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ABSTRACT

Informal Search, Bad Search? The Effects of Job Search Method on Wages among Rural Migrants in Urban China*

The use of informal job search method is prevalent in many countries. There is, however, no consensus in the literature on whether it actually matters for wages, and if it does, what are the underlying mechanisms. We empirically examine these issues specifically for rural migrants in urban China, a country where one of the largest domestic migration in human history has occurred over the past decades. We find that there exists a significant wage penalty for those migrant workers who have conducted their search through informal channels, despite their popularity. Our further analysis suggests two potential reasons for the wage penalty: 1) the informal job search sends a negative signal (of workers' inability to successfully find a job in a competitive market) to potential employers, resulting in lower wages; and 2) there exists a trade-off between wages and search efficiency for quicker entry into local labor market. We also find some evidence that the informal job search may lead to low-skilled jobs with lower wages. We do not find strong evidence supporting alternative explanations.

JEL Classification: J31, J64, P2, P5

Keywords: social network, rural-urban migrants, wage, search friction, information asymmetry, chinese economy

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1. Introduction

The use of informal job search method through social networks is prevalent in many countries.[1] There has been much research, whether theoretical or empirical, on the importance of informal job search in the job search process. While there is conclusive evidence on the positive effects of informal job search on employment opportunities (e.g., Cingano and Rosolia, 2012; Zhang and Li, 2003; Oregan and Quigley, 1993) and job search time (Pellizzari, 2010), there is no consensus on whether and how it matters for one's wages. Both theoretical predictions and empirical evidence are mixed regarding the link between informal job search and wages. Most of the existing literature has typically focused on developed countries such as U.S. and European countries, and empirical examination is still quite scarce in developing countries. Also largely missing in the literature is a careful evaluation of the competing theories in the same framework.

We contribute to this broad literature in two ways. First, we examine the role of informal job search in determining the labor market outcomes of internal migrants of rural origin in urban China, one of the largest developing countries. Specifically, we focus on those rural migrants who currently hold jobs in urban areas and have conducted job search through either informal and formal channels. We focus on this subpopulation because they are usually more disadvantaged and create more social issues than other internal migrants such as urban-urban migrants in China (as further discussed below). The use of social network in job search is also prevalent among rural migrants. Second and more important, we provide a comprehensive review of the competing theories and hypotheses and discuss ways to evaluate their empirical relevance. While there have been some attempts for the first goal, we are not aware of any similar analysis for the second goal in the Chinese context (to the best of our knowledge).

Over the past three decades China has seen "probably the largest domestic migration in human history" (Zhao et al., 2010). Despite China's strict household registration (*hukou*) system that remains in effect to control labor migration, the rural migrants in urban cities increased from about 30 millions in 1989, to 62 millions in 1993, and further to 145 millions in 2010 (Demurger et al., 2009; National Bureau of Statistics, 2010). Also well documented is the important role of social network – family, friends, and acquaintances – in the Chinese rural-urban migration.[2] Numerous studies have found that rural workers are more likely to migrate to an urban area where there are many early migrants from their hometown (e.g., Rozelle et al., 1999; Meng, 2000; and Zhao, 2003). de Brauw and Giles (2017), using the China Urban Labor Survey in 2001, also find that over 90 percent

[1] For example, Corcoran, Datcher, and Duncan (1980) and Granovetter (1995) both report that more than 50 percent of all new jobs are found through friends and relatives in developed countries such as the U.S.. Holzer (1988) finds that 36 percent of firms filled their job vacancies with referred applicants (Ioannides and Loury, 2004).

[2] The network effect on domestic migration has also been documented in other contexts, e.g., in the U.S. (Millimet and Ye, 2014).

of the rural-urban migrants moved to a destination where they knew an acquaintance from their hometown, and half of these migrants secured employment even before their migration. Using the China part of the 2007 Rural-Urban Migration in China and Indonesia (RUMiCI) data (recently made publicly available), we similarly document the importance of social network in job search process among the Chinese rural migrants (Note that throughout the paper whenever referring to RUMiCI data in our analysis, we mean the China part of the data, excluding the Indonesia data.) Specifically, we find that about two-thirds of the workers in our sample have found their jobs through social networks.

The historical significance of China's large domestic migration and the potential importance of social networks in this process make it very much important to evaluate the empirical relevances of the competing theories in the Chinese context. However, empirical research on the link between informal job search and wages in China is still largely missing, partly because of "insufficient statistical methods and lack of data availability" (Zhao et al., 2010). One of the long recognized challenge is the possible selection of migrants into the use of different job search methods, which can bias simple comparisons of outcomes for those who use a particular method and those who do not. In our case, selection bias arises if migrants whose current job is obtained through informal job search methods and those whose current job is obtained through formal channels differ on unobservable dimensions such as abilities and the quality of social networks, which could themselves have an effect on wages. Moreover, job search method may be mis-reported in the survey data, similarly rendering simple regression estimates inconsistent; the so-called measurement error problem.

To circumvent these empirical problems, we adopt a novel instrumental variable (IV) approach in the spirit of Klein and Vella (2009b) (hereafter the KV approach) and Millimet and Tchernis (2013). This approach has recently gained popularity in many areas of labor economics because of its more transparent and testable assumption; for example, Klein and Vella (2009a), Wang (2012), Farre, Klein, and Vella (2013) on returns to education; Emran and Sun (2011) on educational attainment; Millimet and Tchernis (2013) on health program participation. Specifically, the KV IV approach exploits the heteroskedastic error structure of the choice for job search methods to construct an *internal* IV, unlike the conventional IV approach, which often relies on an external IV that is often unavailable and whose validity is debatable. It may also be preferred to the fixed-effect approach, which often requires panel data (which are typically unavailable in the Chinese context) and assumes the omitted variables are constant over time. We will discuss this approach in more details below and justify the underlying assumption on both statistical and economic grounds.

Using the RUMiCI data, we find that there exist significant wage penalties for the rural migrants whose current jobs are obtained through informal channels (despite their popularity). In particular, our IV result indicates that rural migrants who find jobs through social network earn on average 56.5 percent less than their counterparts who find jobs in a competitive market. To put this result in perspective, note that average monthly wages are about 1461 RMB (for workers utilizing market-based search methods) in our sample, and the wage penalty is roughly about 826 RMB in absolute term. Moreover, the IV result is larger in magnitude than the OLS result, suggesting existence of a positive selection into use of social networks in the job search process. For example, abler workers may more likely utilize social networks (probably due to both the quality and quantity of their social networks). These results are remarkably robust to the use of alternative dependent variables, alternative specifications, and alternative dataset. The magnitude of our estimates is also strikingly similar to those reported in the literature, though using different approaches. For example, Fang, Gunderson, and Lin (2016) find the estimates in the range of 33 to 43%, and Long, Appleton, and Song (2013) find an estimate of 55 percent.

Our further analysis examines some potential explanations for this seemingly surprising result. First, we find strong evidence supporting the signaling role of the informal job search method in explaining the observed results. Job search through social network sends a negative signal (of workers' weak labor market attachment and inability to successfully find a job in a competitive market) to potential employers. In a relatively noisy labor market like China, where employers have even more difficulties in observing a worker's ability and her job opportunities, such negative signal could lead employers to pay the worker lower wages, and hence the observed wage penalty. This is the signal of limited choice hypothesis proposed in Loury (2006). To test this theory, we exploit the implications of the signaling hypothesis – the signaling value may decrease or even disappear in the long run. Consistent with these implications, we find that the wage penalty drastically decreases and becomes even statistically insignificant for those workers at the later stage of migration.

Second, we find that the wage penalty associated with the informal method could also be a result of a trade-off between job quality and search efficiency for quicker entry into local labor market. While wages may be lower for those who find jobs through personal contacts, informal job search methods could greatly shorten their job search time and thus increase job search efficiency. Such trade-off between wages and search time may arise because of large financial constraints as well as institutional barrier facing rural migrants when they first enter the urban labor market. Due to these constraints, these workers cannot afford to search longer to find desirable jobs that pay higher wages.

Finally, we also find some evidence that informal job search are more prevalent in filling unskilled jobs with lower wages.

In addition to these mechanisms, we also examine a variety of alternative theories: for example, we test if the wage penalty is due to workers' preferences for non-pecuniary job features (e.g., in-kind benefits), or if it is due to mismatch between a worker's talent and her occupation and industry, or if it is a result of reduced search intensity by both the worker and the referee. However, we fail to find strong evidence supporting them.

These results are, in our view, interesting and make important contributions to the literature. We are one of the few attempts to isolate the causal impacts of informal job search on wages and to differentiate between competing theories put forth in the literature. Our results have several important implications for the literature. First, our results can be useful to understand the trend of widening inequality in China (Kanbur and Zhang, 2005).[3] As noted in Zhao et al. (2010), very few studies have examined inequality among rural migrants, and there is still a large proportion of wage inequality unexplained by observable characteristics. Given its negative wage effects, the widespread use of social networks in the job search process could thus contribute to the increase in the within-group inequality among rural migrants and hence overall inequality in China.[4] Similarly, due to its significant wage impacts, the use of informal job search method could also play a potentially important role in understanding between-group inequality such as the wage gap between rural migrants and urban residents (e.g., Meng and Zhang, 2001; Demurger et al., 2009), or between rural migrants and urban migrants (Messinis, 2013).[5]

Second, together with other empirical evidence obtained in the literature, our paper could help to characterize some important features of China's labor market and economy. Specifically, our finding of a large wage penalty may be indicative of 1) the severity of urban-rural divide resulted from the China's unique two-track labor market system and 2) the relatively underdeveloped and noisy labor market. Moreover, the large wage penalty could also reflect the unique meaning of social networks in Chinese culture. Social networks are generally considered to be a useful way to increase the quality of matches between employers and employees and help to eliminate uncertainty. Counter to such conventional beliefs, this paper indicates that social networks may actually work in the opposite way in the Chinese context. This feature of social networks is especially different from that in more developed labor markets. This also underscores the importance of the role of culture in understanding labor market phenomena.

Finally, our results also contribute to the context beyond Chinese economy and to economics in general. As noted in Munshi (2014), "[s]ocial networks are a ubiquitous feature of developing countries." Taken together with the results for other developing countries, our results help to paint a more complete picture of the role of social networks in the job search process – it is more likely to find negative effects in emerging markets where information asymmetry is more pervasive and the

[3]For example, Kanbur and Zhang (2005) find that Gini coefficients increased from 22.4 in 1952, to 29.3 in 1978 and to 37.2 in 2000. Gustafsson, Li, and Sicular (2008, p.1) state that "Income inequality is ... now considered high by international standard. ... [I]n China the speed with which the increase has occurred, and the level to which inequality has risen, is striking."

[4]Using household survey data, Yang (1999) finds that income inequality in rural areas account for a sizable share of the overall inequality index in China.

[5]This possibility has been examined in the international contexts. For example, Korenman and Turner (1996) find that differential returns to employment contacts between groups could help to explain part of the racial differences in wages in the U.S..

informal channels are more prevalent in filling unskilled jobs. Furthermore, our results are useful for advancing theoretical research in job search (at least in the Chinese context). For example, because of using an IV approach, we are one of the few studies that could differentiate between a causal story and a correlation; this allows us to rule out the theories that suggest the relationship between job search methods and wages is merely a correlation that reflects other driving forces. Our results could be of great interest to both development and labor economists.

This paper is organized as follows. Section 2 reviews both theoretical and empirical literature. Section 3 discusses the KV-IV approach. Section 4 describes the data, and Section 5 presents our baseline results. Section 6 evaluates various mechanisms, and Section 7 considers alternative mechanisms. Section 8 concludes.

2. Literature Review

The existing theories are ambiguous about the direction of the relationship between job search method and wages, and unsurprisingly, the empirical results are also mixed. In this section we provide two sets of reviews of the literature. We first provide a review of the competing theories that are put forth to hypothesize and explain the potential association between informal job search and wages. We then review the identification strategies used in the literature and their potential shortcomings. Such review motivates us to take an alternative strategy to approach the question at hand.

2.1. Theoretical Considerations and Hypotheses

Below we categorize the existing theories by the possible directions of the association, and point out the mechanisms through which informal job search can affect wages.

2.1.1. Theories/Hypotheses for Positive Relationships

The early literature, which dates back to Rees (1966), has emphasized the informational advantages of the use of social networks in the job search process. In the presence of market imperfections, people use social ties to avoid information problems (Munshi, 2003). For example, job seekers can learn of more job opportunities and obtain more information about a particular job from their social networks (e.g., Mortensen and Vishwanath, 1994). On the other hand, if employers like their current workforce, and if productive traits are correlated among relatives, friends and acquaintances, the employers would prefer to hire someone who are referred by their employees because she may be similar to the current (desirable) workforce (e.g., Simon and Warner, 1992; Saloner, 1985). Either way, job search through social networks likely reduces uncertainty about the quality of a match between worker and employer, resulting in better job matches and hence higher wages; we call this hypothesis "the good match hypothesis".

2.1.2. Theories/Hypotheses for Negative Relationships

In contrast to the early literature that highlights the beneficial effects of informal job search method, Loury (2006) highlights the negative role of social networks as low-wage-offer source of information. Specifically, he argues that some job seekers may yet to have contacts or access to formal sources that can provide external high-wage offers that exceed their reservation wages. Moreover, using low-wage-offer contacts could signal a limited range of job alternatives (and indirectly one's ability and weak labor market attachment) to potential employers, thereby leading to lower wages; the so-called *signaling of limited choices hypothesis*. Similarly, Antoninis (2006) suggests that the use of social networks may "reveal a weak bargaining position" and "implicitly be suggestive of higher exposure to unemployment risk". These explanations could be particularly relevant in our context because rural migrants usually have access only to contacts that are similar to them and have low-wage potential.

Bentolila, Michelacci, and Suarez (2004) similarly emphasize the negative role of social networks, but with a different argument. They argue that the negative impact of informal job search on wages can be due to the mismatch between one's natural talent and her actual occupation. Specifically, contacts within a candidate's social networks may not necessarily be able to refer her to occupations or sectors for which she has "a natural talent". As a trade-off for finding a job more quickly, the candidate may be willing to accept a wage penalty for working in an occupation or sector that does not maximize her productivity.

2.1.3. Theories/Hypotheses for Mixed Relationships

Some recent theoretical developments have emphasized the mechanisms that could give rise to both positive and negative effects. For example, Pellizzari (2010) assumes referees are heterogeneous in their reputation or willingness to refer unfit workers. Pellizzari argues that if referees are more likely to refer lower (higher) quality candidates, then there exists a wage penalty (premium) associated with the informal search. The intuition behind this theory is that the use of social networks indirectly conveys the expected quality of the job candidates, which impacts their wages.

Tumen (2013) puts forth a job search model where the *correlation* between informal job search and wages is driven by two factors: unobservable heterogeneity in the cost of informal search and the degree of peer effects. Tumen shows that informal job search leads to higher wages in the environments with greater cost heterogeneity, while the opposite is true in the environments with stronger peer effects. His paper does not necessarily suggest an independent (or causal) wage effect of informal job search, which can be directly tested by our IV approach. Existence of a statistically significant IV coefficient can eliminate this particular hypothesis.

Zaharieva (2013) shows that informal job search could have either positive or negative effects, depending on the bargaining power in the ex-post negotiation between the firm and the job seeker.

She also finds that search intensity by weak social networks (such as friends and acquaintances, as opposed to strong ones such as family members) is below the optimal level, resulting in less desirable jobs with lower wages. This negative effect may prevail in our context if rural migrants possess relatively weak ties in the urban labor market.

2.2. Summary of Existing Empirical Studies

Similar to theoretical studies, empirical studies of this issue also find mixed results. Some empirical studies find a wage premium of network search (e.g., Granovetter, 1974, Simon and Warner, 1992, Fernandez, Castilla, and Moore, 2000, Marmaros and Sacerdote, 2002, and Kugler, 2003),[6] while some document a negative effect (e.g., Bentolila, Michelacci, and Suarez, 2004 for both the U.S. and Europe, Pistaferri (1999) in countries such as Finland, Greece, Italy and the United Kingdom; Antoninis (2006) for Egypt). Instead of these two extremes, some studies show that there exist no significant wage effects (e.g., Bridges and Villemez, 1986 and Marsden and Gorman, 2001).

These empirical studies differ also in their empirical approaches. The point estimates from earlier studies typically utilize the ordinary least squares (OLS) approach, which are susceptible to the endogeneity and measurement error bias. Given the importance of isolating the causal effects of informal job search, it is thus also useful to discuss different identification strategies employed in the literature.

Using the sibling-pairs data, Bentolila, Michelacci, and Suarez (2004) are able to obtain the estimate by comparing the wages of one sibling who uses social networks to find a job and the wages of the other who uses alternative methods. Such comparison allows them to control for unobserved heterogeneity in family and economic background (that are common to siblings), but not necessarily other dimensions such as innate ability and motivation (that are person-specific).

To eliminate unobserved individual heterogeneity, Loury (2006) controls for an extensive list of individual characteristics, including Armed Forces Qualifying Test scores (a proxy for individual ability). Pellizzari (2010), on the other hand, uses fixed-effect panel data approaches to further control for all the time-invariant individual characteristics. The identification in her paper comes from 1) the sample of workers who change their job search methods over time and 2) the assumption that there are no time-varying unobservables driving the relationship between job search methods and wages. Both assumptions may fail to hold. The identifying sample could be a selected sample and does not necessarily represent the whole population. Indeed, Pellizzari (2010) shows that the sample of workers who change their job search methods can be as low as 5% of the whole sample. Moreover, the second assumption also precludes the impact of potentially important variables such as peer influences (as suggested in Tumen, 2013), which may vary over time.

[6] There is also other evidence of productivity-enhancing positive network effects by taking into account spatial components in the network (e.g., Hellerstein, Kutzbach, and Neumark (2014)).

To address both time-varying and time-invariant unobservables, a typical solution is to employ either an instrument variable or a control function approach. For example, two papers closely related to ours are Long, Appleton, and Song (2013) and Fang, Gunderson, and Lin (2016). Using the same data as ours, Long, Appleton, and Song (2013) find a large negative impact of network use on wages among rural migrants in China. Long, Appleton, and Song (2013) employ a specific control function approach, namely endogenous switching regression. To identify the parameter of interest, they use marital status, ratio of migrants in the home village and hukou status as exclusion restrictions. However, the literature has suggested that both marital and hukou statuses may themselves have a direct impact on wages, hence violating the requirement for a valid exclusion restriction.[7] Fang, Gunderson, and Lin (2016) use IVs such as the number of greetings during Chinese New Year, which itself can be a measure of social network subject to the same set of determinants as use of social networks. Validity of these IVs cannot be readily tested statistically (see footnote 9 for more explanation). Our paper differ from these two papers in that we use different identification strategy, and more important, we provide a comprehensive examination of the underlying mechanisms behind the effect.

Our discussions here are *not* intended to criticize the methods used in the literature. Instead, these discussions highlight the difficulty in identifying the true role of social networks in the job search process, which is needed to distinguish between competing mechanisms.[8] Different methods used in the literature depend on a different set of identifying assumptions on the nature of the endogeneity problem. These assumptions are often debatable and cannot be readily verified.[9] Methodologically speaking, it is thus important to use alternative methods (relying on different sets of assumptions) to further assess the robustness of the existing results. A comparison of results based on different models can provide evidence on the plausibility of alternative assumptions as well as additional confidence on the robustness of the results. We believe such exercise is necessary

[7]For example, the literature has generally found a large, positive impact of marriage on wages (e.g., Maasoumi, Millimet, and Sarkar, 2009) and significant effects of hukou on one's social and economic circumstances (e.g., Chan, 2010). The ratio of migrants in the village may also fail to be exogenous. For example, Chen and Yue (2010, p.3) note that "clustered migration may be driven by villagers having similar individual characteristics or facing similar institutional environments."

[8]For example, an observed negative wage effect can be a result of either true effects due to the signal of limited choices hypothesis (Loury, 2006) or a simple correlation driven by an omitted variable such as peer interactions among low earners (Tumen, 2013).

[9]For example, even with multiple IVs, the traditional overidentification tests cannot necessarily help to test the validity of the IVs. Remember that the traditional exogeneity/overidentification test relies on the assumption that a subset of the IVs are valid; the idea behind the test is that if all IVs are valid, then the estimates using the full and subset of IVs should not differ statistically (Wooldridge, 2010, p.134-137). However, if *all* IVs are invalid in similar ways, we should expect them to deliver similar estimates. As a result, the traditional exogeneity tests may still conclude that they are valid ones. Wooldridge (2010) gives an example of estimation of returns to education where both mother's and father's educations are used as IVs, while they may be correlated and invalid in similar ways.

for scientific inquiry. Bearing these discussions in mind, we now turn to our empirical method.

3. Empirical Methodology

3.1. Basic Set-up

We begin by considering a simple semi-structural model of job search decision and wages as follows:

$$\ln(wages)_i = \beta \cdot Informal_i + X_i'\gamma + \epsilon_i \quad (1)$$

$$Informal_i = I[X_i'\lambda - v_i \geq 0] \quad (2)$$

where $\ln(wages)_i$ stands for the log of wages for an individual i.[10] $Informal_i$ is a binary variable indicating whether an individual finds her *current* job through social networks such as friends and relatives; it equals to 1 if she does, zero otherwise. It is important to note that the job search throughout is the completed job search. $I[\cdot]$ is an indicator function, equal to 1 if an individual uses informal search method. ϵ_i and v_i are the error term as usual, and the vector X is a set of individual exogenous characteristics, discussed below (i.e., $\mathbb{E}[\epsilon|X] = 0$ and $\mathbb{E}[v|X] = 0$). β is the parameter of interest, measuring the returns to the use of informal job search method.

Note that we follow the literature by employing a linear specification of the wage equation. As is well-known, linear models are the best approximation of the unknown conditional mean function in terms of mean squared errors; and the coefficient, β, captures the average effects of completed informal search on wages. Following the literature, we maintain the assumption. However, we do use flexible functions of Xs in our estimation including higher order of continuous variables and interactions among these variables. Below we also estimate heterogenous effects of completed informal search by examining various sub-populations.

Our formulation is consistent with the conventional Roy model where the choice of job search methods is based on the comparison of potential wages associated with each method. The argument in the selection equation (Equation 2) can be considered as a reduced-form approximation to the differences in wage offers between formal and informal job search methods, both of which are a function of X_i.[11] In practice, we use flexible specifications of X, including higher orders of continuous

[10] As detailed in the data section, we also control for destination fixed effects. Given the log nature of the dependent variable, any destination-specific variables (such as the cost of living in each destination) will also be absorbed by the destination fixed effects.

[11] As a referee notes, the observed choice of job search method can also be thought of as a result of both employee self-selection (e.g., in pursuit of better labor market outcomes such as wages) and employer selection (in pursuit of e.g., low cost in the case of informal employee search through referrals, or more effective selection in the case of formal employee search for much sought-after skills). While not formally modeling such joint determination of the search choice, our formulation implicitly takes into account this possibility since the comparisons are based on

variables and interactions among covariates (see, e.g., Table (4) for a list of the variables included in the specification.). This formulation highlights the source of endogeneity, which arises when v_i and ϵ_i (unobservable wage determinants such as ability) are correlated. For example, abler individuals who have higher wages may have more and better social networks and more likely utilize them to search for jobs (v_i and ϵ_i are positively correlated; positive selection); or, their job offers may be higher via informal job search than formal search. In addition, there may also be self-reporting error in the job search method, e.g., reflecting the self-serving attribution bias.[12]

A typical solution to overcome both the endogeneity and measurement error issues is to employ an instrumental variable (IV) approach. The conventional IV approach relies on the existence of an exogenous variable that determines whether someone uses social networks to find a job, but does not have any (direct) impacts on wages (*exclusion restriction* or *external IV*). However, our formulation highlights the fact that due to wage comparisons in decision making, all the determinants of wages, X, also enter the choice equation for the use of informal job search methods, and therefore it is difficult to find an *external* IV. This also explains why the IVs used in previous studies (Long, Appleton, and Song 2013 and Fang, Gunderson, and Lin 2016) could be controversial.

Recent econometrics literature has developed alternative IV approaches that exploit the error structure in the system to construct a valid (*internal*) IV. For a binary endogenous variable like ours, Klein and Vella (2009b) (hereafter KV) propose using the conditional error variance in the binary response equation (the decision equation in our case) to construct a valid IV.[13] In particular, they consider the case of multiplicative heteroskedasticity in the decision equation (2), given by

$$v_i = S(X_i'\theta)v_i^* \tag{3}$$

where v_i^* is a homoskedastic error term, which is independent of X_i and allowed to be dependent on the error term in the wage equation (1). Function $S(\cdot)$ captures heteroskedasticity in v_i. Equations (1) and (3) imply that

wage offers using different methods, and wage offers capture all aspects of the employer selection. More important, employer selection decisions are usually exogenous to individual decisions, and thus omission of it should not affect the estimates in our paper, which are based on individual choices. However, formal models of employer selection can certainly provide potentially useful sources of identification, e.g., external IV, and richer information on the determination process. However, this would require much more detailed information that is usually not available in most datasets, and we therefore leave this potential extension for future research.

[12]The self-serving bias refers to individuals attributing their successes (in our case, locating a good job) to internal or personal factors but attributing their failures to external or situational factors (Campbell et al., 2000). As a result, while some respondents who actually use network to find a (good) job may report that they find their jobs on their own in a competitive market, others who find a (bad) job may report it as a result of use of social networks.

[13]For a continuous endogenous variable, please refer to Ebbes and Bockenholt (2009), Klein and Vella (2009a), Klein and Vella (2010), and Lewbel (2012) for related approaches. See, e.g., Chung and Zhang (2015) for an application of this type of IV approach. We thank Junsen Zhang for pointing this out.

$$\mathbb{E}[Informal_i|X_i] = Pr[Informal_i = 1|X_i] = F[\frac{X_i'\lambda}{S(X_i'\theta)}] \quad (4)$$

where $F[\cdot]$ is the probability function for v^*.[14] The predicted probability, $\widehat{F[\cdot]}$, is a valid IV as (1) it is correlated with the endogenous decision to use the informal job search method; and (2) it is uncorrelated with the error term. The latter follows directly from the law of iterated expectations and the fact that $F(\cdot)$ is a (nonlinear) function of exogenous variables, X, ($\mathbb{E}[u|X] = 0$) (see, e.g., Wooldridge, 2002, p.15). Indeed, any functions of exogenous variables are themselves exogenous.

Note that even if $S(\cdot) = 1$ (i.e., the absence of heteroskedasticity), $\widehat{F[\cdot]}$ is still a valid IV and the corresponding IV estimator performs reasonably well in terms of bias (Mroz, 1999). However, as pointed out in KV, identification relies on the nonlinearity that typically arises in the tails and thus extreme observations. By contrast, if $S(\cdot) \neq 1$ (i.e., the presence of heteroskedasticity), the KV IV is frequently linearly independent of X and identification does not rely on extreme observations.

Following Klein and Vella (2009b) and Millimet and Tchernis (2013), we use a LM test for heteroskedasticity to assess the plausibility of the heteroskedasticity assumption, as well as to identify variables significantly related to the variances of the latent error in the search choice equation.[15] We also provide a nonparametric test of our heteroskedasticity and distributional assumptions below. We supply further identification tests such as first-stage F-test to verify the validity of our IV.

3.2. Practical Implementation

3.2.1. Selection of Control Variables

Selection of control variables is always an important yet difficult issue in practice. As noted in Angrist and Pischke (2009), "more control is not always better". There are generally two types of variables other than, but could be correlated with, the variable of interest (i.e., job search methods): 1) the variables that determine both the use of informal search and wages, and 2) the variables that determine only the wages but themselves are the outcomes of job search. Omission of different type can lead to different consequences in estimations.

Omission of the first type of variables effectively leaves them in the unobservables in both the choice equation and the wage equation, which is the reason why the endogeneity arises (the unobservables ϵ and v share common factors and are hence related). Omission can lead to biased

[14] To see this, $\mathbb{E}[Informal_i|X_i] = \sum_{Informal=0,1} Informal_i \times Pr[Informal_i = 1|X_i] = 1 \times Pr[Informal_i = 1|X_i] + 0 \times Pr[Informal_i = 0|X_i] = Pr[Informal_i = 1|X_i] = Pr[X_i\lambda - v_i \geq 0] = Pr[v_i \leq X_i\lambda] = Pr[S(X_i\theta)v_i^* \leq X_i\lambda] = Pr[v_i^* \leq \frac{X_i\lambda}{S(X_i\theta)}] = F[\frac{X_i\lambda}{S(X_i\theta)}]$.

[15] Specifically, the LM test is calculated by taking N (sample size) multiplied by R^2 from an artificial regression of ones on the product of generalized residual and explanatory variables and the product of generalized residual, the single index from the probit model, and the explanatory variable potentially causing heteroskedasticity. The test statistic is χ^2 with J degrees of freedom (the number of explanatory variables potentially causing heteroskedasticity). See Verbeek (2004, p. 201) for more detail.

estimates. Given the complicated wage determination and choice process, it is difficult to argue that one can ever control for enough in practice. This is indeed the motivation for us to employ the IV approach. In practice, we also try to control for those variables such as demographic variables (e.g., gender and ethnic groups) that are fixed at the time the job search methods are determined and often considered to be exogenous in the literature. Angrist and Pischke (2009) call such control variables "good controls".

The second type of variables, on the other hand, are what Angrist and Pischke (2009) refer to as "bad controls". These variables are potentially endogenous variables that could be determined by the use of informal search (these variables themselves could be the reasons why network search affects individuals' earnings). Examples include types of jobs in terms of skill levels (captured by, e.g., education, occupation, sectors, and industries). Controlling for or conditioning on these variables could actually induce selection bias in our estimates (see, e.g., Angrist and Pischke (2009, p.65) for more detailed explanations). As most studies do, we therefore exclude such variables from the baseline estimation and condition only on the exogenous variables that are commonly used in the literature. Omission of these variables does not affect the estimation; instead, it simplifies the interpretations of β, which captures the *total*, causal effects of job search method on wages (including *both* the direct effect *and* indirect effect through channels such as occupation and industries). Below we do experiment with inclusion of some additional variables that characterize the type of jobs to evaluate importance of such mechanisms.

3.2.2. Implementation of KV-IV

In practice, we parameterize the unknown functions $F(\cdot)$ and $S(\cdot)$. The parametrization has two distinct advantages. First, while theoretical identification results are based on nonparametric representation of the heteroskedaticity, practical parameterization "would greatly reduce the required computation" in this kind of context (Farre, Klein, and Vella, 2013). Second, "[i]t also eliminates the need for continuously distributed exogenous variables in the [semi-parametric approach]." (Klein and Vella, 2009a)

Following Millimet and Tchernis (2013), we assume a normally distributed latent error term, v_i^*, and $S(\cdot) = \exp(Z_i\theta)$ where Z_i is a subset of variables in X_i that produce the heteroskedasticity in Equation (3). We also thank Francis Vella for this suggestion. Such parametric specification for heteroskedasticity has a long-standing history in econometrics since Harvey (1976) and also been used in similar contexts as ours (see, e.g., Farre, Klein, and Vella, 2013 and Millimet and Roy, 2011). Both Monte Carlo simulations and empirical Monte Carlo simulations in Millimet and Tchernis (2013) show that this parametric approach works particularly well in the presence of heteroskedastic errors in the binary response equation (we will further discuss the test of this assumption below.). Moreover, this specification allows us to flexibly use different sets of variables in the mean and variance equations. The parameters, λ and θ, could be estimated by maximum likelihood, with the likelihood function as follows:

$$\ln(L) = \sum_i [\ln \Phi(\frac{X_i'\lambda}{\exp(Z_i'\theta)})]^{Informal_i}[\ln(1-\Phi(\frac{X_i'\lambda}{\exp(Z_i'\theta)}))]^{(1-Informal_i)} \tag{5}$$

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

Our discussions lead to the following estimation procedure:

1. Conduct LM test for heteroskedasticity and select Z, a subset of X that contribute to heteroskedasticity.
2. Obtain $\widehat{\lambda}$ and $\widehat{\theta}$ from heteroskedastic probit of $Informal$ on X in the mean part and Z in the heteroskedastic variance part. Obtain the predicted values, $\widehat{F[\cdot]}$ using Equation (4).
3. Estimate Equation (1)

$$\ln(wages)_i = \beta \cdot Informal_i + X_i'\gamma + \epsilon_i$$

   by 2SLS (Two Stage Least Square Estimation), using instruments $(X_i, \widehat{F[\cdot]})$.
4. Inference for Step 3. is clustered at both origin and destination geographic levels. As shown in Klein and Vella (2009b), the KV-IV estimator is asymptotically distributed as normal with the standard White heteroscedastic corrected variance-covariance matrix.

3.2.3. Further Comments on the Assumptions in Practical Implementation

One may be concerned about the misspecification of the functional and distributional assumptions. However, such misspecification will only lead to measurement errors in the IV, and it is practically innocuous in this context because of an important robustness property of the IV procedure.

Note that once the predicted $\widehat{F}[\cdot]$ are obtained, the standard two-stage least squares estimations are still performed with $\widehat{F}[\cdot]$ being the IV. In this step, the "first" stage "always involves writing an endogenous variable as a linear projection onto all exogenous variables", and "there is nothing necessarily structural about" the first stage (Wooldridge (2002, p.84)). The consistency of IV estimates depends only on the exogeneity and strength of the IV, not on the correct specification of the "first"-stage equation, an insight that goes back to Kelejian (1971) (Angrist and Pischke, 2009). This insight is very important because it also allows for measurement errors in the IV due to various reasons, e.g., misspecification of the distributional or heteroskedasticity assumptions (see, e.g., Wooldridge, 2010, p.939, last paragraph). The only requirement that we need is that the IV should be strongly correlated with the endogenous variable, which we can indeed test through the statistical significance of its coefficient, as well as the first-stage F test.

We also conduct a nonparametric test of the distributional and heteroskedasticity assumptions below. Further, to illustrate the robustness of the parametric approach, we also conduct some

Monte Carlo (MC) simulations; the results are reported in the supplemental material. These MC results show that the parametric approach performs extremely well in finite samples.

3.3. Further Discussions of Our Empirical Methodology vs. Conventional Approach

Compared to the conventional IV approach, the KV approach may be preferred because of its more apparent and statistically testable assumption. For the conventional IV approach, the assumption of the exogeneity of an external variable could be tested only when 1) *both* multiple IVs are available *and* 2) the parameters of interest, β, are constant and do not vary across the population. In the presence of heterogeneity, different IVs identify different local average treatment effects (LATEs), and as a result, the traditional test of exogeneity/overidentification may fail in this situation (see footnote 9).[16] By contrast, we can assess the validity of our IV by testing the heteroskedasticity assumption and examine which variable indeed contributes to heteroskedasticity and whether it is supported by economic theories.

4. Data

This paper uses the China part of the Migrant Household Survey of the 2007 RUMiCI data that are recently made publicly available to researchers.[17] The data are particularly suitable for our purpose since the RUMiCI survey is the first representative data set on rural-urban migrants in China (Qu and Zhao, 2011). The data comprise rural migrants randomly sampled from 15 of the major urban destinations in China, and it thus provides "an accurate representation of the migrant population, including temporary workers." (Akay et al., 2014)

We focus on rural migrants in the sample, defined as those holding rural *hukou*.[18] We restrict our sample to individuals who are aged 16 to 65, since the majority of the rural migrants start working after graduating from middle schools when they are about 16 years old. Many older migrants continue to work full time even after they reach the official retirement age of 60. Also, as noted in Wang (2012), the legal minimum working age in China is 16 and the maximum mandatory retirement age is 65. We further exclude the self-employed individuals and those who work for less than 35 hours per week.

Following the standard practice in the literature, the dependent variable is monthly wages from the primary job. It is broadly defined, including both wage payments and other measurable fringe

[16]an IV identifies only the wage effects for the sub-population whose decision of utilizing the informal job search method is indeed influenced by this particular IV; the so-called *Local Average Treatment Effect* (LATE) (Imbens and Angrist, 1994).

[17]Note that the 2007 RUMiCI data are the same data as the widely used national representative data, Chinese Household Income Project 2007.

[18]Urban-urban migrants account for only 1% of the sample.

benefits associated with the job, such as bonus and allowance.[19] In China, the Labor Law regulates that "wages shall be paid to the workers themselves in legal tender and on a monthly basis" (Article 50).[20] Moreover, the data only ask working hours per week, and we do not have accurate information on weeks worked per month to calculate hourly wages. Note that annual earnings is simply monthly wages multiplied by a factor of 12. We therefore focus on monthly wages in this paper. However, we do repeat our analysis using the computed hourly wages, and the results are largely the same and even strengthened in some cases (see below for more discussion). We also consider a wide range of detailed in-kind benefits below when testing alternative explanations. The results suggest that combining these detailed items will not affect our results, but separating them will for sure give us more information on the source of the effects, if any.

The variable of interest is whether a migrant's current job is obtained through informal job search methods, equal to 1 if it is and zero if it is through a market-based method. The market-based job search method includes job search through private commercial employment agency, job advertisement, internet, school internship or through job interview. The informal job search through social networks includes jobs obtained using personal contacts such as friends, relatives or acquaintance. These two channels account for nearly 90 percent of the full sample. Note that we exclude government-aided job searches (including jobs assigned by the government, through government employment agency or through community employment service station). The government-aided search method is rarely used, accounting for only 2 percent of the sample (this is not surprising given that we consider only rural migrants). The category of "others" is also excluded because it is not well defined. This category includes employer recruitment that could involve either market-based hiring or network-based hiring, which makes it difficult to interpret the results.

In estimations, we also include a set of exogenous variables that are both predetermined and affect the choice of job search method, namely gender, minority, the interaction of minority and gender, birth order, age, age squared, dummy variables for regions of origin, dummy variables for destination provinces, and the types of *hukou* (local vs. non-local rural *hukou*).[21] Note that these are the control variables that are typically used in the previous literature and implicitly assumed to be exogeneous, a practice that we follow in our analysis. We also experiment with different sets of exogenous variables and different set of interaction between exogenous variables, and our results remain similar (which is not surprising as discussed above in light of the consequences of misspecification in this context) and are available upon request from the authors.

[19] As noted in Granovetter (1974, p.25), "wages or, in more refined formulations, the total benefits accruing to a worker by virtue of holding a given job" reflect the price of labor.

[20] Source: `http://www.gov.cn/banshi/2005-08/05/content_20688.htm`

[21] Since the data were collected from the destination provinces, there are very few observations for some of the provinces of origin. We therefore group them by region as follows: North Coast, Central Coast, South Coast, Central, Northwest, Southwest, and Northeast.

The distribution of the use of social networks in the job search process is reported in Table (1). We first note that the use of social networks is prevalent among the rural migrants. Specifically, workers finding jobs through such informal channel account for roughly 73 percent of our full sample. This result is surprisingly close to those found in the literature. For example, Munshi (2003, p.562) finds that, among the Mexican migrants to the United States, over 70 percent of the employment was established through social networks. Similar patterns have been found in contemporary studies of Salvadoran immigrants (Menjivar, 2000), Guatemalan immigrants (Hagan, 1994), as well as historical studies during the Great Black Migration (Gottlieb, 1991; Grossman, 1989; Marks, 1989). We can also see that the pattern of the use of social networks is similar across the population, independent of the strength of the workers' labor market attachment (whether they are on their first jobs or whether they have been in the urban cities for more than 5 years) or of their tenures.

Summary statistics are reported in Table (2). Panel A compares the wage outcomes between workers finding their jobs through social networks and those using market-based methods. To put things in perspective, we use the levels of wages here while the logs in estimations. We can see that job seekers who use social networks earn significantly lower wages than those who do not. Their average monthly earning is 1376 yuan, about 5.8 percent lower than the one obtained by the market job searchers, which is 1462 yuan. Note that such wage penalty is only a raw difference without adjusting for any differences in individual characteristics.

Panel B indicates that there are indeed substantial differences in various characteristics between workers using different search methods. Specifically, even though there does not appear to be any statistical significant difference in the utilization of social networks between men and women, we do find that workers who find jobs through networks tend to be older, less educated, and those holding local rural *hukou*. These differences highlight the importance of controlling for these factors in the estimations. More important, this indicates that workers using different job search methods could also be different in other unobservable dimensions such as ability. We now turn to the results using more rigorous econometric methods that attempt to control for both observable and unobservable heterogeneity.

5. Empirical Results

This section presents our baseline results. We first test the distributional assumption and the heteroskedasticity assumption required for the validity of our IV and discuss economic rationales behind existence of heteroskedasticity. We then present both OLS and IV estimates of the wage effects of the job search method, using both monthly and hourly wages. We also investigate the importance of job types (in terms of skills) in explaining our results. Finally, we use alternative dataset to showcase the robustness of our results. Throughout the paper our estimations are clustered at both origin and destination geographic levels.

5.1. Validity of IV

5.1.1. Existence of Heteroskedasticity

The validity of our IV approach hinges on the assumption of heteroskedasticity in the probit model for the use of social networks in the job search process. We first provide statistical evidence in favor of this assumption. Specifically, following Klein and Vella (2009b), we employ the conditional moment test proposed in Pagan and Vella (1989) to test the presence of heteroscedasticity in this context. The results are reported in Table (3). We easily reject the null of no heteroscedasticity for all variables together at $p \leq 0.001$ level, confirming the existence of heteroskedasticity in the search choice equation. Closer examination of the table shows that gender, age, and hukou status (interacting with gender) are sources of heteroskedasticity in the choice equation, while ethnicity and birth order are not. We also find that within-region variations contribute to the heteroskedasticity. These results provide direct *statistical* evidence of the plausibility of the assumption underlying our approach.

Interestingly, the comparison of Tables (3) and (4) indicates that some of the variables that contribute to the heteroskedasticity also affect the choice equation. For example, we find there is a statistically significant difference in the utilization of social networks as well as variance of networks (heteroskedasticity) across gender and across ages.

These interesting results are broadly consistent with the economic explanations proposed in Holzer (1988). Specifically, Holzer (1988) emphasizes that an individual's search choice may reflect the productivity of her social networks, as well as market opportunities and her needs. Workers with larger and better and hence more productive social networks tend to use informal search methods more often. On the other hand, individuals who are financially more constrained and have fewer job opportunities will have more needs to make use of their social networks in finding a job. We now illustrate how Holzer's framework can be used to interpret the patterns observed for two important variables – age and gender. Note that although interaction terms with either age or gender included have some effects, most of them are too small to offset the main effects.

First, younger people generally have less access to the labor market and hence have more needs to rely on network search than older workers. This implies that there exists a negative relationship between age and the utilization of informal job search. This is indeed what we find. For the age support in our sample (between 16 and 65), the estimated coefficients on age and age squared imply a monotonically declining relationship between the probabilities of use of informal search method and age. Meanwhile, compared to their younger counterparts, older migrants may have encountered more social contacts and potentially more diverse contacts as well; as a result, the heteroskedasticity of the choice equation could increase with age.

Second, with respect to gender, the literature has generally found significant gender differences in the *average* quality of social networks, while women and men usually have networks of similar size (see, e.g., Moore, 1990; Marsden, 1987). Specifically, women tend to have contacts of lower quality (which are less productive in terms of delivering job offers) than men, and thus they are less likely to use social networks in their job search. This implies a negative coefficient of gender on the utilization of social networks. Meanwhile, the literature has also found large gender differences in the variation of their social networks, which contributes to the existence of heteroskedasticity in the choice equation. For example, Moore (1990) and Renzulli and Moody (2000) find that men tend to have more diverse and extensive social networks useful in finding jobs and advancing their careers than women. By contrast, women tend to have more homogeneous networks in terms of kin composition (see, e.g., Marsden, 1987).

5.1.2. A Statistical Test of Functional and Distributional Assumptions

Despite the strong evidence supporting the existence of heteroskedasticity in the selection equation, it is also important to note that the test results are based on our assumptions of both normality and mulitplicativity in heteroskedasticity. Although violations of these assumptions will only lead to measurement errors in the IV, which should not bias our estimates, it could bias the test results above, as well as cause some efficiency loss in our estimations. It is therefore important to assess the validity of these assumptions in our practical implementation of the KV-IV estimator.

To proceed, note that no matter how complicated the distributional and functional forms are, the selection equation (Equation (4)) is simply a function of X and can be written as follows:

$$\mathbb{E}[Informal_i|X_i] = Pr[Informal_i = 1|X_i] = m(X) \tag{6}$$

Under the null hypothesis, $\mathbb{E}[Informal_i|X_i] = F(\frac{X\lambda}{S(X\theta)}) = m(X)$. However, under the alternative, these two functions will differ. To test this, we adopt Ullah (1985) specification test. This test is to evaluate the relative difference of the sum of the squared residuals between the parametric and the nonparametric models. Specifically, the test statistic is given by

$$\widehat{I}_N = \frac{\sum_{i=1}^{N} \widehat{u}_i^2 - \sum_{i=1}^{N} \tilde{u}_i^2}{\sum_{i=1}^{N} \tilde{u}_i^2} \tag{7}$$

where $\widehat{u}_i, \tilde{u}_i$ are residuals from the nonparametric and parametric models, respectively. To estimate the nonparametric model (6), we consider the local-linear least-squares (LLLS) estimator. Note that X contains both continuous and discrete variables. We thus use Generalized Kernel Estimation (Li and Racine, 2004; Racine and Li, 2004), which accommodates mixed continuous and categorical variables, to estimate the conditional mean model.

The inference is done via bootstrapping. Formally, the steps are as follows

1. Compute the test statistic, $\widehat{I}_N$, based on the original sample.

2. Randomly sample with replacement from the original sample, and calculate the test statistic for the bootstrap sample and call it $\widehat{I}_N^*$.
3. Repeat step 2 for 399 times and then construct the sampling distribution of the bootstrapped test statistics. We reject the null hypothesis that our distributional and heteroskedasticity assumptions are correctly specified if the estimated, $\widehat{I}_N$, is greater than the 95^{th} percentile (i.e., the upper 5^{th} percentile) of the sampling distribution of the bootstrapped test statistics.

The test results are reported in Table (3). The test statistic is .0546, much smaller than even the median of the sampling distribution of the bootstrapped test statistics, let alone the 95^{th} percentile. We thus fail to reject the distributional and heteroskedasticity assumptions at any conventional significance levels.

Having verified our identification assumption behind the IV estimation both *statistically* and *economically*, we now turn to our baseline results.

5.2. Effects of Informal Job Search on Wages

This subsection presents some baseline estimates and assesses the robustness of the results. Interpretations of these results are in Sections 6 and 7.

5.2.1. OLS Results

Column 1 of Table (5) presents the estimated effects of informal job search on the log monthly wages using OLS. The OLS results show that the use of social networks is associated with a wage penalty. Specifically, the monthly wages of workers who had help from personal contacts are, on average, 2.4% less than the monthly wages of those who did not ($\widehat{\beta} = -0.024$). This result is statistically significant at the 5 percent level.

The OLS result is not necessarily indicative of the underlying mechanisms through which the use of social networks affects one's wages, because the OLS estimates could be biased. The direction of such bias is *a priori* unclear, depending on the direction of selection bias. Comparison of the OLS and IV estimates (discussed below) could help inform the direction of the selection bias and also distinguish between potential mechanisms. For example, if there exists a negative selection into the use of the informal job search method (i.e., less able workers may have lower wages as well as rely more on social networks to find jobs), the OLS estimates are biased downward. By contrast, there could be a positive selection, if abler workers who tend to earn more have better and more productive social networks and thus are more likely to use them. In this case, the OLS estimates are biased upward.

5.2.2. IV Results

Turning to our IV results (Table (5), column 2), we first notice that our IV fares well in terms of weak IV tests. The F-test statistic is larger than the rule-of-thumb value of 10 (Bound and Baker,

1995) and statistically significant, suggesting that there is no weak IV issue. In terms of actual estimates, we continue to find negative returns to network search. More strikingly, we find that the negative effect increases drastically to 56.5% ($\beta = -0.448$). To put this result in perspective, note that average monthly wages are about 1461 RMB for those who use formal search methods, and thus the wage penalty is roughly about 826 RMB. Note that our estimates are surprisingly similar to the result found in Long, Appleton, and Song (2013) and Fang, Gunderson, and Lin (2016) that use alternative identifying assumptions as well as estimation techniques. Specifically, Fang, Gunderson, and Lin (2016) find the estimates in the range of 33 to 43%, and Long, Appleton, and Song (2013) find an estimate of -0.438.

The IV estimate is higher in magnitude than the OLS estimate, suggesting that the OLS estimates bias upward. Following our discussions above, this result implies that there exists a positive selection into the use of social networks. Our IV result also rules out the peer influence hypothesis proposed in Tumen (2013) or and any theories that suggest the relationship is merely a correlation driven by other forces.

5.2.3. The OLS and IV Results Using Hourly Wages

We have thus far focused on monthly wages, which reflect both hourly wages and working hours per month. As such, our results could be an artifact of different labor supply decisions at intensive margin across workers using different search methods. For example, if workers using informal search method work fewer hours, we could still find a negative effect of informal search method on monthly wages, even though workers' hourly wages may be the same across search methods (i.e., the effect on hourly wages is nil).

To assess the robustness of our results, we repeat our analysis using hourly wages and report the corresponding results in Table (6). As we can see, the large negative returns to network search become even stronger. In particular, we find that the coefficient on network search is -0.761; this estimate is statistically significant at the 1 percent level. This is an interesting result. The difference between the results using monthly and hourly wages may be because migrant workers who use network job search respond to the large wage penalty by increasing their labor supply at the intensive margin. We indeed find that those workers using network search on average work 2.632 more hours per week; this estimate is statistically significant at the 1 percent level.

5.2.4. Inclusion of Additional Variables for Type of Labor in terms of skills

The type of jobs in terms of skills can matter a great deal for wages. This is indeed true. As discussed in Section 3.2.1, we exclude these variables from our baseline estimations because they can be the outcomes of job search methods. It is nevertheless important to investigate whether the job types are indeed an important channel or mechanism through which the use of informal search methods negatively affect wages. For example, one explanation of our findings is the mismatch hypothesis proposed in Bentolila, Michelacci, and Suarez (2004). Recall that the mis-match hypothesis argues that social contacts help to find jobs, but not necessarily in the occupations where workers are most productive. Rather, social contacts can generate mismatch between workers' occupational choices and their productive advantage, leading to lower wages. The literature has found some evidence that workers using social networks of less productivity are more likely to be directed into the low-paying occupations (e.g., Beggs and Hurlbert, 1997; Mencken and Winfield, 2000 and Smith, 2000).

Here we consider education, occupation, sectors, and industries. We believe that for rural migrants who have relatively homogenous levels of skills, these variables should sufficiently characterize the type of their jobs in terms of skills.

To proceed, we include these variables in the baseline equation. If a variable is indeed an important channel, when it is included in the wage equation, the magnitude of the penalty associated with the use of informal search should decrease.

First, we include education in our estimations to investigate to what extent the coefficient of interest is affected. The results are reported in Columns (1) and (2) in Table (7). We find that the qualitative conclusions remain the same. The coefficient decreases (in magnitude) slightly from -0.448 to $-.397$ for monthly wages, and from $-.761$ to $-.685$ for hourly wages. Second, we also restrict our sample to migrants with education level less than middle school (i.e., 9 years of schooling) and repeat our analysis. As shown in Columns (3) and (4) in Table 7, we again find very similar results. Specifically, the coefficient on network search is $-.329$ for monthly wages and $-.627$ for hourly wages. The decrease in the magnitude of the coefficients may be an indication that the skill levels of the type of the jobs (specifically captured by education) could be an important channel, but does not explain all the wage penalty of informal search.

In Table (8), we include occupations, sectoral choices, and industries in the baseline model. Inclusion of these variables hardly changes the estimates. The magnitude of the coefficients remains large for both the models using monthly wages and hourly wages; this result suggests that the mis-match hypothesis cannot account for the observed wage penalty; neither can sectors and industries.

Note that the exercise above is only preliminary because the channels are endogenous and their coefficients are not necessarily consistently estimated. To further investigate the importance of the job types captured by education, we can also borrow insights from the literature to impose *true* returns to education in the wage equation and re-estimate our models.[22] Specifically, we consider

[22]Unfortunately, we cannot conduct such exercise for other variables such as occupation since the IV estimates for these variables are generally non-existent in the literature. The lack of such estimates also indicates the challenge that we face to correctly control for these variables in our baseline estimations.

the following model with education

$$\ln(wages)_i = \beta \cdot Informal_i + \alpha \cdot Education + X_i'\gamma + \epsilon_i \quad (8)$$

$$\ln(wages)_i - \alpha \cdot Education = \beta \cdot Informal_i + X_i'\gamma + \epsilon_i \quad (9)$$

Since the effect of education is correctly controlled for, the coefficient, β, captures only the direct effect of informal search and indirect effects through other channels. If the skill type of a job captured by education is an important channel, we should expect the effect of the informal search to become smaller or even close to zero (the latter holds if it is the only mechanism). The question is how we can obtain the true returns to education (α). To achieve our goal, we borrow the IV estimates of the returns to education for year 2002 obtained in Wang (2013, Table A2). Specifically, we use the estimate from his log hourly wage equation for men ($\alpha = .105$). This estimate is close to the worldwide average returns to education (roughly 10 percent) reported in Psacharopoulos and Patrinos (2004). The literature has also generally shown that the returns to education have been increasing over time. Hence, the number we use can be considered as a lower bound for α. We find that the wage penalty associated with informal job search indeed decreases drastically. Specifically, the coefficient decreases to -.127 (s.e.= .267) for log monthly wages and -.448 (s.e. = .338) for log hourly wages, respectively. In other words, job types can indeed be an important channel through which informal job search affects wages. Even considering the importance of job types, there still exists a wage penalty associated with informal job search. Below we further explore potential explanations for the observed effect.

5.2.5. Use of Alternative Dataset

We also use 2009 survey of migrant workers in Zhusanjiao cities (Zhusanjiao Migrant Worker Survey), conducted by Zhongshan university, to further assess the robustness of our results. The survey interviewed 1766 migrant workers in such cities as Guangzhou, Shenzhen, Zhuhai, Foshan, Zhaoqing, Dongguan, Huizhou, Zhongshan and Jiangmen. We use comparable samples and definitions of variables as in the RUMiCI data. We also restrict our sample to rural migrants.

We include a similar set of control variables such as female, age, age square, minority, the interaction term of female and minority and origin regions. Since all migrants worked in Guangdong province, this dataset provides us with a unique opportunity to control for more refined geographic areas, namely destination cities (rather than destination provinces). Due to the smaller sample size of the survey, we group the regions of origin into four categories: southeast, middle, southwest and other regions. Our inference is again clustered at both destination cites and origin regions.

We find similar results using the Zhusanjiao Migrant Worker Survey. We, again, find significant evidence of heteroskedasticity in the selection equation. For example, there exists a statistically significant difference in the use of social networks across ages, as well as a significant difference in the variance of networks (heteroskedasticity) across gender. Moreover, we again fail to reject that our distributional and heteroskedasticity functions are correctly specified. The test statistic is .01531, and the 95^{th} and 90^{th} percentiles of the sampling distribution of the bootstrapped test statistics are 18.27224 and 21.14894, respectively. In the interest of space, these results are omitted but available from the authors upon request.

The actual estimates of the effects of completed job search methods are presented in Table (9). We again find a significant penalty for the use of informal job search in securing the current job, regardless of the measures of wages. These effects are also similar in magnitude to our baseline results. The coefficients are $-.695$ for monthly wages and $-.742$ for hourly wages, respectively. We further control for whether the worker is high school graduate. The corresponding wage penalty becomes smaller, but remain significant and sizable. The coefficients are -0.551 for monthly income and -0.528 for hourly wage.

6. Testing Mechanisms

A wage penalty associated with the informal job search seems to be a robust finding (even after we consider the job types). In this section we evaluate two more potential mechanisms giving arise to such penalty: (1) the signal effect of network search and (2) the trade-off between wages and search efficiency. We believe that both are important channels through which job search method affects wages, and that they may also reinforce each other's impact. Understanding these mechanisms can also help us better interpret the magnitude of our estimates below.

6.1. Signal of Limited Choice Hypothesis

As discussed above in the literature review, a wage penalty for informal job search is consistent with the limited choice hypothesis proposed in Loury (2006) and Antoninis (2006). In the presence of information asymmetry, use of low-wage-offer contacts could signal a limited range of job alternatives, and candidates could thus have little bargaining power in negotiating their wages. Our sample of rural migrants indeed consists of a relatively homogeneous group of individuals who very likely have low-wage-offer contacts only. As a result, the migrants who use such contacts may suffer a wage loss because of the negative signal of using them.

To test the signal of limited choices hypothesis, we exploit the implications of the changing nature of the market frictions over time. In particular, we should expect that the information asymmetry problem be more severe at the early stage of migration. Before working, migrants generally lack means or channels to convey information on their productivity to potential employers. However, once the migrants enter the market and start to work, their true productivity should be gradually revealed over time. As a result, we should see the information asymmetry problem is reduced in the long run. Thus, it is more likely for the workers to be paid at their productivity in the long run, and the negative signal of the use of informal search method should then gradually decrease and even disappear.

Here, we examine the wage effects of informal job search for (1) migrants who have been in the urban market for less than five years versus those more than five years; (2) the workers who have job tenure for less than a year versus those more than a year; (3) the workers on their first jobs versus those on their non-first jobs. The results are reported in Table (10).

Consistent with the intuition provided above, we find that the wage penalty mostly exists among the rural migrants with weaker labor market attachment (those who have just moved to the urban market, those having shorter job tenures, those on their first jobs), whereas there is generally no statistically significant penalty for those who have stronger labor market attachment and whose true productivity has more likely been revealed. For example, the estimated coefficient is as large as -.589 for those workers who have been in the urban market for less than five years, but that effect decreases (in magnitude) drastically to only -.177 and becomes statistically indistinguishable from zero for those who stay in the market for more than five years. Similar patterns are observed for other group comparisons. We also find that the negative wage effects are present mostly among workers with shorter job tenure, but completely absent among those with longer tenure (consistent with Pellizzari, 2010). Finally, the coefficient is about -0.24 for those still on their first jobs, while the estimate decreases to -0.193 for those on their non-first jobs.

These results suggest that the wage penalty could indeed reflect the negative signaling value of the use of network search, which is a consequence of information asymmetry in the frictional labor market.

6.2. Job Search Efficiency versus Wages

The literature has also generally found that the use of social networks helps to shorten the job search time (Pellizzari, 2010). The wage penalty could then reflect the trade-off between job quality and job search efficiency. Such trade-off may lead workers to sacrifice their wages in order to get a job more quickly (Bentolila, Michelacci, and Suarez, 2004).

To assess this explanation, we examine the impact of network search on job search time. The results are reported in Table (11). In line with the literature, we indeed find the job search time for the searchers using social networks is shorter than those using alternative methods. Specifically, IV estimates of the effects of informal job search on search time (measured in days) are negative and sizable; the IV coefficients is -16.5. Examining the results separately by workers with varying degrees of labor market attachment shows similar results. For example, use of informal job search reduces the search time by close to 20 days for the new entrants, much more than the effect for those who have been in the urban labor market for more than five years. We observe similarly large effects on job search time for other subgroups.

As we mention in the introduction, de Brauw and Giles (2017) find that over 90 percent of the rural-urban migrants moved to a destination where they knew an acquaintance from their hometown, and half of these migrants secured employment even before their migration. Therefore, we also look at the effects of informal job search on whether a migrant spent any time on job search (i.e., positive job search days). For those with less attachment to the urban labor market (i.e., those entering the market less than five years, those with less than one year tenure, or those on their first jobs), the use of informal job search again reduces the probabilities of spending *any* time on job search.

Remember that these estimates are conditional on being employed. The literature has generally found that network search also increases the probability of obtaining employment (e.g., Holzer, 1988; Munshi, 2003). If this is the case, the gap in the search time between informal and formal search methods could potentially be even larger, and our estimates should be considered as a lower bound.

The above results suggest that the use of informal job search indeed greatly increases job search efficiency, and that the wage penalty may be a result of migrants' willingness to trade off their wages for job search efficiency. But the question is why such large trade-off is acceptable? We believe that there are two reasons. First, migrants are financially constrained, and given the strict hukou system in China, they do not have enough support to stay unemployed in the urban market. The monthly cost of living in urban cities where these migrants work could potentially be many times larger than their annual income in rural areas. This problem is even more acute for new migrants who is financially less established. It is thus not surprising that migrants are eager to locate a job quickly to survive in the city at the cost of lower wages, and new migrants are even more so. Second, the migrants may also be well aware of the information asymmetry problem. They are willing to gain quicker access to formal employment in order to accumulate more experience and quickly reveal their productivity, which may then mitigate the informational problem. This problem is again more acute for new migrants (in terms of the observed effect size). Thus, migrants, especially new migrants, are willing to accept lower wages in order to gain quicker entry into the local labor market so that the noise about their productivity can be eliminated quickly. Both explanations are consistent with our findings that migrants on their first jobs who use network search have a much larger wage penalty but shorter job search time than those on non-first jobs.

6.3. Some Implications of the Mechanisms

The two mechanisms above can also help to answer several interesting questions. First, can migrants switch to another job immediately after landing the first job? The answer is no. As shown above, the wage penalty is due to both information asymmetry and financial constraints. Neither of these issues can be resolved immediately after landing the first job. A migrant needs to work for some time so that she can accumulate skills to clear the noise about her ability, and to save enough to support herself financially before finding another job.

Second, why do rural migrants continue to use informal job search method even when there exists a *overall* wage penalty? This seems puzzling at first, but it is actually not in light of the above mechanisms. Note that the wage penalty exists mostly for new entrants. After a migrant has worked and stayed in the city for some time, both information asymmetry problem and financial burden are then alleviated, and as a result, the wage penalty drastically decreases or even disappears for these migrants. It is then not surprising why we still observe a large, albeit slightly reduced, fraction of rural migrants continue to use informal job search later (see Table (1)).

7. Alternative Explanations

We have thus far interpreted our estimates as showing that the negative signaling value of informal job search, as well as the trade-off between search efficiency and wages can account for the observed wage penalty. Here we further examine several alternative explanations, but fail to find strong evidence supporting them.

One possible alternative explanation is based on the theory of compensating differentials. The literature has noted that workers are heterogeneous in preferences, while jobs are heterogeneous in their wages and non-pecuniary characteristics (Loury, 2006).[23] When making their decisions, workers take into account not only the wages but also other factors of their utility profile such as better benefits and flexible working conditions (Fontaine, 2007). Moreover, lower paying jobs may be associated with better non-pecuniary job characteristics such as benefits and other amenities. Workers can access the non-pecuniary aspects either through social networks that have inside information or by directly experiencing the job (Polachek and Siebert, 1993, p.183). Therefore, workers who find jobs through social networks may have better information about non-pecuniary job features; and thus they are more willing to accept lower wages (i.e., the wage penalty) in exchange for these job attributes.

To explore this possibility, we examine the effects of informal job search on a variety of job attributes. In particular, we repeat our baseline regressions but replacing the monthly wages with the variables that characterize major employment benefits and work conditions. If the theory of compensating differentials holds, we should expect to find beneficial effects on these characteristics. However, as shown in Table (12), we generally do not find strong evidence supporting the compensating differentials hypothesis. Specifically, we find that workers using the informal job search tend to have worse benefits, lower job security, as well as poorer amenities. The only exception is

[23] These are also the assumptions generally made in the job-shopping approach. See, e.g., Johnson (1978) and Jovanovic (1979)

that informal job search may lead to jobs with slightly better meals and accommodations, which, however, accounts for very small share of the total benefits. These results altogether suggest that informal job search actually leads to worse total benefits (both monthly and annual benefits).

Another possibility is that the use of social networks may reduce the search intensity by both migrants and their social contacts, which in turn leads to lower wages. First, it may crowd out migrants' own efforts in seeking jobs. As noted in Holzer (1988, p.2), the informal search method "is less costly in time and money" but "may be more productive than most in terms of generating job offers." Moreover, it is relatively easy and quick for migrants to find a job through social networks (as shown in Section 6.2.). Thus, migrants may search less and exert less effort in the job search and use social networks more often. Second, as Zaharieva (2013) shows, referees (especially those weak ties such as friends) may have lower search intensity for candidates than optimal. The reduced search intensity (by both migrants themselves and their contacts) suggests that migrants could have fewer opportunities and less complete information about their wage potential, thereby leading to lower wages. Unfortunately, the data do not contain information about job search intensity, and thus we cannot directly test this hypothesis and leave it for future research. Note, however, that this hypothesis is not consistent with our findings that the wage penalty exists only in the short run. It is not immediately straightforward to see why the crowding out effect as well as the reduced search intensity by contacts should necessarily reduce over time.

8. Conclusion

Using the recently available RUMiCI data, this paper empirically examines the wage impact of utilizing social network on wages. We study this topic for a particularly important group of disadvantaged individuals in the Chinese context – rural migrants. We find that there is a large wage penalty associated with the use of informal job search method, despite its popularity. There have been many theories put forth to explain such finding. One of our main contributions is that we carefully evaluate these theories and find that both the negative signal of the use of network search (suggested by the limited choice hypothesis in Loury (2006)) and the trade-off between wages and job search efficiency may be important reasons for the observed results. We also find some evidence that informal job search are more prevalent in filling unskilled jobs with lower wages. Nevertheless, examining whether these results continue to hold using alternative datasets and methods and also further exploring the potential mechanisms certainly seem like important future research topics.

Compliance with Ethical Standards:

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Table 1: Job search methods among migrant workers

Percentage		Migration		Tenure		First job	
	Full Sample	<= 5 years	> 5 Years	<= 1 years	> 1 Years	Yes	No
Network job search	73.2%	71.8%	74.7%	72.0%	74.3%	76.7%	70.4%
Market job search	26.8%	28.2%	25.3%	28.0%	25.7%	23.3%	29.6%
No. of obs	4197	2086	2065	1945	2245	1843	2338

[1] Data Source: Our own calculations using the China part of the 2007 Rural-Urban Migration in China and Indonesia.

Table 2: SUMMARY STATISTICS

	Full Sample	Network	Market	Difference (Network-Market)	
Panel A: Outcomes					
Monthly wages	1399.10	1376.19	1461.82	-85.63	***
Hourly wages	6.37	6.15	6.98	-0.84	***
Panel B: Individual Characteristics					
Female	0.39	0.39	0.40	-0.01	
Minority	0.02	0.02	0.02	-0.01	
Age	29.85	30.30	28.61	1.68	***
Birth Order	2.14	2.16	2.09	0.07	
Education	9.23	9.05	9.75	-0.70	***
Local rural hukou	0.20	0.21	0.18	0.03	**

[1] Data Source: the China part of the 2007 Rural-Urban Migration in China and Indonesia. Geographic variables are included in all analysis but omitted here in the interest of brevity. Asterisks denote the statistical significance of the difference between search methods. $***, (p \leq 0.01)$, $**, (p \leq 0.05)$, and $*, (p \leq 0.10)$.

Table 3: Lagrangian Multiplier Tests of Heteroskedasticity

Panel A: Lagrangian Multiplier Tests of Heteroskedasticity

	Test Statistics	P-value
Female	5.950	0.015
Age	10.159	0.001
Age Squared	8.974	0.003
Local Rural Hukou	1.299	0.254
Minority	0.271	0.602
Female*Minority	0.133	0.715
Birth Order	1.933	0.164
Age*Hukou	0.022	0.882
Age Squared*Hukou	0.899	0.343
Age*Birth	5.831	0.016
Age Squared*Birth	6.491	0.011
Female*Age	1.605	0.205
Female*Age Squared	0.170	0.680
Female*Birth	0.441	0.507
Female*Hukou	4.223	0.040
North Coast	0.178	0.673
Central Coast	1.650	0.199
South Coast	9.115	0.003
Central	2.790	0.095
Northwest	2.542	0.111
Southwest	1.964	0.161
All Variables	45.986	0.000

Panel B: Ullah's Specification Test

Test Statistic	.0546
$90^{th} percentile$	9.9802
$95^{th} percentile$	11.8769
$99^{th} percentile$	13.9922

[1] Data Source: the China part of the 2007 Rural-Urban Migration in China and Indonesia. Asterisks denote the statistical significance of the difference between search methods. $***, (p \leq 0.01)$, $**, (p \leq 0.05)$, and $*, (p \leq 0.10)$.

Table 4: Probit Model of Informal Job Search Decision (Marginal Effects)

Variables	Probit Coefficient	Marginal Effect
Female	-5.291	-0.556**
	(3.536)	(0.265)
Age	-0.520	-0.071***
	(0.391)	(0.024)
Age Square	0.011	0.001***
	(0.009)	(0.000)
Local rural hukou	1.110	0.142
	(1.402)	(0.166)
Minority	-0.643	-0.082
	(0.772)	(0.086)
Female*minority	0.064	0.008
	(0.868)	(0.111)
Birth Order	-0.417	-0.053
	(0.862)	(0.095)
Age*local Hukou	-0.008	-0.001
	(0.098)	(0.013)
Age Squared*Hukou	-0.001	-0.000
	(0.002)	(0.000)
Age*Birthorder	0.053	0.004
	(0.070)	(0.007)
Age Squared*Birthorder	-0.001	-0.000
	(0.001)	(0.000)
Female*age	0.381	0.049**
	(0.271)	(0.021)
Female*age squared	-0.007	-0.001**
	(0.006)	(0.000)
Female*Birthorder	-0.287	-0.037
	(0.250)	(0.025)
Female*Local Hukou	-0.391	0.130***
	(0.405)	(0.043)
North coast	-0.731	-0.093
	(0.782)	(0.075)
Central coast	-0.634	-0.081
	(0.642)	(0.058)
South coast	1.205	0.154**
	(0.951)	(0.063)
Central	0.174	0.022
	(0.459)	(0.057)
Northwest	-0.916	-0.117*
	(0.836)	(0.069)
Southwest	-0.316	-0.040
	(0.505)	(0.057)
No. of Obs.	4,197	4,197

[1] Data Source: the China part of the 2007 Rural-Urban Migration in China and Indonesia. Asterisks denote the statistical significance $***$, $(p \leq 0.01)$, $**$, $(p \leq 0.05)$, and $*$, $(p \leq 0.10)$.

Table 5: Baseline Results (Log Monthly Wages)

	OLS (1)	IV (2)
Panel A: Estimates		
Informal job search	-0.024*	-0.448**
	(0.013)	(0.199)
Panel B: First Stage Test Statistics		
K-P Ranktest F statistics		32.90
P-value		0.000
Covariates	Yes	Yes
Origin Region Dummies	Yes	Yes
Destination Provincial Dummies	Yes	Yes
No. of Obs.	4,197	4,197

[1] Data Source: the China part of the 2007 Rural-Urban Migration in China and Indonesia. Asterisks denote the statistical significance of the difference between search methods. $***, (p \leq 0.01)$, $**, (p \leq 0.05)$, and $*, (p \leq 0.10)$. In addition, we control for gender, age, age squared, Hukou status, minority, birth order, interaction terms between age and other variables (Hukou, Birth order, and Gender), an interaction between gender and *Hukou* status in all specifications. Estimations are clustered at both origin and destination geographic levels.

Table 6: Baseline Specifications Using Log Hourly Wages

	OLS (1)	IV (2)
Panel A: Estimates		
Informal job search	-0.071***	-0.761***
	(0.019)	(0.284)
Panel B: First Stage Test Statistics		
K-P Ranktest F statistics		32.73
P-value		0.000
Covariates	Yes	Yes
Origin Region Dummies	Yes	Yes
Destination Provincial Dummies	Yes	Yes
No. of Obs.	4,173	4,173

[1] Data Source: the China part of the 2007 Rural-Urban Migration in China and Indonesia. Asterisks denote the statistical significance of the difference between search methods. $***, (p \leq 0.01)$, $**, (p \leq 0.05)$, and $*, (p \leq 0.10)$. In addition, we control for gender, age, age squared, Hukou status, minority, birth order, interaction terms between age and other variables (Hukou, Birth order, and Gender), an interaction between gender and *Hukou* status in all specifications. Estimations are clustered at both origin and destination geographic levels.

Table 7: IV Estimates: Baseline Specification with Education

	Log Monthly Wages (1)	Log Hourly Wages (2)	Log Monthly Wages (3)	Log Hourly Wages (4)
	All		Only Education with Less than High School	
Panel A: Estimates				
Informal job search	-0.397*	-0.685**	-0.329*	-0.627**
	(0.217)	(0.308)	(0.191)	(0.273)
Education	0.017***	0.026***		
	(0.005)	(0.008)		
Panel B: First Stage Test Statistics				
K-P Ranktest F statistics	21.53	21.60	26.11	26.34
P-value	0.000	0.000	0.000	0.000
Covariates	Yes	Yes	Yes	Yes
Origin Region Dummies	Yes	Yes	Yes	Yes
Provincial Dummies	Yes	Yes	Yes	Yes
No. of Obs.	4,197	4,173	2,879	2,860

[1] Data Source: the China part of the 2007 Rural-Urban Migration in China and Indonesia. Asterisks denote the statistical significance of the difference between search methods. $***, (p \leq 0.01)$, $**, (p \leq 0.05)$, and $*, (p \leq 0.10)$. In addition, we control for gender, age, age squared, Hukou status, minority, birth order, interaction terms between age and other variables (Hukou, Birth order, and Gender), an interaction between gender and *Hukou* status in all specifications. Estimations are clustered at both origin and destination geographic levels.

Table 8: Baseline Specifications with Occupation, Industry, and Sector Variables

	Log Monthly Wages (1)	Log Hourly Wages (2)	Log Monthly Wages (3)	Log Hourly Wages (4)
Panel A: Estimates				
Informal job search	-0.534***	-0.800***	-0.532***	-0.787***
	(0.200)	(0.300)	(0.204)	(0.298)
Panel B: First Stage Test Statistics				
K-P Ranktest F statistics	19.57	19.20	19.41	18.99
P-value	0.000	0.000	0.000	0.000
Covariates	Yes	Yes	Yes	Yes
Origin Region Dummies	Yes	Yes	Yes	Yes
Provincial Dummies	Yes	Yes	Yes	Yes
Occupational Dummies	Yes	Yes	Yes	Yes
Ownership Dummies	Yes	Yes	Yes	Yes
Industry Dummies	No	No	Yes	Yes
No. of Obs.	4,113	4,090	4,113	4,090

[1] Data Source: the China part of the 2007 Rural-Urban Migration in China and Indonesia. Asterisks denote the statistical significance of the difference between search methods. $***, (p \leq 0.01)$, $**, (p \leq 0.05)$, and $*, (p \leq 0.10)$. In addition, we control for gender, age, age squared, Hukou status, minority, birth order, interaction terms between age and other variables (Hukou, Birth order, and Gender), an interaction between gender and *Hukou* status in all specifications. Estimations are clustered at both origin and destination geographic levels.

Table 9: Results Using Data from Zhusanjiao Migrant Worker Survey

Dependent Variable:	log(Monthly Wage)		log(Hourly Wage)		log(Monthly Wage)		log(Hourly Wage)	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Estimates								
Informal job search	-0.049**	-0.695***	-0.057**	-0.742***	-0.020	-0.551**	-0.020	-0.528**
	(0.020)	(0.180)	(0.024)	(0.196)	(0.022)	(0.239)	(0.025)	(0.261)
Panel B: First Stage Test Statistics								
K-P Rank test F statistics		31.94		31.94		31.30		31.30
P-value		0.000		0.000		0.000		0.000
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination Cities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education	No	No	No	No	Yes	Yes	Yes	Yes
No. of Obs.	1,241	1,241	1,241	1,241	1,241	1,241	1,241	1,241

[1] Data Source: Zhusanjiao Migrant Worker Survey. $***, (p \leq 0.01)$, $**, (p \leq 0.05)$, and $*, (p \leq 0.10)$. In addition, we control for gender, age, age squared, minority, interaction terms between gender and minority, and region of origin dummies in all specifications. Estimations are clustered at both origin and destination geographic levels.

Table 10: Estimates of The Effects of Informal Job Search: Short- vs Long-Term

		(1) OLS	(2) IV	(3) OLS	(4) IV
Panel A:		Migration <= 5 years		Migration > 5 years	
	Informal job search	-0.046***	-0.589***	0.001	-0.177
		(0.016)	(0.069)	(0.018)	(0.241)
	Observation	2,086		2,065	
Panel B:		Job tenure <= 1 years		Job Tenure > 1 years	
	Informal job search	-0.047*	-0.446***	-0.007	-0.018
		(0.025)	(0.131)	(0.019)	(0.421)
	Observation	1,945		2,245	
Panel C:		First Job		Non First Job	
	Informal job search	-0.051**	-0.240	-0.003	-0.193
		(0.021)	(0.194)	(0.013)	(0.162)
	Observation	1,843		2,338	

[1] Data Source: the China part of the 2007 Rural-Urban Migration in China and Indonesia. Asterisks denote the statistical significance of the difference between search methods. $***, (p \leq 0.01)$, $**, (p \leq 0.05)$, and $*, (p \leq 0.10)$. In addition, we control for gender, age, age squared, Hukou status, minority, birth order, interaction terms between age and other variables (Hukou, Birth order, and Gender), an interaction between gender and *Hukou* status in all specifications. Estimations are clustered at both origin and destination geographic levels.

Table 11: IV Estimates of The Effects of Informal Job Search on The Length of Job Search Time

VARIABLES	All	Migrant <= 5 years	Migrant > 5 years	Tenure <= 1 year	Tenure > 1 year	First Job	Non-first job
Panel A: Dependent Variable = Days							
Informal Job Search	-16.500**	-19.859**	-8.856	-11.565***	-16.682	-14.620*	-23.008*
	(6.671)	(7.811)	(22.510)	(4.443)	(15.600)	(8.552)	(12.948)
Panel B: Dependent Variable = 1 if Job Search Days > 0							
Informal Job Search	-0.215**	-0.400***	0.065	-0.388**	0.145	-0.152	-0.369
	(0.0924)	(0.107)	(0.253)	(0.191)	(0.106)	(0.112)	(0.259)
Observations	4,184	2,081	2,057	1,942	2,235	1,840	2,328

[1] Data Source: the China part of the 2007 Rural-Urban Migration in China and Indonesia. Asterisks denote the statistical significance of the difference between search methods. $***, (p \leq 0.01)$, $**, (p \leq 0.05)$, and $*, (p \leq 0.10)$. In addition, we control for gender, age, age squared, Hukou status, minority, birth order, interaction terms between age and other variables (Hukou, Birth order, and Gender), an interaction between gender and *Hukou* status in all specifications. Estimations are clustered at both origin and destination geographic levels.

Table 12: Tests of Compensating Differentials

Dependent Variables	Full sample (1)		First job (2)		Non-first job (3)	
Panel A: Benefits						
Unemployment insurance	-0.062	(0.043)	-0.156**	(0.069)	-0.011	(0.022)
Pension insurance	-0.104***	(0.038)	-0.155**	(0.060)	-0.079***	(0.025)
Injury insurance	-0.083**	(0.039)	-0.135**	(0.065)	-0.051**	(0.023)
Housing fund	-0.074*	(0.044)	-0.161**	(0.071)	-0.032*	(0.019)
Panel B: Job Security						
Permanent	-0.037***	(0.011)	-0.057***	(0.010)	-0.024	(0.016)
Long term contract	-0.040***	(0.010)	-0.067***	(0.014)	-0.024	(0.015)
Short term contract	0.004***	(0.001)	0.007**	(0.003)	0.003*	(0.002)
Non-contract temp	0.074***	(0.020)	0.117***	(0.021)	0.045	(0.029)
Panel C: Amenities						
Have catering	-0.046*	(0.025)	-0.077**	(0.029)	-0.019	(0.030)
Value of meals	0.063**	(0.030)	0.082*	(0.043)	0.060	(0.041)
Have accommodation	0.035	(0.029)	0.040	(0.033)	0.055**	(0.026)
Value of accommodation	-0.048	(0.046)	0.020	(0.082)	-0.080	(0.050)

[1] Data Source: the China part of the 2007 Rural-Urban Migration in China and Indonesia. Asterisks denote the statistical significance of the difference between search methods. $***, (p \leq 0.01)$, $**, (p \leq 0.05)$, and $*, (p \leq 0.10)$. In addition, we control for gender, age, age squared, Hukou status, minority, birth order, interaction terms between age and other variables (Hukou, Birth order, and Gender), an interaction between gender and *Hukou* status in all specifications. Estimations are clustered at both origin and destination geographic levels.

Supplemental Material (Not for Publication):

Simulation Results for the Impacts of Misspecification on KV-IV Estimates

In our empirical analysis we follow Millimet and Tchernis (2013) and employ a parametric variant of the KV-IV approach by specifying both the distributional and heteroskedastic errors functions. This practice has two distinct advantages as it greatly reduces the computation burden; and it also eliminates the need for continuously distributed exogenous variables in the semi-parametric approach. As argued in Millimet and colleague's paper, this practice is innocuous. Wooldridge (2010, p.939) and Angrist and Pischke (2009) also note that the consistency of IV estimates does not depend on the correct specification of the first-stage equation. In other words, mis-specification of the distribution and heteroskedastic functions should not necessarily impact the KV-IV estimates, provided that the other assumptions hold.

Monte Carlo (MC) simulations corroborate this theoretical point. Specifically, we undertake two sets of MC experiments using simulated data. The finite-sample performances of the KV-IV estimator under correct specifications have been shown elsewhere (e.g., Millimet and Tchernis, 2013).

The first set of MC experiments consider only the impacts of the mis-specification of the distribution functions, while the second set of MC experiments consider the impact of the mis-specification of both the distribution and the heteroskedastic functions. We perform this exercise twice for each case using 1000 simulations of sample sizes 4200 (roughly the size in our application) and 10,000.

The first MC design is based on the following data-generating process:

$$y = 1 + D + x_1 + x_2 + \epsilon \tag{10}$$

$$D = I(x_1 + x_2 - v > 0) \tag{11}$$

$$v = \exp(x_1 + x_2)v^* \tag{12}$$

$$\epsilon = 0.2v^* + \eta \tag{13}$$

$$\eta, x_1, x_2 \sim \mathbb{N}(0,1) \tag{14}$$

$$v^* \sim \chi^2_1 \tag{15}$$

Note that Equation (12) specifies the heteroskedastic function, while Equation (15) specifies the distribution function (which is chi-squared distributed). The endogeneity arises because of Equation (13).

For comparison, we choose the best scenario as our benchmark where the correctly specified predicted value, $F(\frac{x_1+x_2}{\exp(x_1+x_2)})$ (where $F(\cdot)$ is the cumulative chi-squared distribution with 1 degree of freedom), is used as the IV. This is the best scenario not only because we use the correct specification, but also because we use the true parameter values (as opposed to the estimated ones); this is denoted as **True IV**. We then compare the benchmark results to the results using our mis-specified parametric IV, $\Phi(\frac{\widehat{\lambda_1}x_1+\widehat{\lambda_2}x_2}{\exp(\widehat{\theta_1}x_1+\widehat{\theta_2}x_2)})$ (where $\Phi(\cdot)$ is the cumulative distribution function for standard normal variables); this is denoted as **Parametric IV**.

The second MC design is based on the following data-generating process:

$$
\begin{aligned}
y &= 1 + D + x_1 + x_2 + \epsilon && (16)\\
D &= I(x_1 + x_2 - v > 0) && (17)\\
v &= (x_1 + x_2)^2 v^* && (18)\\
\epsilon &= 0.2v^* + \eta && (19)\\
&\eta, x_1, x_2 \sim \mathbb{N}(0,1) && (20)\\
&v^* \sim \chi_1^2 && (21)
\end{aligned}
$$

Note that the true heteroskedastic function is now different (Equations 18 vs 12). Therefore, for the second MC design, the best scenario case uses $F(\frac{x_1+x_2}{(x_1+x_2)^2})$ (where $F(\cdot)$ is the cumulative chi-squared distribution with 1 degree of freedom), is used as the IV. For **Parametric IV**, we continue to use $\Phi(\frac{\widehat{\lambda_1}x_1+\widehat{\lambda_2}x_2}{\exp(\widehat{\theta_1}x_1+\widehat{\theta_2}x_2)})$. Note that we now mis-specify both distribution and heteroskedastic functions.

The results are presented in Table (13); OLS results are also included for comparison. The simulations indicate that in the presence of endogeneity, OLS is severely biased, which is not surprising. What is surprising is the outstanding performances of the parametric approach, relative to the best scenario. First, in the smaller sample (as ours), the parametric IV, although mis-specified, performs extremely well and similarly to the true IV (the best scenario). Second, as the sample size increases, both IVs have an average bias nearing zero, and the difference between two IVs becomes even smaller and barely distinguishable. In sum, these MC results corroborate the theoretical expectations above.

Table 13: Monte Carlo Results

	N = 4,200			N = 10,000		
	OLS	True IV	Parametric IV	OLS	True IV	Parametric IV
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Model 1			
Mean ($\widehat{\alpha}$)	0.7302	0.9931	0.9890	0.7344	1.0023	1.0022
Median ($\widehat{\alpha}$)	0.7297	0.9909	0.9814	0.7344	1.0010	1.0031
			Panel B: Model 2			
Mean ($\widehat{\alpha}$)	0.7783	0.9992	0.9989	0.7811	0.9999	0.9996
Median ($\widehat{\alpha}$)	0.7771	1.0015	0.9994	0.7805	0.9984	0.9986

[1] 1000 simulations used when N = 4,200 and 10,000, respectively.