or rented accommodations instead of living at home. For girls boarding at school, their standardized math score would decrease 0.1494 if they turn to live at home. For girls rented accommodations, their standardized math score would decrease 0.1286 if they turn to live at home.

4.5.4 Robust test using the augmented inverse-probability weighting (AIPW)estimator

The augmented inverse-probability weighting (AIPW) estimator is also a double robust estimator ⁴. The AIPW estimator also computes inverse probability weights

⁴We use the official *Stata* command *teffects aipw* in *Stata* 14.2 to imply the AIPW estimator. Standard errors are calculated by using the bootstrap method with 1000 replications.

from the treatment model using multinomial logit model. But unlike IPWRA estimator, the weights are used to compute the weighted means of the treatment-specific predicted outcome from separate outcome models that do not use weights (see Cattaneo (2010);Cattaneo et al. (2013)).

Comparing the relative efficiency of the IPWRA estimator and the AIPW estimator with multivalued treatments allows more robust results, so for this reason we use the AIPW estimator as a robust test. We are unable to find similar comparisons in other studies.

Table 4.13: The predicted standardized math score: AIPW

	All		Boys		Girls	
Home	-0.1335	0.1260	-0.2844	0.2883	-0.1677	0.1082
School	-0.0549	0.0287	-0.1452	0.0426	0.0495	0.0432
Rent	0.0330	0.0406	0.0149	0.0579	0.0817	0.0612

Note: Bootstrap standard error in the second row.

Comparing Table 4.10 and Table 4.13, both the AIPW and the IPWRA estimators show that students who rented accommodation have the highest predicated standardized math score for both boys and girls. Unlike the results from the IPWRA estimator, the AIPW estimator indicates that boys who living at school have the lowest predicated standardized math score. For girls, both the AIPW and IPWRA report that girls who living at home have the lowest predicated standardized math score.

Table 4.14: ATE of living arrangements on math score: AIPW

	All		Boys		Girls	
School VS Home	0.0786	0.1294	0.1391	0.2912	0.2172*	0.1200
Rent VS Home	0.1665	0.1329	0.2993	0.2940	0.2494**	0.1268
Rent VS School	0.0879*	0.0508	0.1601**	0.0724	0.0322	0.0748

Note: SE are calculated by using the bootstrap method with 1000 replications..

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Comparing Table 4.12 and Table 4.14, both the IPWRA and AIPW estimators indicate that if boys change their living arrangement from boarding at school to rented accommodation, their math score would be increased. The IPWRA and

AIPW estimators also show that if girls change their living arrangement from living at home to boarding at school or to rented accommodation, their math score would be increased.

4.5.5 The advantage of rented accommodation

We did not examine sources of the positive effect of rented accommodation on academic performance in this paper. During the field interview, however, we found there are at least three advantage of rented accommodation for students' academic performance.

Firstly, parents who rented accommodation for their children are more like to pay more attention on children's education and engage more with children and teachers. Parental motivation is partly from the cost of rented accommodation. As suggested by Siebert et al. (2018), communication and feedback among students, parents, and teachers can improve students' academic performance.

Secondly, in our sample, 88 percent of students in rented accommodation are living with their mothers, while 57 percent of them have their fathers being present as well. Most of mothers have no jobs. So student in rented accommodation are more likely to get direct supports from their parents than those boarding at school.

Thirdly, students in rented accommodation may feel more pressure as their education cost more than others. This kind of pressure may push them to pursue higher academic performance.

4.6 Chapter conclusions

In this paper we have attempted to understand the effects of rural school consolidation on students' living arrangement and, as a consequence, how students' living arrangements affect their academic performance as measured by mathematics attainment scores. Using students survey data from Yulin, Shaanxi Province in China, the results shows that more than two-fifths of grade four and five students

are boarding at school and one quarter live in rented accommodation near school. Boarding at school results from the need to travel long distances from home to school together with the unavailability or low quality of schools near the students' home villages. Renting accommodation is also related a way to solve the problem of distance and travel times. However, the effects of the school merger policy are different for those boarding and for those in rented accommodation. Many students are forced to live in rented accommodation when they began their first grade. The impact of school merging policy on decisions to rent accommodation is still not clear.

We find positive effects of rented accommodation on both boys' and girls' academic performance in mathematics. Differing from previous studies by Mo et al. (2012) and Chen et al. (2014), we find that boarding school can improve academic performance in mathematics for girls, but not for boys. Our results also find negative effects of living at home on girls' academic performance in mathematics.

The school merger policy in China was temporarily stopped by the central government in September 2012 because of its reported negative effects. In fact, the effects of the school merger policy remain controversial. Our results show that the school merger policy has led to more students living in boarding school and rented accommodation. We conclude that rented accommodation would improve students' academic performance in mathematics and boarding at school would weak boys' academic performance in mathematics.

We should be cautious in interpreting our results. First, we rely on data from one poor province in northwest China, Shaanxi Province. The living arrangement and environment may differ in other parts of China so we cannot generalise our findings to the whole of China. Also we only focus on rural primary school students and on achievement in mathematics. Boarding rate for junior middle school students is much higher than for primary school students though the boarding effect for junior middle school students, however, is unknown.

Second, we do not look at the costs of renting accommodation and boarding

school. The benefits from living in rented accommodation and boarding schools might come from the high cost of it. Furthermore, we did not include the effects of nutrition intervention programs because of the unviability of data, though we realise the importance of government nutrition intervention programs for boarding students (Li and Luo 2011; Qi and Zhao 2012) .

Third, we only focus on students who are still at school. Students who dropped out school or went to city are not included in the analysis. Since the school merger policy may have increased school dropout rates Ding and Zheng (2013) and girls usually are more likely to dropout than boys in rural China (Li and Liu 2014), the effects of the school merger policy on girls are mixed, both positive and negative. The school merger policy can increase the probability of rural-urban migration (Liu and Huang 2016). “Migration for education” may become a common phenomenon for rural households.

Finally, a major limitation in our paper is the difficulty of determining causality, since it may be mutual or two-directional between living arrangement and academic performance in mathematics. Academic performance may affect students’ living arrangements but the directions are unknown. Parents may be more likely to rent rooms if their children’s academic performance is good or if the parents have high aspirations for their children and the reverse can be the case too. As to our sample, we focused on students from grade 4 and 5. Parents may be not care much about children’s academic performance when they consider children’s living arrangements. The mutual causality between living arrangements and academic performance would not be a big problem in this study.

Appendices of Chapter 4

Table C.1: Descriptions of variables for all sample (1)

	Living at home	Boarding at school	Rented accommodation	Total
Time from home to school (minutes)	12.74	39.89	66.91	37.31
<i>Transport</i>				
On foot	75.64	26.96	25.2	42.45
Bicycle, motorcycle	12.21	31.96	22.34	23.08
Vehicle and others	12.15	41.08	52.46	34.47
<i>Type of school transfer</i>				
no transfer	64.86	33.41	45.22	46.68
teaching point	6.8	22.95	15.94	15.9
village school	4.91	11.7	8.52	8.68
township school	10.77	17.84	14.62	14.72
other school	12.66	14.1	15.72	14.03
Male	52.68	55.14	51.54	53.43
age	11.23	11.54	11.34	11.39
Grade Five	46.79	55.22	49.47	51.01
Grade Four	53.21	44.78	50.53	48.99
Repeated one grade	26.01	34.97	30.19	30.83
Number of Young siblings	1.19	1.32	1.24	1.26
Have old siblings	0.46	0.55	0.46	0.50
Household size	4.35	4.55	4.38	4.44
<i>Parental migration</i>				
no parents out	59.27	61.7	50	57.96
Father out only	30.93	23.29	41.18	30.28
Mother out only	3.47	4.06	1.84	3.31
Both father and mother out	6.33	10.96	6.98	8.44
Father's age	38.24	39.4	38.43	38.78
Mother's age	36.12	36.78	36.08	36.39

Table C.2: Descriptions of variables for all sample (2)

	Living at home	Boarding at school	Rented accommodation	Total
<i>Father's education</i>				
Illiteracy	5.68	9.51	7.1	7.65
Primary school	34.46	42.67	38.78	39
middle school	43.01	35.97	41.65	39.7
High school and above	16.86	11.85	12.47	13.65
<i>Mother's education</i>				
Illiteracy	17.28	25.83	20.73	21.74
Primary school	39.45	41.98	44.11	41.69
middle school	29.65	22.84	27	26.12
High school and above	13.62	9.36	8.16	10.46
<i>House values</i>				
less than 5000 yuan	33.48	30.96	50.49	36.7
5000-10,000 yuan	19.03	25.03	21.06	22.07
10,000-50,000 yuan	20.14	21.97	16.5	19.99
50,000-100,000 yuan	27.35	22.05	11.95	21.24
Math teacher is female	57.05	53.77	58.78	56.1
Math teacher is male	42.95	46.23	41.22	43.9
Math teacher's age	32.36	31.29	32.93	32.05
Math teacher has bachelor degree	55.47	61.9	53.82	57.77
Number of students in school	514.8	413.14	540.96	478.53
Class size	39.87	37.02	41.37	39.01
Distance from school to county town(KM)	34.29	41.58	34.30	37.40
Rich county	23.83	12.43	28.04	19.95
middle county	34.40	50.26	28.18	39.71
poor county	41.77	37.32	43.78	40.34
<i>N</i>	2971	3822	2278	9071

Table C.3: Marginal effects from multinomial logit model for all students

	Living at home	Boarding at school	Rented accommodation
Time from home to school (minutes)	-0.0094***	0.0048***	0.0046***
<i>Transport: on foot</i>			
Bicycle, motorcycle	-0.2839***	0.2171***	0.0668***
Vehicle and others	-0.3779***	0.2340***	0.1440***
<i>Type of school transfer: no transfer</i>			
Teaching point	-0.1276***	0.1670***	-0.0394**
Village school	-0.0947***	0.1430***	-0.0483**
Township school	-0.0691***	0.1383***	-0.0692***
Other school	-0.0551***	0.1039***	-0.0488***
Male	0.0060	-0.0070	0.0010
Age	-0.0257***	0.0562***	-0.0305***
Number of Young siblings	0.0100	-0.0479***	0.0379***
Household size	-0.0047	0.0349***	-0.0302***
Father's age	-0.0016	0.0057***	-0.0041**
Mother's age	0.0018	-0.0029	0.0010
Father's education: middle school or above	0.0167*	-0.0288***	0.0121
Mother's education: middle school or above	0.0180**	0.0037	-0.0218**
<i>House values:less than 5000 yuan</i>			
5000-10,000 yuan	-0.0001	0.0822***	-0.0820***
10,000-50,000 yuan	0.0228*	0.0688***	-0.0916***
50,000-100,000 yuan	0.0699***	0.0760***	-0.1458***
Distance from school to county town	-0.0021***	0.0029***	-0.0008
Number of students of school	0.0000	-0.0001**	0.0001***
<i>Economic development of counties: middle</i>			
Rich county	0.1425***	-0.2884***	0.1458***
Poor county	0.0110	-0.1069***	0.0959***
<i>N</i>	7766	7766	7766

Cluster stand error at school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Marginal effects from multinomial logit model for boys

	Living at home	Boarding at school	Rented accommodation
Time from home to school (minutes)	−0.0090***	0.0047***	0.0043***
<i>Transport: on foot</i>			
Bicycle, motorcycle	−0.2128***	0.1679***	0.0449*
Vehicle and others	−0.3173***	0.2000***	0.1173***
<i>Type of school transfer: no transfer</i>			
Teaching point	−0.1253***	0.1713***	−0.0460**
Village school	−0.0871***	0.1714***	−0.0843***
Township school	−0.0631***	0.1389***	−0.0759***
Other school	−0.0432***	0.1036***	−0.0604***
Age	−0.0309***	0.0592***	−0.0283***
Number of young siblings	−0.0021	−0.0223*	0.0245**
Household size	0.0045	0.0315***	−0.0359***
Father's age	−0.0029	0.0082***	−0.0053**
Mother's age	0.0028	−0.0051**	0.0022
Father's education: middle school or above	0.0018	−0.0189	0.0171
Mother's education: middle school or above	0.0243**	−0.0030	−0.0213
<i>House values:less than 5000 yuan</i>			
5000-10,000 yuan	0.0001	0.0725***	−0.0726***
10,000-50,000 yuan	0.0182	0.0451**	−0.0632***
50,000-100,000 yuan	0.0562***	0.0864***	−0.1426***
Distance from school to county town	−0.0024***	0.0034***	−0.0010
number of students of school	0.0000	−0.0001**	0.0001**
<i>Economic development of counties: middle</i>			
Rich county	0.1539***	−0.3098***	0.1559***
Poor county	0.0049	−0.1036***	0.0986***
<i>N</i>	4098	4098	4098

Cluster stand error at school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: Marginal effects from multinomial logit model for girls

	Living at home	Boarding at school	Rented accommodation
Time from home to school (minutes)	−0.0099***	0.0047***	0.0052***
<i>Transport: on foot</i>			
Bicycle, motorcycle	−0.2378***	0.1852***	0.0525**
Vehicle and others	−0.3187***	0.2048***	0.1139***
<i>Type of school transfer: no transfer</i>			
Teaching point	−0.1231***	0.1446***	−0.0216
Village school	−0.0935***	0.1080***	−0.0145
Township school_before	−0.0623***	0.1259***	−0.0636***
Other school_before	−0.0608***	0.0953***	−0.0345
Age	−0.0199**	0.0532***	−0.0332***
Number of young siblings	0.0178**	−0.0631***	0.0453***
Household size	−0.0151**	0.0395***	−0.0243***
Father's age	0.0003	0.0030	−0.0032*
Mother's age	0.0000	0.0003	−0.0003
Father's education: middle school or above	0.0341***	−0.0397***	0.0055
Mother's education: middle school or above	0.0111	0.0113	−0.0223
<i>House values:less than 5000 yuan</i>			
5000-10,000 yuan	−0.0044	0.0796***	−0.0752***
10,000-50,000 yuan	0.0234	0.0840***	−0.1074***
50,000-100,000 yuan	0.0880***	0.0651***	−0.1531***
Distance from school to county town	−0.0018***	0.0023***	−0.0006
Number of students of school	0.0000	−0.0001**	0.0001***
<i>Economic development of counties: middle</i>			
Rich county	0.1340***	−0.2813***	0.1473***
Poor county	0.0061	−0.1003***	0.0943***
<i>N</i>	3663	3663	3663

Cluster stand error at school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.6: OLS model for standardised math score

	All	Boys	Girls
<i>Living arrangement: rented accommodation</i>			
Living at home	−0.0637**	−0.0691*	−0.0656
Boarding at school	−0.0600**	−0.1072***	−0.0126
Male	−0.0227		
Age	−0.1754***	−0.1872***	−0.1595***
Repeated one grade	−0.0940***	−0.1030***	−0.0843**
Have old siblings	0.0222	0.0583	−0.0110
<i>Type of school transfer: no transfer</i>			
Teaching point	0.0243	0.0675	−0.0179
Village school	0.0180	0.0115	0.0282
Township school	0.0119	0.0201	−0.0038
Other school	−0.0369	0.0305	−0.0920*
Father's age	−0.0082**	−0.0097**	−0.0065
Mother's age	0.0097**	0.0122**	0.0062
Father's education: middle school or above	0.1034***	0.0970***	0.1087***
Mother's education: middle school or above	0.0848***	0.0967***	0.0736**
<i>House values:less than 5000 yuan</i>			
5000-10,000 yuan	0.0339	0.0270	0.0443
10,000-50,000 yuan	0.0765**	0.0789*	0.0671
50,000-100,000 yuan	0.0525*	0.0532	0.0515
Math teacher is male	−0.1700***	−0.1554***	−0.1898***
Math teacher's age	0.0009	−0.0012	0.0032
Math teacher has bachelor degree	−0.0194	−0.0621*	0.0260
Class size	0.0005	0.0004	0.0008
Number of students in school	0.0001*	0.0000	0.0002***
<i>County dummies controlled.</i>			
R ²	0.0860	0.0912	0.0881
N	7959	4202	3752

Robust stand error are caculated.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 5 Concluding Remarks

5.1 Main findings

The human capital theory and social capital theory are two powerful tools to explain the last forty years of reform and opening-up in China (Morales 2016). China surpassed Japan as the world's second-largest economy in the second quarter of 2010. However, the inequity is been paid more and more attention (Piketty et al. 2019; Wu 2019), and so is urban-rural gap in income. Despite the variety of methods for the Gini coefficient, it is agreed by most researchers that Gini coefficient in China has climbed above 0.4 (Björn and Li 2001; Dong and Li 2004; Li and Luo 2007), which indicates that China is now a society with great inequity. In order to solve the problem of inequity, China need to pay more attention on rural people, especially on rural-urban migrants and rural students.

The thesis consists of three essays related to rural-urban migration, looking at the discourse and consequences of rural-urban migration in China. The first essay is about the impact of social network on wage. The second essay, based on the first one, examines the impact of social network on the job quality. The third essay shifts the focus from urban labour market to rural education, exploring the relationship between the school consolidation policy, rented accommodation, and children's academic performance.

The first essay in Chapter 2 is about how rural-urban migrants use social network to find jobs and how social network affects their wages. In nationally representative household data from the 2008 wave of Rural Urban Migration in China (RUMIC),

nearly two thirds of rural-urban migrants found their employment through family members, relatives, friends or acquaintances. This essays investigates why the use of social network to find jobs is so prevalent among rural-urban migrants in China, and whether migrants face a wage penalty as a result of adopting this job search method. Using a switch regression approach, we find evidence of positive selection effects of the use of networks on wages. Users of networks tend to be older, to have migrated longer ago and to be less educated. In addition, married workers and those from villages with more out-migrant are more likely to use networks, while those without local residential registration status are less likely. Controlling for selectivity, we find a large negative impact of network use on wages. Using job contacts brings access to urban employment, but at the cost of markedly lower wages.

The second essay in Chapter 3 provides a four dimensional job quality index for rural-urban migrants, looking at the effect of job contact network on job quality. The multidimensional job quality index has captured job reality, combining information on earnings, working time, job stability, and work-related social insurances in one index. By using the data of RUMIC 2008 and employing the endogenous switching regression for ordered outcomes, we find unobservables that affect the use of network also impact the job quality of the non-users of network. The positive selectivity does not exist in users of network. We demonstrate that the use of social network brings low job quality for rural-urban migrants, especially for the users of network. The findings are robust to a range of alternate measures of the job quality index, and to using other identification methods.

The third essay in Chapter 4 explores the effects of the rural school consolidation on the living arrangement of rented accommodation for students and how rented accommodation affects students' academic performance in rural China. It is the first paper –to examine the effect of rented accommodation on children's academic performance and to use a double robust estimator with multivalued treatments on this topic. Using a survey of 9,071 Grades 4 and 5 students in 133 primary

schools in Yulin Prefecture, Shaanxi Province in 2013, we find that one quarter of students are rented accommodation near their schools. Rented accommodation results from students living long distances from schools, the unavailability of local schools and the low quality of schools near their home village. Overall, rented accommodation brings students better academic performance, especially for boys. The study indicates that rented accommodation might offer another way to avoid the negative effects of school merge policy and boarding school.

5.2 Contributions

The thesis is composed of three essays related to social network, wages, job quality and rural education in China. The thesis is trying to understand ongoing process of rural-urban migration and rural education in China, with the use of the social capital and social network theory and human capital theory. Since the three essay is focusing on China, especially on rural-urban migrants and rural students, the results have strong policy implications for the employment, the labour market, and the rural education in China and other developing counties.

The main contribution of the thesis is fourfold:

First, the thesis augments the study of social network and social capital by addressing the selection bias of social network. Although previous studies have shown the importance of social network on job search, the impact of social network on labour market outcomes is mixed. Many studies have ignored the selection bias of network use, which creates misleading results. The thesis uses endogenous switching regressions to address the bias from the selection of network use. This approach can be further used in other similar topics.

Second, the thesis enriches the study of rural-urban migrant in China by employing the concept of job quality. Most of previous study about labour market outcomes of rural-urban migrants put much attentions on just one dimension of job quality. Scholars have no consensus on how to measure the quality of employment,

and the conclusions obtained by using different data and variable processing methods are inconsistent. The thesis defines job quality by four dimensions of wage, working hours, job stability, and social insurances. The thesis provides a new picture of rural-urban migrants in China. The methodology formed in the thesis can be broadened to the whole urban labour market in China and the labour market in other counties.

Third, the thesis provides a new topic by linking the use of social network and job quality and examining the impact of job contact network on job quality for rural-urban migrants. As far as I know, the thesis is the first to study this topic.

Four, the thesis is the first to explore the relationship among the school consolidation, rented accommodation, and children's academic performance. Most of studies related to the school consolidation are about boarding school students. The thesis shows that there is large amount of students living in rented accommodations. Those students are ignored by previous studies and the government. The thesis provides a new angle to improve rural education in China, which can help China to overcome the middle income trap (Li et al. 2017a; Wang et al. 2018; Yue et al. 2018; Bai et al. 2019).

In summary, by studying new topics and employing new methodologies, the thesis makes contributions to the study of migrant, the economics of network, social capital, human capital, and rural education policy.

5.3 Limitations and further research

The thesis tries to understand the discourse and consequences of rural-urban migration in China, focusing on the impact of social network on the wage and job quality for rural-urban migrants, and the impact of rented accommodation on children's academic performance in rural area. Due to data availability and limitation, there are three main shortages in the thesis:

First, the dataset used in social network, wage, and job quality analysis is

collected in 2008. It is an old dataset with one year information only. China's labour market has changed dramatically after 2008, partly due to the new labour contract law implemented since 2008 (Akee et al. 2019). The new development deserves more attention.

Second, the thesis only studies the social network and labour market outcome of migrant employees. The thesis did not include the self-employed and urban residents in the analysis. While the self-employed have more autonomy at work, they usually have poor job quality in terms of social environments, working time, and training (Eurofound 2018). Measuring the job quality for self-employed migrants is more challenging.

Third, the dataset used in the analysis of rented accommodation is limited to the fourth and fifth grade students at township level schools in Yulin, Shaanxi province. We cannot generalise the findings in other rural areas.

For the social network and job quality topics, further research can use new dataset, perfectly with panel information, to explore the dynamic changes of job quality and the impact of social network on job quality, like in Mustosmäki et al. (2017). The measurement of job quality can be improved with more dimensions. If possible, all labour should be put in the comparative analysis, including urban residents and the self-employed migrants.

For the rented accommodation topic, further research needs to collect more representative data. Rented accommodation may have long term effects on children's development, which should be addressed in future research.

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