Worker Benefits of Rural Urban Migrants in China

Xuchao Gao[*]

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Abstract

Despite the rise in rural-urban migration since the 1980s, many migrants in China remain without access to formal worker benefits. Using panel data from the 2008-2009 RUMiC survey, this paper examines how job search methods affect benefit provision among rural-urban migrants. Comparing cross-sectional and fixed effects approaches, I find that apparent negative associations between network job search and formal benefits largely reflect worker selection rather than causal effects. Most relationships disappear when controlling for individual fixed effects, indicating that workers who rely on networks are negatively selected. The exception is pension benefits, where network job search maintains a significant negative effect, suggesting network-based hiring genuinely channels workers into jobs that avoid long-term benefit obligations. These findings reveal that networks primarily matter through selection rather than direct causal effects.

Keywords: Network jobs, internal migration, worker benefits

1 Introduction

According to the National Bureau of Statistics of China, the total number of migrant workers reached 290.77 million in 2019, including approximately 135 million rural-urban migrant workers. Despite their large population and important contributions to urban economic growth, rural-urban migrants do not enjoy equal worker benefits compared to local urban workers. While many studies focus on wages earned by rural-urban migrants, little attention has been paid to worker benefits for this population.

This paper examines how job search methods affect worker benefit provision among rural-urban migrants in China, distinguishing between network-based and formal hiring channels. While social networks are widely recognized as important for migrant job search, their effects on job quality—particularly non-wage benefits—remain under-researched. This distinction matters because worker benefits represent a significant component of total compensation and are crucial for long-term economic security, yet they are often less transparent than wages during the hiring process.

Using panel data from the 2008-2009 RUMiC survey, I compare cross-sectional and fixed effects approaches to distinguish between genuine effects of different hiring channels and selection bias. The fixed effects specification exploits within-individual variation in job search methods to control for unobserved worker characteristics, while cross-sectional analysis provides baseline correlational evidence.

I find that while cross-sectional analysis reveals strong negative associations between network hiring and most formal benefits, these relationships largely disappear when controlling for individual fixed effects, indicating that the relationship is primarily driven by worker selection rather than causal effects. The notable exception is pension benefits, where network job search maintains a significant negative effect even in the fixed effects specification, suggesting consequences of hiring channel choice for long-term worker welfare.

2   Background

The flow of rural workers into cities began increasing dramatically in the late 1980s as a response to economic reform and increasing demand for cheap labor in urban areas [Zhao, 1999]. The population of rural migrant workers grew from 2 million in the mid-1980s to 94 million in 2002, accounting for 12% of the total labor force [Rupelle et al., 2008]. However, due to hukou regulations, migrant workers do not have access to local social welfare systems.

To address the lack of social protection for this large population, a new worker benefit system was launched in the 1990s, designed to make employers the main contributors for social insurance and benefits. This reform coincided with the ownership transformation of state-owned enterprises from 1992 to 2003 [Song, 2018]. The new system was designed to be co-financed by employers and workers, with some benefits partially funded by the state. However, many medium and small-sized firms tend to avoid paying the required contributions, and local governments find it difficult to enforce compliance without hurting the local economy.

The regulatory framework evolved gradually. The Labor Law enacted in 1994 only outlined rights and duties of workers in general terms, with more specific provisions on worker benefits added in following years [Brown, 2016]. While the Social Insurance Law from 2011 integrated previous separate provisions into a comprehensive national system, stating that "all employees, including rural migrant workers, should be covered by the social insurance system" and "social insurance benefits should remain with workers when they move.", implementation remains challenging.

Currently, there are five mandatory "insurances" that employers must provide by law but often fail to, especially for disadvantaged rural urban migrant workers: pension, medical, work-related injury, unemployment, and maternity insurance. Housing fund contributions are generally included but are not officially part of China's social insurance system. Despite these legal requirements, millions of migrant workers still do not enjoy entitled worker benefits due to high mobility and limited knowledge of labor contracts and legal rights.

3   Related Literature

This study contributes to several strands of literature on social networks and labor market outcomes. Previous research has shown that social networks affect migration decisions and wages differently depending on network strength [Giulietti et al., 2018]. Regarding job search methods, Fang et al. [2016] find that migrant workers searching through informal channels earn 33% to 43% less than those using formal channels, consistent with the pattern in worker benefits observed in this study. They identify education as the most important determinant of whether migrants use informal or formal search procedures.

The seemingly counterintuitive relationship between social networks and wages can be rationalized by networks serving as a safety net—workers only choose formal job offers when wages exceed their network-based alternatives, resulting in formal offers having higher average wages [Goel and Lang, 2019].

This paper also relates to literature on job amenities and worker preferences. Studies have found that workers often sacrifice wages for better working conditions [Villanueva, 2007, Lubotsky and Olson, 2015, Mas and Pallais, 2017]. Wiswall and Zafar [2018] show that gender differences exist in willingness to trade income for job characteristics, while Maestas et al. [2018] find that incorporating preferences for working conditions increases wage differentials by demographic characteristics.

This paper adds to this literature by examining how job search methods affect benefit provision in the specific context of Chinese migrant workers, with particular attention to distinguishing selection effects from causal relationships, contributing to understanding of labor market segmentation in developing economies.

4   Data

4.1   Data source and Survey Design

Longitudinal Survey on Rural Urban Migration in China (RUMiC) focuses on migration patterns in China. While the research team is conducting the seventh wave of the survey, only the first two waves (2008 and 2009) are currently available for the public use. I use data from the two public waves. Both waves were conducted

in 15 major migrant-receiving cities across 5 provinces (see Figure 1): Guangzhou, Dongguan, Shenzhen, Zhengzhou, Luoyang, Hefei, Bengbu, Chongqing, Shanghai, Nanjing, Wuxi, Hangzhou, Ningbo, Wuhan, and Chengdu.

The 2008 survey consists of three components: rural household surveys, urban household surveys, and rural-to-urban migrant surveys. For the purpose of this paper, rural-to-urban migrant surveys will be used. Rural-to-urban migrants are defined as individuals who have a rural hukou but work and reside in urban areas, while urban household survey participants possess urban hukou ([Frijters et al., 2009]). The 2009 survey maintains the same structure but distinguishes between continuing migrant households from the 2008 survey and newly added households in the 2009 survey. The survey contains comprehensive information about individual migrants, such as household characteristics, health conditions, educational background, employment status, children's education, family and social relationships, and worker benefits. Summary statistics on the key variables used in this paper are included in Table 1. The dataset contains 5,007 rural-to-urban migrant households (8,446 individuals) in the 2008 survey and 5,243 total households (9,347 individuals) from 2009, including 3,422 newly sampled households.

Figure 1: Geography of rural urban migration. Source: RUMiC project website

Table 1: Summary Statistics: 2008 Survey

Variable	Mean	Std. Dev.	Min	Max
A. Demographics				
Age	29.78	10.11	15	71
Gender (Male = 1)	0.61	0.49	0	1
Schooling (years)	9.24	2.58	0	20
Married	0.52	0.50	0	1
Number of children	0.71	0.85	0	5
Han ethnicity	0.98	0.14	0	1
B. Migration				
Experience (years)	8.01	6.14	1	46
Cities/towns worked in	2.06	1.85	0	20
Monthly income (yuan)	1404.27	668.92	0	8000
Has connection	0.63	0.48	0	1
C. Worker Benefits				
Unemployment insurance	0.14	0.35	0	1
Injury insurance	0.22	0.41	0	1
Pension	0.21	0.41	0	1
Housing subsidy	0.09	0.28	0	1
Accommodation	0.65	0.48	0	1
Catering	0.70	0.46	0	1

Note: Sample of 4,809 wage earners from 2008 survey. Worker benefits equals 1 means they are partially or fully provided by employers.
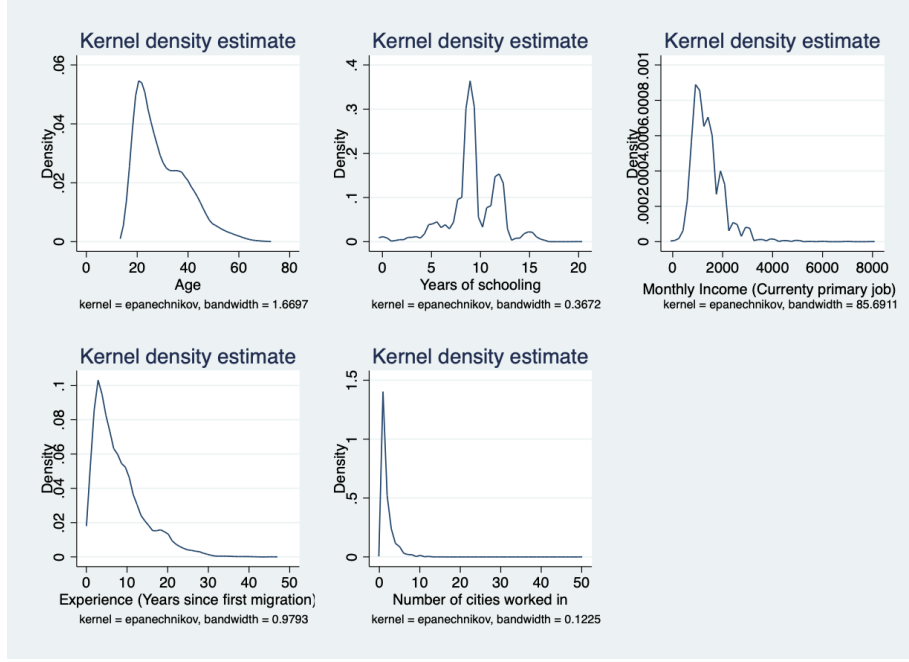
Figure 2: Summary statistics: 2008 Survey

Table 1 is based on wage earners in the 2008 survey. They sketch a profile of the rural-urban migrant workers. They are mostly young, with around half of them being in their early 20s. Most of them are undereducated, having approximately 9 years of schooling. Many young people in the rural areas migrate to cities for work once they finish 9 years of compulsory education as junior high school graduates. Most of them earn a monthly wage below 2,000 RMB. Because it is not easy for migrants to obtain urban hukou and settle down in cities, they tend to work in the cities for a few years, build up savings, and return to their hometowns. In the 2008 sample, most of them have experience of working and living in the cities for fewer than 10 years. The average number of cities in which the migrants have worked is approximately 2. 60% of the rural-urban migrants in the sample are males. Almost half of the migrants are married. The full or partial provision of catering and accommodation are relatively common to attract these low-wage earners to work in the cities, while formal social insurance, such as unemployment insurance, injury insurance, and pension, is not as commonly provided by employers. Housing funds are the least commonly seen for this group of workers.

Among the 27 industry categories in which the rural-urban migrants work in, manufacturing (21.81%), construction enterprises(14.66%), wholesale and retail trade

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(14.15%), and hotel and catering services (19.26%) are the main industries that employ rural-urban migrants. See Figure 3.
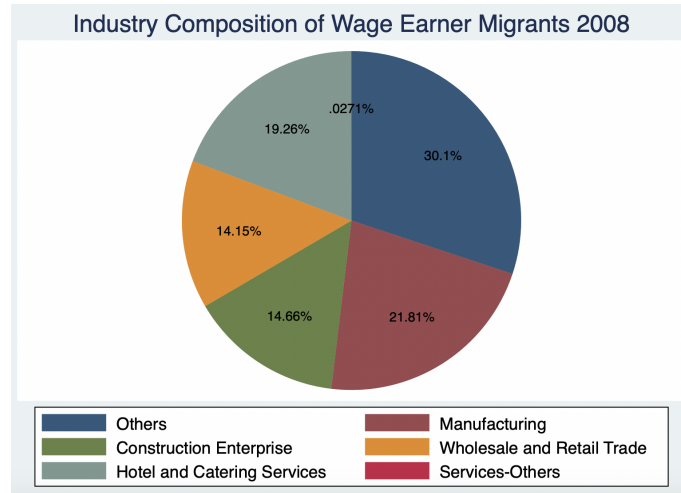

Industry Composition of Wage Earner Migrants 2008

- Others — 30.1%
- Manufacturing — 21.81%
- Construction Enterprise — 14.66%
- Wholesale and Retail Trade — 14.15%
- Hotel and Catering Services — 19.26%
- Services-Others — .0271%

Figure 3: Industry Composition of Wage Earner Migrants in 2008 Survey

4.2 Sample Construction

I construct three analytical samples from the RUMiC data, each tailored to specific empirical approaches detailed in Section 5 and Section 7.

Fixed Effects Sample: For the panel analysis that exploits within-individual variation over time, I use a balanced sample of individuals who appear as wage earners in both survey waves. This yields 2768 observations from 1384 individuals. The restriction to consistent wage earners ensures that observed changes in benefit provision reflect job search methods rather than transitions between employment types.

Pooled Cross-Section Sample: To establish baseline relationships and test robustness to sample selection, I expand the fixed effects sample to include 2008 wage earners who left the sample by 2009. This results in 6178 total observations and helps assess whether panel results are sensitive to non-random attrition.

Attrition Analysis Sample: To directly test for selection bias, I analyze all 2008 wage earners (4809 observations) to examine whether worker benefit provision predicts remaining in the 2009 survey.

Technical details on data cleaning and variable construction are provided in the

Appendix.

5 Empirical Strategy

I start with pooled OLS estimation to establish baseline relationships between job search methods and worker benefit provisions by employers. Equation 1 presents the pooled OLS specification:

$$
\begin{aligned}
y_{it} = \ & \beta_0 + \beta_1 connectionjob_{it} + \beta_2 connectionjob_{it} \times exper1_{it} \\
& + \beta_3 connectionjob_{it} \times ncity_{it} + \beta_4 exper1_{it} + \beta_5 ncity_{it} \\
& + \beta_6 year2009_t + X_{it}\beta_7 + \mu_{it}
\end{aligned}
\tag{1}
$$

The dependent variable y_{it} represents binary indicators for whether specific worker benefits are provided to individual i in year t. They take the value of 1 if benefits are provided fully or partially by employers, and 0 otherwise. Worker benefits include formal social insurance, such as unemployment insurance (UI_{it}), injury insurance ($Injury_{it}$), and pensions ($pension_{it}$); housing subsidies ($housing_{it}$); and informal benefits such as accommodation ($accommodation_{it}$), and catering services ($catering_{it}$). The key explanatory variable, $connectionjob$, captures whether the worker obtained their current job through network connections, such as family members, relatives, friends, and acquaintances, rather than through formal application channels. To explore heterogeneous effects, the model includes interaction terms between $connectionjob_{it}$ and two migration experience variables: $exper1_{it}$, which measures years since first migrating out for work, and $ncity_{it}$, representing the number of cities the worker has worked in since beginning migration. The control vector X_{it} includes predetermined and exogenous characteristics, such as marital status, the number of children in the household, years of schooling, industry indicators, hosting city indicators, and hukou registered province indicators. To avoid potential endogeneity concerns, I exclude job-specific characteristics that may be jointly determined with benefit provision, such as monthly income, company ownership type, job contract terms, and employment type (permanent vs. temporary positions). A year dummy for 2009 controls for aggregate time trends. Standard

errors are clustered at the individual level.

However, pooled OLS may suffer from omitted variable bias if unobserved individual characteristics correlate with both job search methods and benefit outcomes. Workers who rely on networks may systematically differ in motivation, social skills, or family background—factors that could independently affect their access to benefits.

To alleviate this concern, I exploit the panel structure and estimate a fixed effects model that controls for time-invariant unobserved heterogeneity by adding individual fixed effects, as in Equation 2. Because I only have a two-period panel, I do not include year fixed effects alongside the experience variable to avoid perfect multicollinearity, as both capture the same temporal variation from 2008 to 2009. Including a year dummy in the pooled OLS model is necessary because there are two sources of variation: levels of experience and changes in experience. However, in the fixed effects model, the variation in experience levels has been absorbed by the individual fixed effects, leaving only the temporal change component, which would be perfectly collinear with a year dummy. Finally, it is worth noting that identification of the main connection effect comes from individuals who change their job search method between survey waves.

$$
\begin{aligned}
y_{it} = {} & \beta_1 connection job_{it} + \beta_2 connection job_{it} \times exper1_{it} \\
& + \beta_3 connection job_{it} \times ncity_{it} + \beta_4 exper1_{it} + \beta_5 ncity_{it} \\
& + X_{it}\beta_6 + \alpha_i + \mu_{it}
\end{aligned}
\tag{2}
$$

6 Main results

The pooled OLS results reveal striking differences in how network-based job search is associated with formal versus informal worker benefits. Table 2 shows that obtaining jobs through network connections is significantly associated with reduced access to formal social insurance benefits. Specifically, network job search is associated with a 2.3 percentage point lower probability of receiving unemployment insurance, 3.8 percentage points lower for injury insurance, 5.5 percentage points lower for pension benefits, and 3.9 percentage points lower for housing subsidies (Panel A). These

associations are all statistically significant and economically meaningful given the low baseline provision rates shown in the summary statistics.

The interaction terms in Panel B reveal that these associations vary significantly with migration experience. When interaction terms are included, the main network effect becomes less precisely estimated and loses statistical significance for unemployment and injury insurance, suggesting that the relationship between network job search and formal benefits is heterogeneous across workers with different migration experiences. The negative coefficients on Network × Experience for most benefits suggest that the disadvantage associated with network hiring may become more pronounced as workers gain experience. This pattern is consistent with a "trapping" mechanism where experienced workers who still rely heavily on networks may have unobserved characteristics (such as lower formal skills, language barriers, or lack of credentials) that make them less competitive in formal job markets, confining them to informal sector employment.

Conversely, the positive coefficients on Network × Cities interactions for unemployment insurance and housing subsidies suggest that workers with greater geographic mobility experience smaller negative associations with network hiring. This likely reflects superior market information and bargaining power—workers who have worked in multiple cities know standard benefit packages across different markets and can negotiate more effectively even when using network connections. Table 3 demonstrates that network job search has opposite associations with informal benefits and wages. Network connections are associated with a 4.5 percentage point higher probability of receiving employer-provided accommodation, though they show no significant association with catering provision. In contrast to formal benefits, the interaction terms between network job search and migration experience variables are generally insignificant for informal benefits. This suggests that the relationship between networks and informal benefits is relatively uniform across workers regardless of their experience or geographic mobility. This makes intuitive sense because informal benefits like accommodation are more standardized and binary—employers either provide housing or they don't, regardless of worker characteristics. Unlike formal benefits that involve significant costs for employers, informal benefits like accommodation are sometimes essential to attract migrant workers and less subject to

negotiation and discrimination, making them more uniformly distributed based on job characteristics rather than individual worker's bargaining power or knowledge about the market.

Notably, network job search is associated with lower monthly wages, reducing earnings by approximately 43 RMB per month—about 3% of the sample mean wage. These pooled OLS findings suggest a potential trade-off pattern: while network connections are associated with securing accommodation (an important benefit for migrants), they are also associated with reduced formal social protections and lower monetary compensation. However, these associations may reflect selection bias, as workers who rely on networks versus formal job search methods may differ systematically in unobserved characteristics that independently affect their access to worker benefits.

Table 2: Pooled OLS Results: Network Job Search Effects on Formal Worker Benefits

	(1)	(2)	(3)	(4)
VARIABLES	Unemployment Insurance	Injury Insurance	Pension	Housing Subsidy
A. No interaction terms				
Network job	-0.023**	-0.038***	-0.055***	-0.039***
	(0.009)	(0.011)	(0.011)	(0.007)
Migration experience	0.004***	0.004***	0.006***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Number of cities	-0.005**	-0.006**	-0.010***	-0.005***
	(0.002)	(0.003)	(0.003)	(0.002)
B. With interaction terms				
Network job	-0.013	-0.029	-0.051***	-0.034***
	(0.016)	(0.018)	(0.019)	(0.013)
Network × Experience	-0.003*	-0.002	-0.002	-0.002*
	(0.002)	(0.002)	(0.002)	(0.001)
Network × Cities	0.008**	0.006	0.005	0.008**
	(0.004)	(0.005)	(0.005)	(0.003)
Migration experience	0.006***	0.005***	0.007***	0.002*
	(0.002)	(0.002)	(0.002)	(0.001)
Number of cities	-0.009***	-0.009***	-0.013***	-0.009***
	(0.003)	(0.003)	(0.004)	(0.002)
Observations	6,178	6,178	6,178	6,178
Controls	YES	YES	YES	YES
Year dummy	YES	YES	YES	YES

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: This table presents pooled OLS results on the effects of network job search on formal worker benefits. Panel A shows results without interaction terms, while Panel B includes interactions between network job search and migration experience variables. All regressions include controls for predetermined individual characteristics (marital status, number of children, years of schooling), location and industry indicators (industry, hosting city, hukou registered province), and a year 2009 dummy. Job-specific characteristics such as monthly income, company ownership type, and job contract terms are excluded to avoid potential endogeneity. Standard errors are clustered at the individual level.

Table 3: Pooled OLS Results: Network Job Search Effects on Informal Benefits and Wages

VARIABLES	(1) Accommodation	(2) Catering	(3) Monthly Income
A. No interaction terms			
Network job	0.045***	-0.009	-43.406**
	(0.013)	(0.012)	(17.987)
Migration experience	-0.000	0.001	13.927***
	(0.001)	(0.001)	(1.907)
Number of cities	0.016***	-0.003	24.231***
	(0.003)	(0.003)	(7.152)
B. With interaction terms			
Network job	0.065***	-0.013	-51.671
	(0.022)	(0.021)	(34.692)
Network × Experience	-0.003	0.000	0.853
	(0.002)	(0.002)	(3.140)
Network × Cities	0.001	0.001	-16.574
	(0.006)	(0.006)	(12.757)
Migration experience	0.002	0.001	13.777***
	(0.002)	(0.002)	(3.173)
Number of cities	0.015***	-0.004	32.309***
	(0.005)	(0.005)	(10.692)
Observations	6,178	6,178	6,178
Controls	YES	YES	YES
Year dummy	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: This table presents pooled OLS results on the effects of network job search on informal benefits. I also include its effect on monthly wages as a reference to its effect on monetary benefits. Panel A shows results without interaction terms between work experiences and the number of cities a migrant worker has worked in, while Panel B includes interactions. All regressions include controls for predetermined individual characteristics (marital status, number of children, years of schooling), location and industry indicators (industry, hosting city, hukou registered province), and a year 2009 dummy. Job-specific characteristics such as monthly income, company ownership type, and job contract terms are excluded to avoid potential endogeneity. Standard errors are clustered at the individual level.

The fixed effects results in Table 4 and Table 5 show that when controlling for

time-invariant individual characteristics through fixed effects, most significant associations observed in pooled OLS disappear, with only pension benefits retaining a strong negative relationship. This persistent negative effect indicates a more genuine effect of obtaining a job through networks on the coverage of pension benefits.

This contrast reveals that the pooled OLS results largely captured selection effects: workers who rely on networks systematically differ in unobserved characteristics that could affect their access to formal/informal benefits. Specifically, the direction of the selection bias suggests that workers who use networks tend to have characteristics that make them less competitive in formal labor markets—such as lower unobserved skills, weaker formal credentials, or limited access to formal job search channels. In summary, networks primarily matter through selection rather than direct causal effects on most benefit types.

Table 4: Fixed Effects Results: Network Job Search Effects on Formal Worker Benefits

	(1)	(2)	(3)	(4)
VARIABLES	Unemployment Insurance	Injury Insurance	Pension	Housing Subsidy
Network job	0.008	-0.045	-0.091***	-0.047*
	(0.041)	(0.038)	(0.034)	(0.028)
Network × Experience	-0.002	0.003	0.008**	0.001
	(0.004)	(0.004)	(0.003)	(0.003)
Network × Cities	-0.001	-0.004	-0.001	0.006
	(0.006)	(0.009)	(0.006)	(0.005)
Migration experience	-0.038	-0.029	0.005	-0.008
	(0.042)	(0.044)	(0.040)	(0.029)
Number of cities	0.012	-0.005	-0.000	-0.010
	(0.013)	(0.016)	(0.013)	(0.009)
Observations	2,768	2,768	2,768	2,768
R^2	0.056	0.037	0.054	0.079
Number of individuals	1,384	1,384	1,384	1,384
Individual FE	YES	YES	YES	YES

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: This table presents fixed effects results on the effects of network job search on formal worker benefits. All regressions include individual fixed effects and controls for predetermined individual characteristics (marital status, number of children, years of schooling), location and industry indicators (industry, hosting city, hukou registered province). Job-specific characteristics such as wages, company ownership type, and contract terms are excluded to avoid potential endogeneity. Standard errors are clustered at the individual level.

Table 5: Fixed Effects Results: Network Job Search Effects on Informal Benefits

| | (1) | (2) |
VARIABLES	Accommodation	Catering
Network job	-0.031	-0.011
	(0.043)	(0.041)
Network × Experience	0.003	0.002
	(0.004)	(0.003)
Network × Cities	-0.002	-0.000
	(0.010)	(0.009)
Migration experience	-0.097**	-0.110**
	(0.047)	(0.046)
Number of cities	0.033*	0.023
	(0.019)	(0.015)
Observations	2,768	2,768
R^2	0.097	0.072
Number of individuals	1,384	1,384
Individual FE	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: This table presents fixed effects results on the effects of network job search on informal benefits. All regressions include individual fixed effects and controls for predetermined individual characteristics (marital status, number of children, years of schooling), location and industry indicators (industry, hosting city, hukou registered province). Job-specific characteristics such as wages, company ownership type, and contract terms are excluded to avoid potential endogeneity. Standard errors are clustered at the individual level.

7   Addressing Sample Selection

In the main results, I discussed how individuals with particular unobserved characteristics selecting into using networks to secure jobs explains much of the negative relationship between worker benefits and network jobs. Here I examine another type

of selection—whether worker benefits affect the probability that individuals exit the sample. Specifically, do migrants who were present in survey cities during 2008 but left when the 2009 survey took place differ systematically based on their benefit provision? This attrition pattern could bias my main results if workers with certain benefit packages are more likely to leave the sample.

Sample attrition could bias my findings in several ways. If workers with better benefit packages are more likely to stay in survey cities (and thus remain in my panel), this could create an upward bias in the estimated effects of networks on benefits—I might underestimate the negative impact of networks if the workers with the worst network-job outcomes have already left the sample. Conversely, if workers with better benefits are more likely to return to rural areas (having achieved their savings goals), this could create a downward bias.

Following Equation 3, I use the worker benefit status to predict the probability of wage earners in the 2008 survey staying through the 2009 survey.

$$
\begin{aligned}
stay_i = {} & \alpha_0 + \alpha_1 UI_{i,2008} + \alpha_2 Injury_{i,2008} + \alpha_3 pension_{i,2008} \\
& + \alpha_4 housing_{i,2008} + \alpha_5 accommodation_{i,2008} + \alpha_6 catering_{i,2008} \\
& + \beta_1 exper1_{i,2008} + \beta_2 ncity_{i,2008} + \beta_3 wage_{i,2008} + X_{i,2008}\beta_4 + \mu_i
\end{aligned}
\tag{3}
$$

Table 6 presents both linear probability model and probit estimates of how 2008 benefit provision predicts staying in the 2009 survey. When controlling for monthly income and other characteristics, workers with pension benefits are significantly more likely to stay in the sample. Conversely, workers with accommodation benefits are less likely to remain in the sample, with accommodation provision reducing staying probability by 9 percentage points in the probit model with controls. All other form and informal benefits show no significant relationship with the probability of staying. These attrition patterns suggest limited bias in the main fixed effects results. The fact that workers with pension benefits are more likely to stay actually strengthens the main finding of a negative network effect on pensions—if anything, the panel analysis may underestimate the true negative impact of networks on pension provision, since workers with better pension packages are overrepresented in the continuing sample. The negative selection on accommodation (workers with ac-

commodation leaving the sample) could slightly bias the results, but since the fixed effects analysis found no significant network effect on accommodation anyway, this attrition pattern does not materially affect my conclusions.

Table 6: Effect of Worker Benefits on Probability of Staying

VARIABLES	(1) Linear Probability Model	(2) Probit Model
Unemployment insurance	-0.002	0.008
	(0.033)	(0.093)
Injury insurance	0.025	0.092
	(0.026)	(0.076)
Pension	0.106***	0.347***
	(0.028)	(0.082)
Housing subsidy	0.004	0.006
	(0.033)	(0.096)
Accommodation	-0.024	-0.090*
	(0.016)	(0.048)
Catering	0.024	0.088*
	(0.016)	(0.052)
Monthly income	1.67e-05	8.08e-05**
	(1.10e-05)	(3.36e-05)
Observations	4,805	4,794
R^2	0.111	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: This table presents results from regressions predicting the probability that 2008 wage earners remain in the 2009 survey. The dependent variable equals 1 if the worker appears in both surveys, 0 if they exit the sample. All regressions include controls for predetermined individual characteristics (marital status, number of children, years of schooling), migration experience, number of cities worked in, location and industry indicators (industry, hosting city, hukou registered province). Column (1) shows linear probability model results; column (2) shows probit marginal effects. Standard errors are robust.

8 Conclusion

This paper examines how job search methods affect worker benefit provision among rural-urban migrants in China, distinguishing between network-based and formal hiring channels. Using panel data from the 2008-2009 RUMiC survey, I find that the relationship between network job search and worker benefits is primarily driven by selection rather than causal effects. The comparison between pooled OLS and fixed effects—while pooled OLS shows strong negative associations between network hiring and formal benefits, most of these relationships disappear when controlling for individual fixed effects—indicates that workers who rely on networks are negatively selected. They tend to have unobserved characteristics that independently reduce their access to formal benefits, suggesting networks serve as an alternative pathway for workers who face disadvantages in formal hiring processes. The notable exception is pension benefits, where network job search maintains a significant negative effect even in fixed effects specifications. This persistent relationship suggests that network-based hiring genuinely channels workers into employment arrangements that systematically avoid long-term pension obligations, highlighting a specific area where network hiring has real consequences for worker welfare. The attrition analysis confirms that these findings are robust to sample selection concerns.

While networks provide valuable job search assistance for disadvantaged workers, they may also contribute to persistent informality in employment relationships, particularly regarding long-term benefits like pensions. This suggests that policies aimed at improving migrant worker welfare should address both the underlying disadvantages that make workers dependent on informal job search channels and the regulatory frameworks governing benefit provision in network-dominated sectors.

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Appendix

A. Data Cleaning and Detailed Sample Construction

A.1 Detailed Sample Construction Procedures

Panel Sample Construction For panel regressions, I begin with households that appear in both 2008 and 2009 surveys. However, household composition changes between waves as individuals leave cities or new members join households. I first identify individuals who can be matched across both surveys. Among matched individuals, I further restrict the sample to those who are wage earners in both years. This restriction excludes individuals who transition between wage employment and self-employment, as including them would confound the effect of job search methods with employment status changes. If individuals are wage earners in 2008 but become self-employed in 2009, assigning zero values to their worker benefit indicators would bias estimates toward finding negative effects of whatever job search method they used.

Cross-Sectional Sample Construction For pooled OLS regressions, I expand the panel sample to include wage earners from 2008 who left the sample by 2009, treating this as cross-sectional data with robust standard errors. Individuals who were never wage earners in either year remain excluded, as do new individuals who joined households only in 2009.

Attrition Analysis Sample For the probability of staying analysis, I use all 2008 wage earners and create an indicator for whether they appear in the 2009 survey. This tests whether initial benefit provision predicts sample retention.

A.2 Data Cleaning Procedures

Treatment of Missing Values

- **Migration experience (exper1):** Over 1,000 observations had missing values for initial migration year in 2009 despite valid responses in 2008. I imputed missing 2009 values by adding one year to the 2008 response, since this variable measures years since first migration. For 16 cases with conflicting non-missing values for "initial year of migration" across waves, I used the 2008 value for

consistency.

- **Number of children:** Over 500 missing values in 2009 were imputed using corresponding 2008 values.

- **Other variables:** For industry, number of cities worked in, province of origin, and monthly income, I used available non-missing values from either year when one was missing.

- **Scope:** These imputations were applied to samples using 2009 data (panel and pooled samples). No imputations were made for the 2008-only attrition analysis.

Correction of Inconsistent Values

- **Age:** 536 observations (268 individuals) had implausible age changes between surveys. I standardized all 2009 ages to equal 2008 age plus one year.

- **Gender and ethnicity:** A few individuals showed changes in gender or ethnicity between waves. Since these characteristics should remain constant, I used 2008 values for both years.

- **Number of cities (ncity):** Approximately 260 individuals had lower values in 2009 than 2008, which is impossible since this variable should only increase over time. For these individuals, I corrected 2008 values to match 2009 values.