The impact of job contact networks on wages of rural–urban migrants in China: a switching regression approach*

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ABSTRACT
In nationally representative household data from the 2008 Chinese Rural to Urban Migration Survey, nearly two thirds of rural–urban migrants found their employment through family members, relatives, friends or acquaintances. This paper 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.

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.

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* The paper is the revised version based on IZA DP No. 10139.
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Much as the general literature on social capital focused 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 (e.g. 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, Michelacci, and Suarez 2010).

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. Literature review

There are a great number of studies on the relationship between social networks and labour market outcomes. Studies may disagree because they analyse different contexts or use different data-sets. 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 discuss alternative measures of social network and the econometric methods commonly used in the existing literature.

2.1. 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.

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 mobilised 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. 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 Aguilera (2005); Granovetter (1973, 1983); Montgomery (1991); Bian (1997) and Zhang and Li (2003). 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, Schluter, and Wahba 2011). 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). 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.

Using panel data is another way to eliminate unobserved fixed effects (Battu, Seaman, and Zenou 2011; Yakubovich 2005). 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), 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 data-set 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 paper, 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.

3. Data and methodology

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 5000 rural–urban migrant households. Samples were randomly chosen in the fifteen migrant destination cities nationally. The data-set 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, Kong, and Zhang (2010).

Granovetter (1974) notes that individuals may use several methods to find a job and only one method leads to success. But the data-set we use only ask the main source of job finding, i.e. the one leads to retaining the job. The data-set 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.

3.2. Methods: endogenous switching regression model

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 (Dutoit 2007; Lokshin and Sajaia 2004; 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.

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

$$Z^* = W_Y + \nu, \nu \sim N(0, \sigma^2)$$

$Z = 1$ if $Z^* > 0$, $Z = 0$ otherwise

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.

$$Y_1 = X_1 \beta_1 + \mu_1, \mu_1 \sim N(0, \sigma^2_1) \text{ if } Z = 1$$

and

$$Y_0 = X_0 \beta_0 + \mu_0, \mu_0 \sim N(0, \sigma^2_0) \text{ if } Z = 0$$

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 $\nu, \mu_1, \mu_0$ have a trivariate normal distribution with mean vector zero and covariance matrix:

$$\Omega = \begin{bmatrix} \sigma^2 & \sigma_{1\nu} & \sigma_{0\nu} \\ \sigma_{1\nu} & \sigma^2_1 & 0 \\ \sigma_{0\nu} & 0 & \sigma^2_0 \end{bmatrix}$$

where $\sigma^2$ is a variance of the error term in the selection equation, normalising with $\sigma^2 = 1$. $\sigma^2_1$ and $\sigma^2_0$ are variances of the error terms in the wage equations. $\sigma_{1\nu}$ is a covariance of $\mu_1$ and $\nu$, and $\sigma_{0\nu}$ is a covariance of $\mu_0$ and $\nu$. The covariance between $\mu_1$ and $\mu_0$ 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

$$\log L = \sum_{Z=1} \left[ \log \Phi(\eta_1) - \frac{1}{2} \left\{ \log (2\pi \sigma_{1\nu}) - \left( \frac{Y - X \beta_1}{\sigma_1} \right)^2 \right\} \right]$$

$$+ \sum_{Z=0} \left[ \log \Phi(\eta_0) - \frac{1}{2} \left\{ \log (2\pi \sigma_{0\nu}) - \left( \frac{Y - X \beta_0}{\sigma_0} \right)^2 \right\} \right]$$
where
\[ \eta_1 = \frac{W + Y - X \beta}{\sqrt{1 - \rho_0^2}} \] and \[ \eta_0 = \frac{W + Y - X \beta}{\sqrt{1 - \rho_0^2}} \]

Note: \[ \rho_{00} = \frac{\sigma_{\mu_0}^2}{\sigma_{\mu_0} \sigma_{\nu_0}} \] is the correlation coefficient between \( \mu_0 \) and \( \nu \).

\[ \rho_{10} = \frac{\sigma_{\mu_1}^2}{\sigma_{\mu_1} \sigma_{\nu_1}} \] is the correlation coefficient between \( \mu_1 \) and \( \nu \).

\( \phi(\cdot) \) is the standard normal density function.

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

After estimating the models parameters, the following unconditional expectations could be calculated:

\[ E(Y_1 | Z = 1) = X_1 \beta_1 \]  

\[ E(Y_0 | Z = 0) = X_0 \beta_0 \]

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:

\[ E(Y_1 | Z = 1, X_1) = E(Y_1 | Z^* > 0) \]

\[ = E(Y_1 | W_Y + \nu > 0) \]

\[ = X_1 \beta_1 + E(\mu_1 | \nu < W_Y) \]

\[ = X_1 \beta_1 + \sigma_1 \rho_{10} \frac{\phi(W_Y)}{\Phi(W_Y)} \]  

(3)

where \( \frac{\phi(W_Y)}{\Phi(W_Y)} \) 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:

\[ E(Y_0 | Z = 0, X_0) = E(Y_0 | Z^* < 0) \]

\[ = E(Y_0 | W_Y + \nu < 0) \]

\[ = X_0 \beta_0 + E(\mu_0 | \nu > W_Y) \]

\[ = X_0 \beta_0 - \sigma_0 \rho_{00} \frac{\phi(W_Y)}{1 - \Phi(W_Y)} \]  

(4)

where \( \frac{\phi(W_Y)}{1-\Phi(W_Y)} \) 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:

\[
E(Y_1 | Z = 0, X_1) = E(Y_1 | Z^* < 0) = E(Y_1 | W_\gamma + \nu < 0) = X_1 \beta_1 + E(\mu_1 | \nu > W_\gamma) = X_1 \beta_1 - \sigma_Y \phi(W_\gamma) \frac{1}{1 - \Phi(W_\gamma)} \quad (5)
\]

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

\[
E(Y_0 | Z = 1, X_0) = E(Y_0 | Z^* > 0) = E(Y_0 | W_\gamma + \nu > 0) = X_0 \beta_0 + E(\mu_0 | \nu < W_\gamma) = X_0 \beta_0 + \sigma_Y \phi(W_\gamma) \frac{1}{\Phi(W_\gamma)} \quad (6)
\]

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).

4. Descriptions

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 1.

The job search methods in Table 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

Details from Table 1 reveal that the dominant method of obtaining jobs is via migrants’ social network. 31.1 per cent 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%. 7.57 per cent of them used family members and 2.92% used acquaintances.
When aggregating all sources of job search into the four main categories (in Table 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 and others. Table 3 shows the details of grouping.

### 4.2. Homophily

The descriptive data in Tables 1–3 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 migrants 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 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 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 actions 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 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. More detailed information of data description can be found in Table A1, Appendices.

4.3. Job search methods and wages

Migrants who use social networks receive lower wages than those who do not. Table 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.

We plot the logged hourly wage using the kernel density graph (Figure 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.
Table 5. Users of network and non-users of network.

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

Figure 1. Kernel density graph of log of hourly wage.

5. Models for job search methods and wages

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, 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 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.

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
From the variables we have in the data-set, 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, Jin, and Yue (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 7 shows that each of three hypothesised identifying variables have significant effects on the likelihood of using social networks to find

| Table 6. Wage equations: OLS regressions. | All sample | Non-users of network | Users of network |
|---|---|---|---|
| | Coefficient | SE | Coefficient | SE | Coefficient | SE |
| Users of network | −0.0091 | 0.0135 | 0.0294*** | 0.0085 | 0.0477*** | 0.0057 |
| Age | 0.0417*** | 0.0047 | −0.0823*** | 0.0181 | −0.0322*** | 0.0153 |
| 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 |
| Occupation: Base group = White collar | | | | | | |
| 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 |
| Industry: Base group = Manufactory | | | | | | |
| Construction | 0.1204*** | 0.0240 | 0.1506*** | 0.0465 | 0.1141*** | 0.0281 |
| Electricity, gas, water, IT and transportation | 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 |
| Ownership: Base group = State and collective | | | | | | |
| Private enterprises | −0.0477*** | 0.0223 | −0.0724* | 0.0410 | −0.0367 | 0.0263 |
| Self-employed | −0.0790*** | 0.0256 | −0.0807* | 0.0468 | −0.0848*** | 0.0303 |
| Individuals | | | | | | |
| 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 enterprise | −0.2063 | 0.1403 | −0.4682*** | 0.1528 | 0.1451 | 0.1379 |
| Firm size: Base group = Below 8 | | | | | | |
| 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*** | 0.0379 | 0.7912*** | 0.1478 | 0.6458*** | 0.1065 |
| Adjust R² | 0.3330 | 0.3384 | 0.3283 | 0.3212 | 0.3065 | 0.0193 |
| N | 4845 | 1819 | 3026 | 3026 | 3026 | 3026 |

Notes: Dependent variable = log of hourly wage; SE refers to robust standard error; Provinces controlled. *p < 0.10; **p < 0.05; ***p < 0.01.
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

Table 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|

Education: base group = Junior middle school

|                        | Coefficient | SE   |
|------------------------|-------------|------|
| Elementary school or blow | 0.1265** | 0.0593|
| Senior middle school    | −0.1854***  | 0.0443|
| Specialised secondary school | −0.4888*** | 0.0519|
| Constant               | 0.9628***   | 0.2633|
| N                      | 4723        |      |

Notes: Dependent variable: dummy = 1 if user of network. **p < 0.05; ***p < 0.01.

Table 8. Switching regression: wage equation.

|                        | Non-users of network | Coefficient | SE  | Users of network | Coefficient | SE  |
|------------------------|----------------------|-------------|-----|------------------|-------------|-----|
| Age                    | 0.0255***            | 0.0091      |     | 0.0463***        | 0.0059      |     |
| Age squared            | −0.0412***           | 0.0133      |     | −0.0709***       | 0.0084      |     |
| Years of migration     | 0.0284***            | 0.007       |     | 0.0150***        | 0.0045      |     |
| Years of migration squared | −0.0615** | 0.0269      |     | −0.0174          | 0.0161      |     |
| Male                   | 0.0923***            | 0.0244      |     | 0.1275***        | 0.0176      |     |
| Years of schooling     | 0.0346***            | 0.0052      |     | 0.0286***        | 0.0036      |     |

Occupation: base group = White collar

|                        | Non-users of network | Coefficient | SE  | Users of network | Coefficient | SE  |
|------------------------|----------------------|-------------|-----|------------------|-------------|-----|
| Blue collar            | −0.2137***           | 0.0345      |     | −0.1376***       | 0.0315      |     |
| Other occupation       | −0.0708              | 0.1655      |     | −0.1754          | 0.1231      |     |

Industry: base group = Manufactory

|                        | Non-users of network | Coefficient | SE  | Users of network | Coefficient | SE  |
|------------------------|----------------------|-------------|-----|------------------|-------------|-----|
| Construction           | 0.1572***            | 0.0425      |     | 0.1066***        | 0.0281      |     |
| Electricity, gas, water, IT and transportation | −0.0054 | 0.0572      |     | 0.0506           | 0.0414      |     |
| Commerce and trade     | 0.0254               | 0.0383      |     | 0.0076           | 0.028       |     |
| Restaurant and catering | −0.1379*** | 0.0348      |     | −0.1106***       | 0.0268      |     |
| Finance, estate, health, education | −0.025  | 0.0378      |     | −0.0437          | 0.0295      |     |
| Services               | −0.0599              | 0.0393      |     | −0.0588*         | 0.0310      |     |

Ownership: base group = State and collective

|                        | Non-users of network | Coefficient | SE  | Users of network | Coefficient | SE  |
|------------------------|----------------------|-------------|-----|------------------|-------------|-----|
| Private enterprises    | −0.0501              | 0.0399      |     | −0.0411          | 0.0261      |     |
| Self-employed Individuals | −0.0595 | 0.0454      |     | −0.0907***       | 0.0297      |     |
| Foreign, joint venture | 0.0411               | 0.0454      |     | 0.0248           | 0.0349      |     |
| Shared company         | 0.0721               | 0.0475      |     | 0.0024           | 0.035       |     |
| Other enterprise       | −0.4367***           | 0.1797      |     | 0.104            | 0.2394      |     |

Firm size: base group = Below 8

|                        | Non-users of network | Coefficient | SE  | Users of network | Coefficient | SE  |
|------------------------|----------------------|-------------|-----|------------------|-------------|-----|
| 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***        | 1.073       |     |
| 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        |     |                  |             |     |

Notes: Dependent variable = log of hourly wage; Provinces controlled. *p < 0.10; **p < 0.05; ***p < 0.01.
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 8 shows the results of wage equations from the switching regressions. Marginal effects calculated from this model are reported in Table A2, Appendices. The rho values in Table 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 $\rho_{0\nu}$ discussed earlier: its positive value implies that unobserved factors $\nu$ which increase the likelihood of using social networks are positive correlated with the unobserved determinants $\mu_0$ of the wages of those not using networks. Similarly, the positive value of the rho term for users of networks, corresponds to $\rho_{1\nu}$ and implies $\nu$ is positively correlated with the unobserved determinants $\mu_1$ 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.

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.

5.3. Wage difference

Table 9 compares the predicted log wages from the wage equations in Table A3 in Appendices with the observed values. Unconditional log wages are predicted from the switching model using Equations (1) and (2). Conditional log wages are predicted from the switching model using Equations (3–6). 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.

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, Michelacci, and Suarez (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 sizable urban wage discount from using networks, if that gives them access to urban jobs.

5.4. Robustness tests

5.4.1. 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 affect wages through network use. We test this assumption by an over-identifying test for instrumental variables in Table 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.

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

| 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 |

Table 9. Observed and predicted log hourly wages.
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.

5.4.2. 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 large, significant negative impacts on wages. The coefficient implies use of networks would lower log wages by 0.438 points (Table 11). 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.

6. Conclusion

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.

Before drawing strong policy conclusions, further research is required into the possible barriers facing migrants in accessing market or state mechanisms for urban job search. However, our paper does provide prima facie evidence of imperfections in the labour market: many migrant workers appear unable to use such formal mechanisms, so the majority rely on social networks – apparently at the cost of obtaining substantially lower paying jobs. This finding does not reflect a selectivity bias – indeed, correcting for such bias dramatically increases the estimated wage cost of using networks to find employment. Our research suggest that efforts to publicise information about urban job vacancies in rural areas, whether through expanding existing state job exchanges or promoting private alternatives, could bring large benefits for migrant workers. Not only would such efforts increase access to urban employment for migrants, they may also raise the wages paid if they do find urban jobs. Social capital may be substituting for the lack of well-functioning formal labour market institutions, but it is far from a perfect substitute.
Notes

1. Granovetter (1974) divides job search methods into three groups: formal means, personal contracts, and direction application. He argues direction application that does not use a formal or personal intermediary is different from both formal means and from personal contacts.

2. Liang (2010) use a switching regression model to estimate the effect on wages of using social networks to find jobs in eight cities in China. Their exclusion restriction is to use the square of the age at which workers obtained their jobs in the selection model but not in the wage equations. This exclusion restriction seems a questionable a priori given that they include the linear term for age at which workers obtain their jobs in both the selection and wage equations.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the Economic and Social Research Council (ESRC) [grant number ES/1035079/1], [grant number ES/M004333/1].

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**Appendices**

**Table A1.** Data descriptions (mean or frequencies).

|                           | Non-users of network | Users of network | Total  |
|---------------------------|----------------------|------------------|--------|
| Age                       | 29.16                | 30.6             | 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  |
| Female                    | 42.25                | 42.43            | 42.36  |
| Male                      | 57.75                | 47.57            | 57.64  |
| Married                   | 52.99                | 60.01            | 57.38  |
| Unmarried                 | 47.01                | 39.99            | 42.62  |
| Local rural hukou        | 16.72                | 20.77            | 19.26  |
| Non-local rural hukou    | 83.28                | 79.23            | 80.74  |
| Occupation                |                      |                  |        |
| White collar              | 10.87                | 6.25             | 7.98   |
| Blue collar               | 83.82                | 89.11            | 87.13  |
| Other occupation          | 5.31                 | 4.64             | 4.89   |
| Industry                  |                      |                  |        |
| Manufactory               | 26.71                | 20.95            | 23.1   |
| Construction              | 8.44                 | 14.41            | 12.18  |
| Electricity, gas, water, IT and transportation | 3.58            | 4.2              | 3.97   |
| Commerce and trade        | 17.18                | 19.31            | 18.51  |
| Restaurant and catering   | 20.23                | 19.04            | 19.49  |
| Finance, estate, health, education | 12.86          | 11.53            | 12.03  |
| Services                  | 11.00                | 10.56            | 10.73  |
| Ownership                 |                      |                  |        |
| State and collective      | 8.38                 | 10.17            | 9.50   |
| Private enterprises       | 40.65                | 43.61            | 42.5   |
| Self-employed Individuals | 24.39                | 28.73            | 27.1   |
| Foreign, joint venture    | 15.31                | 9.15             | 11.46  |
| Shared company            | 10.97                | 8.22             | 9.25   |
| Other enterprise          | 0.30                 | 0.12             | 0.19   |
| Firm size                 |                      |                  |        |
| Below 8                   | 23.93                | 27.31            | 26.05  |
| 8–50                      | 25.11                | 30.16            | 28.27  |
| Above 50                  | 50.96                | 42.53            | 45.6   |
Table A2. 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   |
| Education: base group = Junior middle school |           |          |
| Elementary school or blow | 0.0404      | 0.0237   |
| Senior middle school | −0.0890     | 0.0194   |
| Specialised secondary school | −0.2046    | 0.0218   |
| N         | 4723            |          |

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

Table A3. 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             |
| Occupation: base group = White collar |           |                    |
| Blue collar       | −0.1781***    | 0.0230             | −0.1759***    | 0.0231             |
| Other occupation  | −0.1389       | 0.0985             | −0.1389       | 0.0991             |
| Industry: base group = Manufactory |           |                    |
| 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             |
| Restaurant and catering | −0.1281***  | 0.0213             | −0.1281***    | 0.0213             |
| Finance, estate, health, education | −0.0438*     | 0.0232             | −0.0467**     | 0.0232             |
| Services          | −0.0665***    | 0.0243             | −0.0657***    | 0.0242             |
| Ownership: base group = State and collective |           |                    |
| 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 enterprise  | −0.2643*      | 0.143              | −0.2612*      | 0.1402             |
| Firm size: base group = Below 8 |           |                    |
| 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             |              |                    |
| $R^2$             | 0.2660        | 0.3230             |              |                    |
| N                 | 4723          | 4723               |              |                    |

Notes: Dependent variable = log of hourly wage; Provinces controlled. *p < 0.10, **p < 0.05, ***p < 0.01.