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Profiling not-in-the-labor-force population: evidence from China

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ABSTRACT

This study challenges the conventional classification of 'Not in the Labor Force' (NIF) individuals as inactive in China's labour statistics. Using a two-year observation window, we find that several NIF subgroups – such as discouraged workers, individuals citing 'other reasons', and homemakers – exhibit substantial employment transition rates, in some cases comparable to those of standard unemployed individuals. We also provide direct evidence that some NIF individuals actively engage in job search. Building on these findings, we construct a variable-weight extended unemployment index that incorporates NIF individuals according to their likelihood of employment. This extended index improves the predictive power of labour market indicators for wages and GDP. The results call for a more inclusive approach to measuring labour market activity in China.

KEYWORDS

Unemployment; not in the labour force; labour market attachment; employment transition; China

JEL CLASSIFICATION

E24; J21; J64

I. Introduction

Labour is a vital economic resource. It is important to understand the rate of resource utilization in the labour market. Traditionally, the population who are 'not in the labor force' (NIF) is not considered a source of labour supply.[1] Official labour statistics typically define the NIF population as individuals who, during a given reference period, were not engaged in paid employment, or who were without work but available to start immediately and had actively searched for a job within the previous four weeks. As a result, the NIF group includes a mix of people: those who do not wish to work, those who are not currently searching but would accept a job if offered, and those who have searched for work but whose most recent job search activity occurred more than four weeks prior to the survey or differed from those specified by the survey.[2] Nonetheless, under standard statistical conventions, all individuals in the NIF category are classified as inactive and excluded from the labour force. Consequently, given the typical size of NIF, significant labour market activities may be overlooked, and the size of labour supply and labour market tightness and resource utilization understated.

This calls for more scrutiny of the labour market attachment of the NIF. Evidence from the previous studies suggest that, in Europe, Canada, and the U.S., some NIF individuals are similarly active to the typical unemployed and active job seekers (Brandolini, Viviano, and Cipollone 2006; Flinn and Heckman 1983; Hornstein, Kudlyak, and Lange 2014; Jones and Riddell 1999, 2006, 2019). Acting on these evidence, some statistics bureaus, such as the U.S. Bureau of Labour Statistics (BLS), have constructed and published complementary labour statistics in addition to the standard unemployment rates, such as the extended unemployment rate (U5) and the nonemployment index (NEI) of the U.S.

Nonetheless, in other countries, the labour force attachment of the NIF and its implication remains poorly understood. This paper focuses on China, the largest developing nation in the world. To date, China's labour statistics have been the subject of much controversy, including: (1) the absence of official labor force participation rate statistics; (2) the limitation of the official registerbased

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[1]This group is also referred to as 'out of the labor force' in the literature.

[2]For example, the NIFs may have 'passive search' activities, such as occasionally browsing job advertisements or even 'waiting' for emerging opportunities, which could also result in employment at some future moment (Coles and Smith 1998; Hall 1983; Riddell 2000) but are not specified by labour surveys as job search activities.

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unemployment rate;[3] and (3) the lack of clarity on the definition of job search in representative labour surveys. These limitations motivate recent research on alternative labour statistics to better signal the condition of the labour market (Sun 2024).

However, studies on the labour force attachment of NIF are still insufficient in China. In this paper, we address two related questions. Do NIF individuals truly lack engagement in job search activities? Furthermore, are there NIF persons who are similar to the unemployed (active job seekers)? A standard way to evaluate labour market classifications is to compare transition probabilities between different states. Following this *evidence-based* approach, we find that the NIF group in China has a significant probability of transition to employment, which is tantamount to 0.8 times that of a standard unemployed worker (U) on average. There are also significant differences in employment probabilities across different types of NIF individuals. Among them, the student/trainee group has the highest employment probability, which is 1.03 times that of standard unemployed individuals with similar characteristics. The 'discouraged' (DG) group ranks the second, with an employment probability 0.96 times that of their unemployed counterparts. Another notable NIF category is those citing 'other reasons' (OT) for non-participation, whose employment probability stands at 0.88 times that of comparable unemployed individuals. Even homemakers demonstrate a meaningful degree of labour market attachment, with an employment probability equal to 0.8 times that of standard unemployed individuals.

In the U.S., individuals classified as DG and OT are referred to as *marginally attached*. Research has found that their employment rates are comparable to those of the long-term unemployed, and roughly half those of the short-term unemployed (Hornstein, Kudlyak, and Lange 2014). Our findings indicate that, in China, the employment rates of DG and OT individuals are likewise similar to those of the unemployed. However, in contrast to the U.S. context – where such analyses are typically based on one-month observation intervals – our results are derived from a two-year observation window, thereby capturing more persistent and long-term dynamics in employment status.[4] Additionally, a novel finding of this study is that, in the Chinese context, homemakers constitute another group of marginally attached individuals, with a two-year employment transition rate reaching 80% of that of standard unemployed individuals. Although this rate is slightly lower than those of the OT and DG groups, it remains substantial and should not be overlooked.

Secondly, we show direct evidence that some NIFs really search for work. Exploiting information in the data on the job search method for currently employed workers, we show that the job search methods used by workers whose past status was NIF do not significantly differ from those who were standard unemployed workers in the past. Furthermore, we reveal a complex, multidimensional heterogeneity between NIF and U in labour market outcomes: there is no significant difference in the chance of transition to public-sector employment or employment with insurance; however, workers who were NIF earn less and work fewer hours than workers who were U; the probability of transition out of employment also differs significantly among workers with past NIF and U statuses.

Moreover, we explore the way to incorporate NIF into unemployment statistics. Consistent with previous studies (Kudlyak and Lange 2014), we find that past labour force status is a strong predictor of the probability of transition from the current nonemployment status to future employment status. Then, extending Hornstein, Kudlyak, and Lange (2014) and Sun (2024), we construct a variable-weight extended unemployment index, which includes NIF individuals into unemployment, with the weight of NIFs equal to the ratio of the probability of transition from NIF to employment to the probability of transition from U to employment, which is predicted using labour force status and worker characteristics and thereby

[3]The register-based unemployment rate only includes individuals registered with public employment agencies as unemployed. Since the registration rate is not one hundred percent, this statistic is considered inadequate for accurately reflecting the labour market's actual condition (Feng, Hu, and Moffitt 2017).

[4]Due to data limitations, we can only adopt the two-year interval in this paper. A concern is that NIF individuals at time t may enter unemployment before transitioning into employment at time t + 2, and their unemployment status may be captured by traditional unemployment measure between t and t + 2, in which case the traditional measure is sufficient. This issue warrants further investigation. Given the constraints of the current data, it will be addressed in future research.

varies in the population. This extended unemployment index exhibits superior predictive accuracy compared to the existing unemployment statistics in predicting China's wage and GDP dynamics.

The rest of the paper is organized as follows. Section II reviews the literature to highlight our contributions. Section III describes the data and the empirical strategy. Section IV presents the results. Section V concludes.

II. Literature

Until 2018, the official unemployment rates in China are register-based, which include only unemployed workers registered with the government. The existing literature primarily revolves around the under-coverage problem of the official unemployment statistics and improvement methods, such as including redundant and laid-off state-owned enterprise (SOE) workers (Solinger 2001, 2002) and using nationally representative labour surveys to compute the unemployment rate based on the international standard definition (Feng, Hu, and Moffitt 2017; Giles, Park, and Zhang 2005; Knight and Xue 2006). Since 2018, the official statistics bureau has finally commenced publishing unemployment rates (survey-based unemployment rate) derived from representative surveys that adhere to the international standard definition of unemployment.

However, the issue of labour market attachment of NIF individuals has not yet received sufficient attention in China, despite the widespread evidence in some other countries of significant similarities in probabilities of transition to employment between those who are conventionally defined as 'unemployed' and those who are conventionally classified as NIF (Brandolini, Viviano, and Cipollone 2006; Clark and Summers 1982; Ellwood 1982; Flinn and Heckman 1983; Gönül 1992; Hornstein, Kudlyak, and Lange 2014; Jones and Riddell 1999, 2006, 2019; Kudlyak and Lange 2014; Tano 1991). Accurately identifying labour market statuses is more than a matter of statistical classification or measurement – it has both political and policy implications. On one hand, unemployment figures are a highly sensitive subject in public discourse. On the other, effective economic and monetary policymaking depends on a nuanced understanding of labour market conditions. While labour market tightness has traditionally been gauged by the number of unemployed individuals, theoretical insights suggest that it also depends on the presence of 'less-intensive' job seekers. Previous research on labour market matching processes emphasizes that hiring rates are influenced not only by those officially unemployed but also by individuals outside the labour force, who may have a lower probability of securing employment compared to the unemployed (see, e.g. Broersma and Van Ours 1999; Mumford and Smith 1999).

Realizing that neglecting NIF individuals would overlook crucial labour market insights, researchers and statistical bureaus are actively exploring alternative unemployment statistics. For instance, the U.S. Bureau of Labour Statistics (BLS) has consistently reported the extended unemployment rate (U5), which broadens the definition of unemployment to include marginally attached individuals (those discouraged or for other reasons). Furthermore, the Federal Reserve Bank of Richmond publishes the nonemployment index (NEI) for the U.S. on a monthly basis, wherein NIF individuals are weighted based on their probability of transitioning to employment relative to that of standard U individuals (Hornstein, Kudlyak, and Lange 2014).

In China, research in this area remains relatively scarce. As a valuable attempt, Sun (2024) constructs alternative unemployment statistics for China, encompassing the U5 and the NEI. That study provides a first demonstration of the value of reclassifying NIF individuals, which proves to be a direction worth further exploration. In this study, we delve into a recent dataset that provides an opportunity to investigate and compare labour market attachment between U and subgroups of NIF for China.

III. Empirical strategy

Data

In this paper, we use data from China Family Panel Studies (CFPS) that cover the period 2012–2022. CFPS is a representative longitudinal household survey conducted biannually since 2010 by the Institute of Social Science Studies at Beijing

University (a.k.a. Peking University). Drawn using a nationally representative stratified design, the CFPS samples cover between 25 and 31 provinces, which account for 94.5% to 100% of China's population on the mainland.[5]

Table 1(A) describes the demographic characteristics of the sample. The sample covers all six regions (North, Northeast, East, Middle/South, Middle/West, West).[6] The percentage of the urban population is 48%. The average age of the sample is 44.91 years. The percentage of the male population is 49.8%. As for the educational composition, 45.7% of the sample has primary (or below) education, 28.6% of the sample has middle school education, 14.8% of the sample has high school education, and 10.8% of the sample has college (or above) education.

The CFPS surveys have a rich number of questions regarding labour force status, structured following the conventional international standard practice (Figure 1).[7] The questions start with 'Have you worked for at least one hour last week?' and end with 'Why are you currently not working?' Compared to other surveys, one advantage of the CFPS is its more detailed investigation of employment status. When identifying respondents' employment status, the CFPS not only asks whether they are currently working but also further inquires whether those who are not working at the moment are on leave, in the off-season, or in an agricultural off-period. When distinguishing between unemployment (actively seeking work) and labour force withdrawal (ceasing labour supply), the CFPS not only asks respondents whether they are looking for a job but also inquires whether they would be able to start working within a short time if a job opportunity arose. According to the CFPS guidelines, a respondent is considered unemployed only if they answer affirmatively to both questions. These features enable the CFPS to arguably more accurately reflect respondents' labour supply status and intentions.

Table 1(B) shows the labour force status of the working age population in the sample. On average, 85.6% of the working age sample are employed, 1.6% are unemployed by the standard definition (U), and 12.8% are NIF.

Table 1. Summary statistics of the sample.

	Obs.	Mean	S.D.	Min.	Max.
(A) Demographic characteristics					
North	202,022	0.118	0.323	0	1
Northeast	202,022	0.127	0.333	0	1
East	202,022	0.196	0.397	0	1
Middle/South	202,022	0.28	0.449	0	1
Middle/West	202,022	0.123	0.329	0	1
West	202,022	0.152	0.359	0	1
Urban	194,127	0.48	0.499	0	1
Age	202,606	44.91	18.37	9	104
Male	202,628	0.498	0.5	0	1
Primary education	198,217	0.457	0.498	0	1
Middle school	198,217	0.286	0.451	0	1
High school	198,217	0.148	0.355	0	1
College	198,217	0.108	0.31	0	1
(B) Labor force status of the working age population					
Employed (E)	121,571	0.856	0.351	0	1
Unemployed (U)	121,571	0.016	0.124	0	1
Not in the labor force (NIF)	121,571	0.128	0.334	0	1

Sources: CFPS 2012–2022.
Working age population refers to men between age 16 and 60 and women between age 16 and 55.

[5]The CFPS adopts a stratified, three-stage probability sampling design with probability proportional to size (PPS). In the first stage, counties are selected; in the second stage, residential communities within those counties are sampled; and in the third stage, household samples are drawn from these communities or village committees. This sampling framework ensures that the final sample is representative in terms of both economic development levels and geographical distribution. The description of sampling frame can be found on CFPS homepage http://www.isss.pku.edu.cn/cfps/.

[6]The North region includes Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia. The Northeast region includes Liaoning, Jilin, and Heilongjiang. The East region includes Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, and Shandong. The Middle/South region includes Henan, Hubei, Hunan, Guangdong, Guangxi, and Hainan. The Middle/West region includes Chongqing, Sichuan, Guizhou, Yunnan, and Tibet. The West region includes Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

[7]The questions in the 2010 wave are substantially different and incomparable with the subsequent waves. Thus, we exclude the 2010 wave from the analysis.

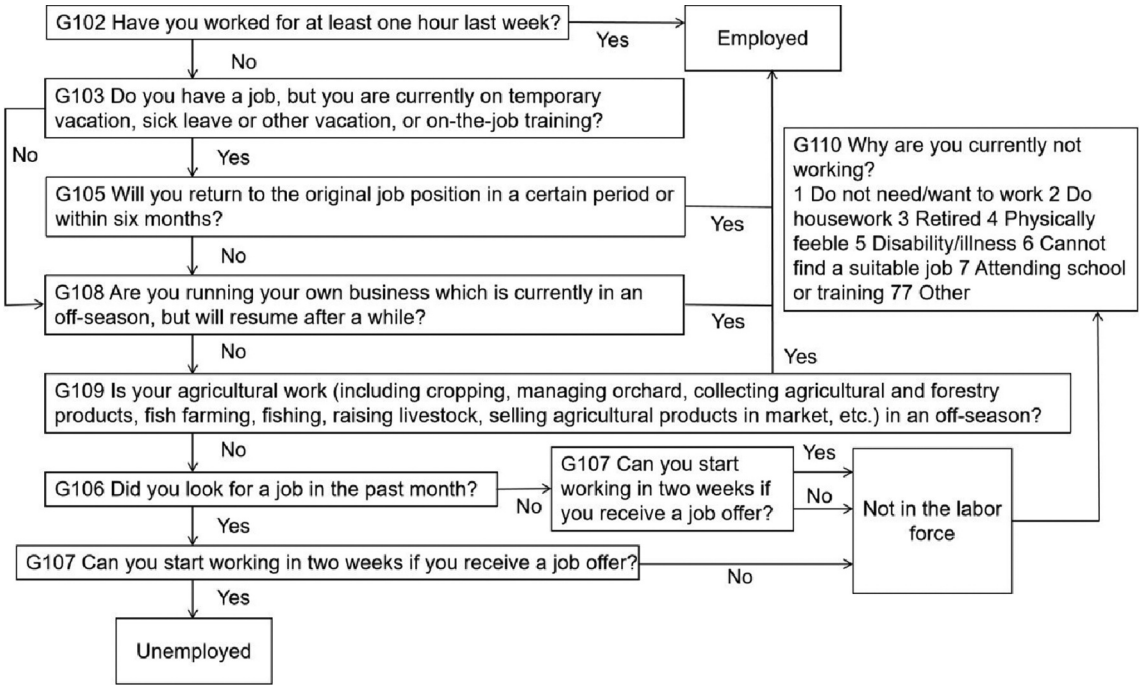


Figure 1. Labour force status survey questions in CFPS. CFPS 2012–2022.

The NIF group is often overlooked in previous studies. However, the difference between the labour market attachment of U and NIF turns out to be the dominant force driving the movement in unemployment in this period (see Section A.1 in the Online APPENDIX), highlighting the importance of understanding the nonemployed population and the labour market attachment of its various subsets. To do so, we turn our attention to data with which we can identify those on the margins between unemployment and non-participation.

Reasons for NIF

Another advantage of the CFPS is that it further investigates the reasons why respondents have withdrawn from the labour supply. The reasons are classified into the following eight categories: 'Do not need/want to work' (NoNeed/Want, or NN/W), 'Do housework' (Homemaker, or H), 'Retired' (RT), 'Physically feeble' (F), 'Disability/illness' (Disabled/Ill, or DI), 'Cannot find a suitable job' (Discouraged, or DG), 'Attending school or training' (Student/Trainee, or S/T), and 'Other' (Other, or OT). These data make it possible for us to uncover the heterogeneity among respondents.

Figure 2 illustrates the distribution of labour force status in subpopulations defined by age groups and gender, region and education. As shown in the figure, regardless of gender, urban-rural status, or education level, employment rates generally decline with age. Among the non-employed labour force, the proportion of individuals classified as unemployed also tends to decrease slightly with age. In other words, the primary reason for the decline in employment rates with age is that more non-employed individuals choose to exit the labour market.

Figure 3 illustrates the differences between men and women in their reasons for exiting the labour market. For men, the top three reasons are 'disable/ill', 'discouraged', and 'other'. For women, the dominant reason is 'homemaker'. Interestingly, the share of 'homemaker' is increasing for men in this period, suggesting changes in domestic division of labour.

Figure 4 illustrates the disaggregation of the distribution of reasons for being NIF across different gender, education, urban-rural areas and by age groups. For highly educated workers, the primary reason for exiting the labour market before the age of 21—regardless of urban or rural residence or gender – is education or training. For male

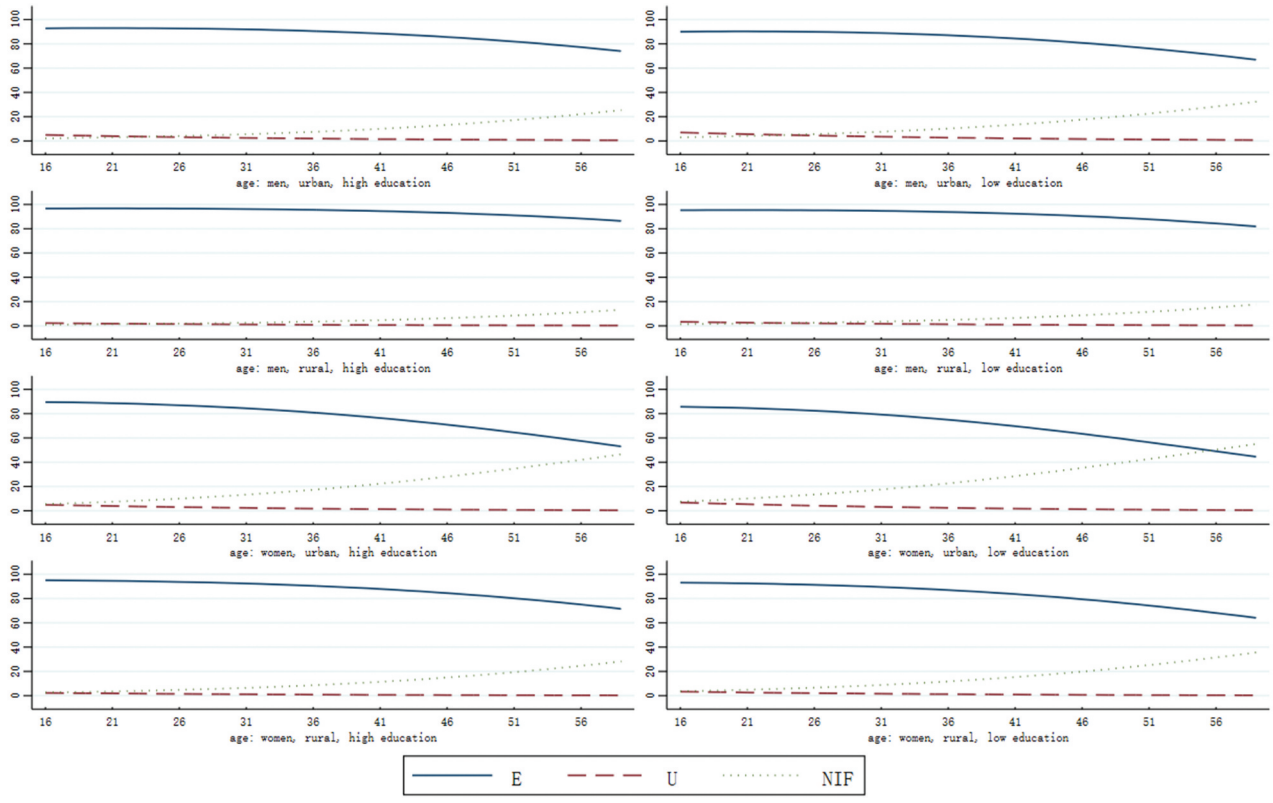


Figure 2. Labor force status: subpopulations. CFPS 2012–2022. Population weights are used. E: employed; U: unemployed; NIF: not in labor force.

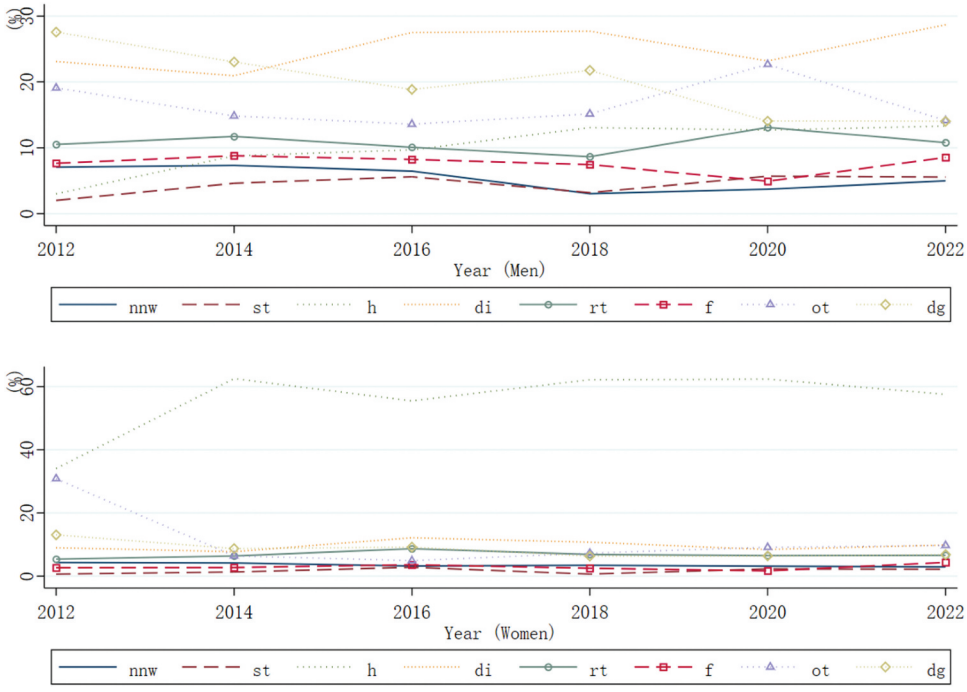


Figure 3. Reasons for NIF. CFPS 2012–2022. NIF: not in the labor force. Working-age population is defined as men between 16 and 60 years of age and women between 16 and 55 years of age. Population weights are used. nnw: do not need/want to work; st: student/trainee; h: homemaker; di: disabled/ill; rt: retired; f: physically feeble; ot: other; dg: discouraged.

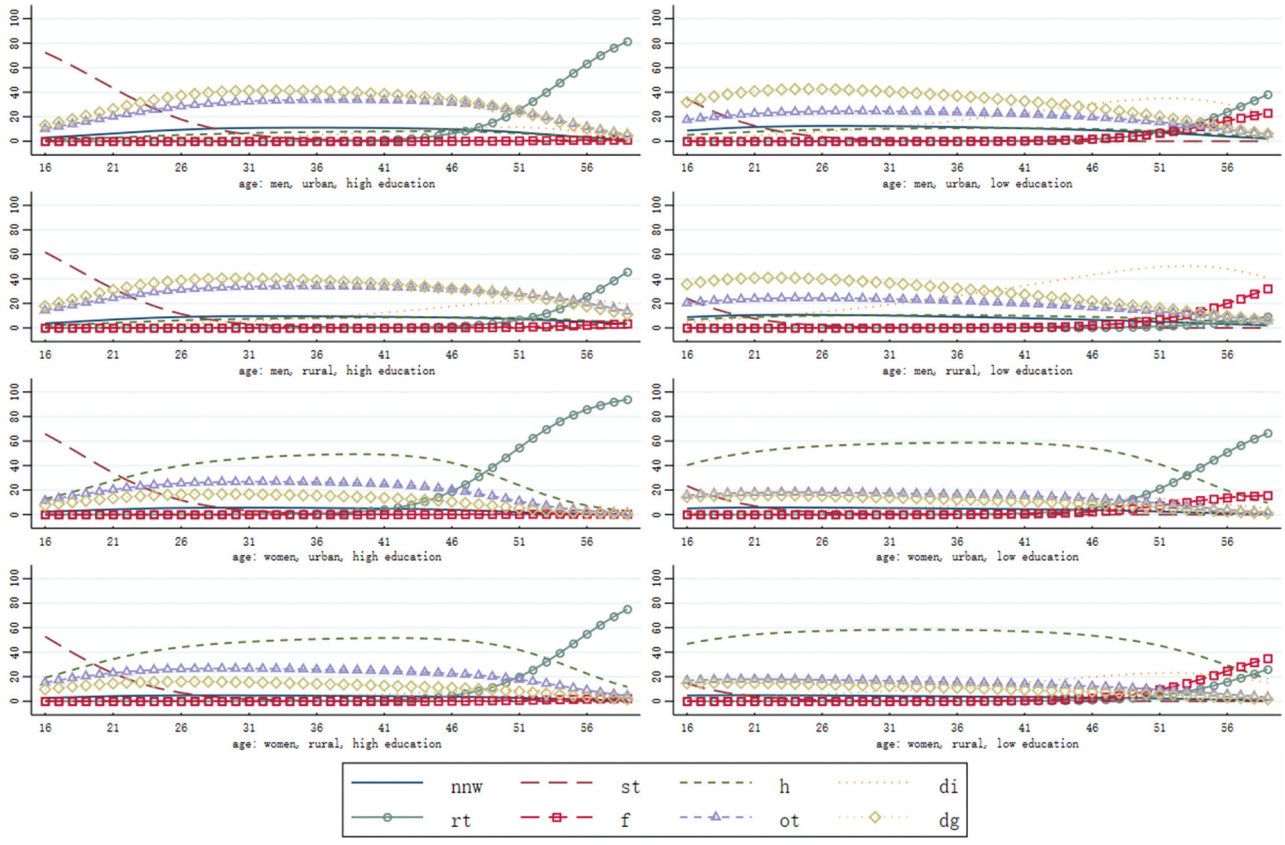


Figure 4. Reasons for NIF: subpopulations. CFPS 2012–2022. Population weights are used. nnw: do not need/want to work; st: student/trainee; h: homemaker; di: disabled/ill; rt: retired; f: physically feeble; ot: other; dg: discouraged.

workers, the main reasons for leaving the labour force during the prime working age of 21 to 51, regardless of location or education level, are 'discouraged' and 'other reasons'. In contrast, for female workers, the leading reason for exiting the labour market during the prime working years is 'homemaker', followed by 'other reasons' and 'discouraged'. Additionally, for all low-educated male workers and highly educated male workers and low-educated female workers in rural areas, disability/illness becomes a relatively important reason for exiting the labour market after the age of 40.

Methodology: an evidence-based approach

The conventional approach to classification of labour force states – and in particular to the separation between participation and non-participation of the nonemployed – is based on a priori reasoning about what constitutes sufficient labour market attachment. Two a priori beliefs are embedded in the ILO guidelines followed by surveys in many countries, including the CFPS in China: (i) job search and (ii) availability for work. From this perspective, individuals simply having a desire for a job or a willingness to work if suitable employment becomes available are not regarded as demonstrating sufficient evidence of active job search to be classified as unemployed.

However, this a prior reasoning may overlook some potential labour supply intentions and actions. For example, people who are 'waiting', such as waiting for appropriate job openings or responses to earlier applications, may become employed at some future moment (Coles and Smith 1998; Hall 1983; Riddell 2000). Previous studies thus advocate the evidence-based approach to the classification of labour force states (Hornstein, Kudlyak, and Lange 2014; Jones and Riddell 1999, 2006, 2019). Rather than relying on a priori reasoning, this approach uses subsequent labour market outcomes, such as employment, to assess the behavioural content of current labour

force statuses. Specifically, if an NIF individual at time t is observed to be employed at some future time t', it suggests that this NIF individual has engaged in job search activity. The rationale is that job search effort is necessary for the transition to employment after a certain length of time, i.e. employment doesn't just fall from the sky. According to this approach, such an NIF individual should be considered similar to a standard unemployed worker, with the degree of similarity measured by the proportion of employment probabilities of the two types of individuals.

We adopt this approach in this paper. The following analysis is based on estimating this model:

$$\Pr(Y_{t+2} = E|Y_t = j, X_t) = f(Y_t, X_t) \qquad (1)$$

where $\Pr(Y_{t+2} = E|Y_t = j, X_t)$ denotes the probability of transition from labor force status j (Y_t) to employment (Y_{t+2}) between t and t + 2 for workers with characteristics X_t.[8] The categories of status are j ∈{E, U, NN/W, S/T, H, DI, RT, F, OT, DG} or j ∈{E, U, NIF} (where NIF ≡{NN/W, S/T, H, DI, RT, F, OT, DG}) depending on the analysis.

Positive $\Pr(Y_{t+2} = E|Y_t = j, X_t)$ for j = NIF is an indicator of non-zero search intensity of NIF. Furthermore, if $\Pr(Y_{t+2} = E|Y_t = j, X_t)$ for j = NIF is similar to $\Pr(Y_{t+2} = E|Y_t = j, X_t)$ for j = U, it implies that NIF is similar to U in labour market attachment.

Following Jones and Riddell (2006), Equation (1) is estimated using a multinomial logit model. In the baseline specification, X includes demographic characteristics (gender, age, education) and regional characteristics (urban/rural, region) and year dummies. In particular, the year dummies control the effects of special periods; for instance, the dummy variable for 2020 accounts for the impact of the COVID-19 pandemic.

The analysis requires to link period t status to period t + 2 status. Like other panel datasets, the CFPS also faces the issue of attrition. As reported in Table A.1, the attrition rate between consecutive waves is from the low teens to the thirties in percentage terms. Across all waves, only 26.39% of the baseline 2010 wave sample is tracked in all consecutive waves.

If Y_t is systematically linked to attrition, it may bias our estimates. To address this concern, we not only condition on demographic and regional characteristics X, which correlate with attrition rate, but also incorporate in the analysis the panel weight provided in CFPS data set, which is designed to adjust the distribution of the sample that is tracked in all waves to represent the population distribution in baseline year 2010.

To see the effect of this adjustment, we conduct a simple analysis where we regress the indicator of attrition between consecutive waves on current labour force status dummies and covariates X and incorporate the panel weights. The result presented in Table A.2 shows that the labour force status dummies have no joint statistical power in predicting sample dropouts. Thus, sample attrition does not pose a great concern, once we condition on X and incorporate the panel weights. In the following analysis, we thus use the sample that is tracked in all surveys, including 8866 individuals.

IV. Results

Probabilities of transition from U and NIF to employment

We first compare the probability of transition from unemployment and NIF to employment. For this, we estimate $\Pr(Y_{t+2} = E|Y_t = U)$ and $\Pr(Y_{t+2} = E|Y_t = NIF)$ from Equation (1) with status categories coded as j ∈{E, U, NIF} and averaged over covariates. The sample is restricted to men between 16 and 57 years of age and women between 16 and 52 years of age at time t. The result in Figure 5 shows that NIF has a significant probability of transition to employment which, averaged at 59.5% over the 2-year observation periods, is tantamount to a substantial 0.8 times that of a U worker.

We then investigate if different NIF reasons embody different and corresponding levels of job search intensity. For this, we estimate Equation (1) with status categories coded as j ∈{E, U, NN/W, S/T, H, DI, RT, F, OT, DG}. Figure 5 shows that all types of NIFs have significant probability of transition to employment. The employment probability is the lowest for a retired individual (28.1%),[9] and

[8]For the sake of convenience, this probability will hereafter be referred to as the 'probability of transition to employment' or just 'employment probability'.
[9]Because we restrict the sample to individuals below legal retirement age, 'retired' here is considered 'early retirement'.

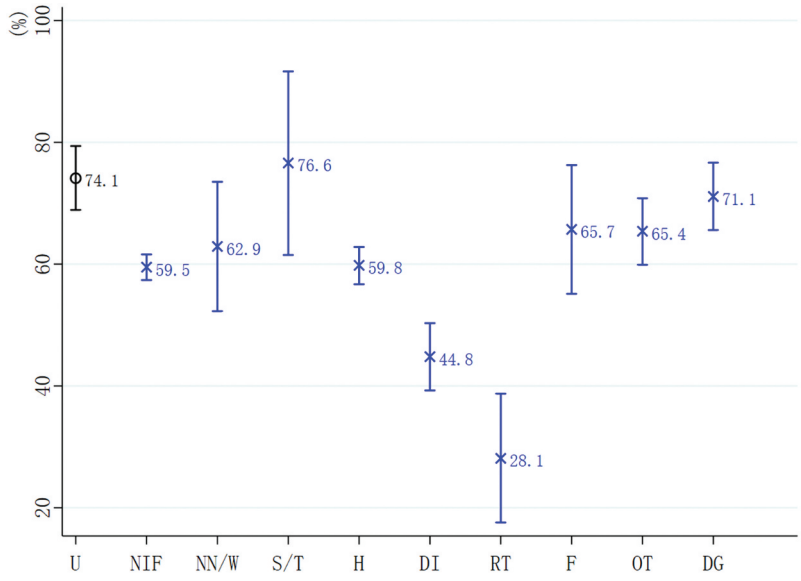


Figure 5. Probabilities of transition from U and NIF to employment in 2 years. Sources: CFPS 2012–2022. Note: On the vertical axis is $p_{j,E'}$ which denotes the probability of transition from status j (x-axis) to status E (employment) in the time frame of 2 years between t and t+2. Probabilities are estimated using multinomial logit model. Covariates include gender, age, education, urban, region, and year dummies. 95% confidence intervals are plotted as vertical spikes. Sample is restricted to men between 16 and 57 years of age and women between 16 and 52 years of age at time t. Panel weights are used. U: unemployed; NIF: not in labor force; NN/W: do not need/want to work; S/T: student/trainee; H: homemaker; DI: disabled/ill; RT: retired; F: physically feeble; OT: other; DG: discouraged.

highest for a student/trainee (76.6%, even higher than that of U). Interestingly, an individual who reports 'not need or want to work' (no willingness) or too feeble to work (no capacity) still has over 60% chance of transition to employment, suggesting that even these NIF individuals are not entirely ceasing supplying labour.

The other types of NIF are of particular interest. For women, the most interesting category is homemaker, which accounts for about 60% of NIF women. For men, the interesting categories are the top three NIF reasons: disabled/ill, discouraged, other. All these types of NIF have significant employment probabilities, which are 59.8% for homemaker, 44.8% for disabled/ill, 71.1% for discouraged, and 65.4% for 'other', on average.

Such probabilities are also significant relative to U for subpopulations and subperiods. Figure 6 Panel (A) illustrates that the ratio of employment probability of homemakers relative to active job seekers U for women is around 0.7 throughout the period and slightly higher in the rural areas than in the urban areas. Panel (B) shows that the ratio of the employment probability of disabled/ill workers relative to U for men is also around 0.7 throughout the period and slightly higher in the rural areas than in the urban areas. Panel (C) illustrates that the ratio of employment probability of 'other reason' NIF workers relative to U for men is higher, at over 0.9 throughout the period. Panel (D) illustrates that the ratio of employment probability of discouraged workers relative to U for men is still higher, at around or over 1 throughout the period, suggesting that the so-called 'discouraged' workers are similar to active job seekers.[10]

Figure 7 further illustrates the relative employment probabilities of NIF compared to U across different age groups. In general, the relative employment probabilities are higher in the rural areas than in the urban areas for all age groups. Furthermore, high education slightly lowers the relative probability for young workers and raises it for older workers in both the rural and the urban areas. Apart from that, there is little difference between high-educated and low-educated workers.

The relative employment probabilities monotonically decline over age for all regions and education levels. For young homemaker women, the

[10]Notably, the results at $t = 2020$ are not significantly different from other time periods, suggesting that the COVID-19 shock did not have a lasting impact on labour market dynamics.

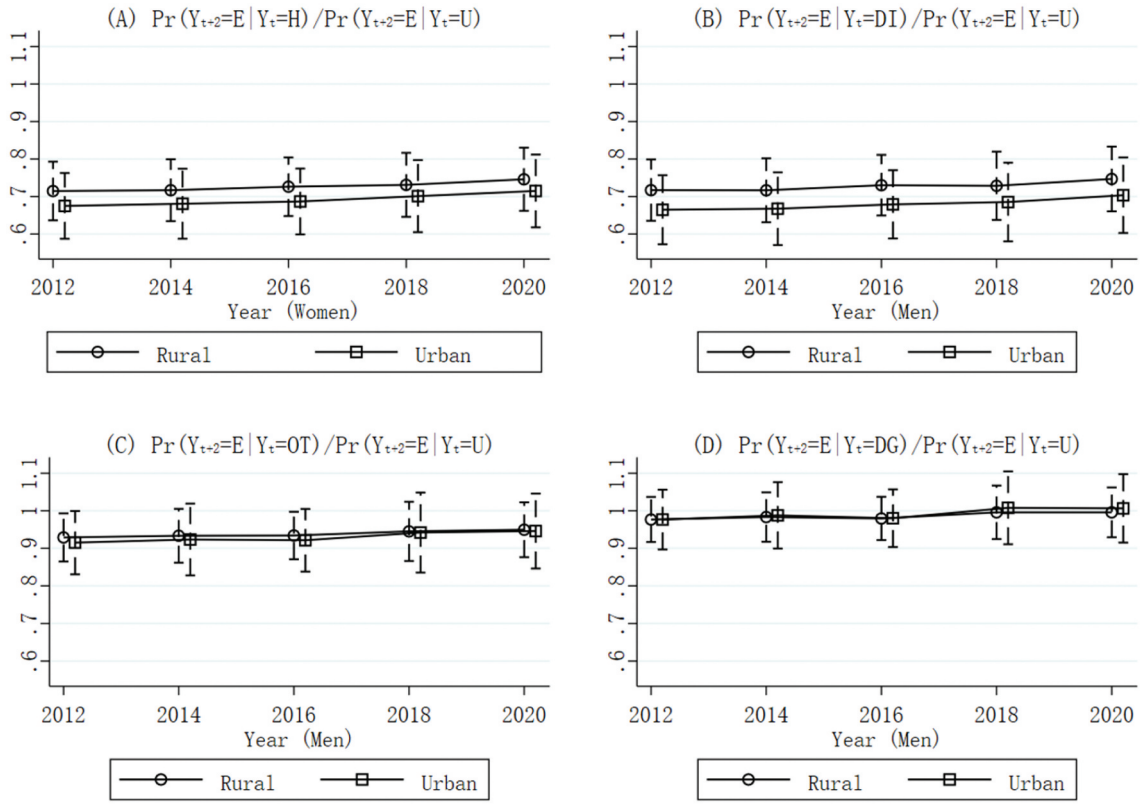


Figure 6. Probabilities of transition to employment in 2 years, NIF relative to U. Sources: CFPS 2012–2022. Note: Probabilities are estimated using multinomial logit model. Covariates include gender, age, education, urban, region, and year dummies. 95% confidence intervals are plotted as vertical spikes. Sample is restricted to men between 16 and 57 years of age and women between 16 and 52 years of age at time t. Panel weights are used. U: unemployed; NIF: not in labor force; H: homemaker; DI: disabled/ill; OT: other; DG: discouraged.

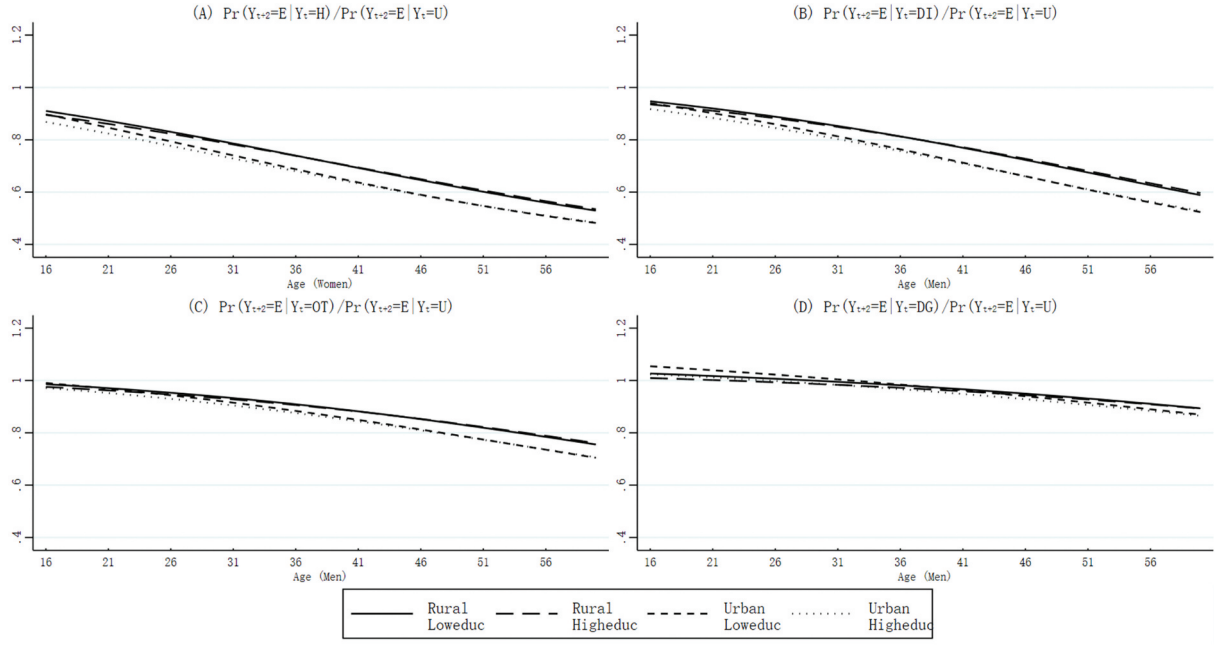


Figure 7. Probabilities of transition to employment in 2 years, NIF relative to U, by age groups. Sources: CFPS 2012–2022. Note: Probabilities are estimated using multinomial logit model. Covariates include gender, age, education, urban, region, and year dummies. Panel weights are used. U: unemployed; NIF: not in labor force; H: homemaker; DI: disabled/ill; OT: other; DG: discouraged.

probability of transition to employment is over 80% of that for a standard unemployed woman of the same characteristics up to age 25. After that age, the employment probability of homemaker women declines to less than 50% of that for a standard unemployed woman of the same characteristics.

The patterns of relative probabilities for disabled/ill men and 'other reason' NIF men are much like that for homemaker women, except that the relative probabilities are higher. For disabled/ill men, the probability of transition to employment is over 80% of that of a standard unemployed man of the same characteristics up to age 30, and declines to 60% or a little under afterwards. Young 'other reason' NIF men show even higher labour market attachment, evidenced by their probabilities of transition to employment that are over 90% of a standard U for men under age 35, and the ratio is still over 80% for men under age 50 in the rural areas and men under age 45 in the urban areas.

The young 'discouraged' men show still higher labour market attachment, evidenced by the probability of transition to employment that exceeds that of a standard U for men under age 30 for all rural-urban regions and high-low education levels. This ratio declines over age, but remains over 80% for all age up to 60. Unlike 'homemakers', 'disabled/ill' and 'other reason' NIFs, for 'discouraged' men, the relative probability of transition to employment is higher in urban than rural areas for younger workers before age 35, and for older workers with either education level, the relative employment probabilities in urban and rural areas begin to converge.

Do (some) NIFs really search for work?

In this section, we provide direct evidence that some NIFs do search for work. Since the 2014 survey, CFPS data contain information on the search method leading to current employment, i.e. how does an employed individual land his/her current job, which has six categories: 'contact employer directly' (self-search), 'job agency; career expo; job posting/ads. through media' (formal search), 'national/organizational allocation' (institutional assignment), 'relatives/friends/acquaintances' (informal search), 'school/university (or the career center therein)' (campus career services), and 'other'.

Using these information, we construct asubsample of 22,584 person-year observations, which includes individuals tracked in all surveys and individuals tracked in some surveys. On average, aworker uses 1.03 search methods to land his/her job, with minimum value 1, maximum value 5, and standard deviation 0.18.

Table 2 reports the relative popularity of each search method. It can be seen that informal search is the most popular method: 41.39% of the workforce uses informal search as the main method, and 41.9% of the workforce ever used this method. The next popular method is self-search: 33.33% of the workforce uses self-search as the main method, and 34.29% of the workforce ever used this method. The third popular method is formal search: used by 14.47% of workers as main method and by 15.21% of workers as one of the methods ever used. The other methods are used by only a small fraction of workers.

Using these information, we match a worker's previous labour status and search method to test if people who transition from NIF to employment actually uses any search method, and if the search methods used by people in subsets of the NIF state are different. Specifically, we run the following regression:

$$Y_t = c + \sum_{j \neq k}^{J} \beta_j 1(S_{t-2} = j) + \beta_X X_t + e_t \quad (2)$$

where Y_t denotes the number of search method used by an individual who is employed at time t,

Table 2. Percent of the working population using each search method.

	Main	Ever used
Self-search: Contact employer directly	33.33	34.29
Formal search: Job agency; career expo; job posting/ads. through media	14.47	15.21
Institutional assignment: National/organizational allocation	4.39	4.42
Informal search: Relatives/friends/acquaintances	41.39	41.90
Campus career services: School/university (or the career center therein)	2.36	2.50
Other	4.06	4.09

Sources: CFPS 2014–2022.
Search method refers to the method a currently employed person uses to land the job.

$1(S_{t-2} = j)$ is a dummy variable indicating that this individual's labour force status at time t − 2 is j, which is one of a total number of J statuses except a benchmark status k, and X_t denotes covariates. We can then test if people in a benchmark status k are different from people in other statuses $j \neq k$ in the number of search method used to land the current job (a measure of search effort) by testing if $\beta_j = 0$.

It should be noted beforehand that β_j is conditional on being employed at time t. It is totally possible that β_j is different for those who are not employed at time t. However, rejecting $\beta_j = 0$ or not for β_j estimated from the currently employed sample can still be informative that at least some (if not all) NIFs are different from U or not in their job search effort.

Table 3 reports the regression results. Only the early retired individuals use significantly fewer search methods than U without controlling for personal characteristics (column (1)), and no one uses significantly fewer search methods than U once controlling for personal characteristics (column (2)).

Columns (3)-(6) report the results for men/women and rural/urban separately. For both men and women, the NIFs are not significantly different from U in the number of search method used to secure the current employment. For the rural areas, only students/trainees use significantly smaller number of search method than U to secure the current employment, whereas no significant differences are found in the number of search method to secure the current employment between NIFs and U for the urban areas.

Besides the number of search methods used, are U and NIF different in the type of search methods used to secure the current employment? To see this, we next use the multinomial logit model to estimate $\Pr(Y_t = l | S_{t-2} = j, S_t = E)$, where Y_t is now a categorical variable of the main search method used and l represents one of the six search methods. This probability represents the fraction of the users of method l among the population who transition from status j to status E between t − 2 and t.

The results are presented in Table 4. For both U and NIFs, the top two main methods of job search that lead to the current employment are self-search and informal search. Compared to U, the

Table 3. Differences in the number of search method used across labour force statuses.

Y : number of search method used to land the job at time t						
	All (1)	All (2)	Men (3)	Women (4)	Rural (5)	Urban (6)
S_{t-2}(omitted category: Unemployed/U)						
Employed (E)	−0.012	−0.012	−0.003	−0.025	−0.034	−0.006
	(0.019)	(0.019)	(0.023)	(0.032)	(0.051)	(0.019)
NotNeed/Want to work(NN/W)	−0.039	−0.038	−0.024	−0.044	−0.058	−0.029
	(0.018)**	(0.019)*	(0.024)	(0.031)	(0.049)	(0.019)
Student/Trainee(S/T)	0.133	0.139	0.153	0.123	−0.054	0.205
	(0.120)	(0.126)	(0.190)	(0.168)	(0.048)	(0.166)
Homemaker(H)	−0.033	−0.032	−0.012	−0.044	−0.061	−0.021
	(0.019)*	(0.019)	(0.023)	(0.032)	(0.053)	(0.019)
Disabled/Ill(DI)	−0.039	−0.032	−0.022	−0.045	−0.055	−0.023
	(0.018)**	(0.019)*	(0.023)	(0.031)	(0.052)	(0.019)
Retired(RT)	−0.003	0.007	−0.014	0.018	−0.069	0.021
	(0.040)	(0.040)	(0.023)	(0.067)	(0.061)	(0.042)
Feeble(F)	−0.039	−0.024	−0.021	−0.026	−0.051	−0.017
	(0.018)**	(0.023)	(0.023)	(0.035)	(0.055)	(0.020)
Other(OT)	−0.014	−0.014	−0.027	−0.010	−0.060	0.002
	(0.023)	(0.024)	(0.022)	(0.039)	(0.050)	(0.027)
Discouraged(DG)	−0.018	−0.017	−0.013	−0.023	−0.061	−0.005
	(0.022)	(0.022)	(0.024)	(0.037)	(0.050)	(0.024)
Constant	1.039	1.046	1.027	1.070	1.078	1.030
	(0.018)***	(0.022)***	(0.028)***	(0.034)***	(0.050)***	(0.024)***
Controls	N	Y	Y	Y	Y	Y
Sample size	7,175	6,964	3,742	3,222	2,582	4,382
R squared	0.0036	0.0107	0.0112	0.0202	0.0130	0.0150

Sources: CFPS 2014–2022.

Standard errors (clustered at personal level) are in parentheses. Significance level: ***1% **5% *10%. Sample is restricted to currently employed workers. Panel weights are used. Controls include gender, age, education, urban, region, and year dummies.

Table 4. Differences in the type of search method used across labour force statuses.

Probability (percent) that the main method is *I*						
I =	Self-search	Formal search	Institutional assignment	Informal search	Campus career services	Other
U	30.3	16.3	3.9	44.4	1.6	3.2
	(4.0)***	(2.5))***	(2.2)*	(3.9)***	(1.1)	(1.3)**
NN/W	*52.1*	10.5	*1.2e-6*	31.5	3.6e-7	5.7
	*(11.9)****	(5.1)**	*(9.5e-7)*	(11.7)***	(1.7e-7)**	(4.4)
S/T	*58.8*	9.3	0.6	*27.5*	3.6	*9.5e-7*
	*(10.3)****	(4.9)*	(0.6)	*(9.1)****	(3.2)	*(3.4e-7)****
H	35.1	12.7	0.5	45.4	2.5	3.6
	(3.5) ***	(3.2)***	(0.5)	(3.8) ***	(1.7)	(1.3) ***
DI	40.5	*3.3*	4.9	40.9	3.3e-6	10.2
	(8.0)***	*(2.9)*	(2.9)*	(8.0)***	(1.5e-6)**	(4.4) **
RT	31.4	15.5	2.6	38.1	5.1	6.9
	(6.5)***	(6.0)**	(1.6)	(6.6)***	(2.8)*	(2.5)***
F	27.3	22.4	5.6	37.4	2.0e-6	7.1
	(7.9)***	(11.0)**	(2.9)*	(8.3)***	(1.1e-6)*	(4.1)*
OT	33.4	14.6	5.3	41.0	3.9e-7	5.4
	(4.9)***	(3.3)***	(1.8)***	(5.3)***	(1.0e-7)***	(3.3)
DG	32.4	13.9	3.6	46.2	0.3	3.2
	(4.6)***	(3.9)***	(2.8)	(4.9)***	(0.3)	(1.8)*

Sources: CFPS 2014–2022.

Probabilities are estimated using multinomial logit model. Standard errors (clustered at personal level) calculated using the delta method are in parentheses. Significance level: ***1% **5% *10%. "e-k" refers to $\times 10^{-k}$. Sample is restricted to currently employed workers. Panel weights are used. U: unemployed; NN/W: do not need/want to work; S/T: student/trainee; H: homemaker; DI: disabled/ill; RT: retired; F: physically feeble; OT: other; DG: discouraged. The italic font denotes that the probability is significantly (at less than 10% level) different from that for U of the same column. Controls include gender, age, education, urban, region, and year dummies. Sample size: 6,964.

percentages of users of each main search method are not significantly different for homemakers, early retired workers, feeble workers, discouraged workers, and 'other reason' NIF workers who transition to employment.[11] Some significant differences exist for not-need-or-want-work NIF workers who are less likely to use institutional assignment and more likely to use self-search, students/trainees who are less likely to use informal search and more likely to use self-search, and disabled/ill workers who are less likely to use formal search as the main search method that leads to their transition to employment.

In sum, these results highlight the similarities and differences in job search activities between U and NIFs who transition to employment.[12] The results provide evidence that NIFs who transition to employment have job search behaviours that, in many aspects, are not significantly different from the job search activity of workers who transition from U to employment.[13]

Identifying the marginally attached

These results suggest that there are marginally attached workers within the NIF population who are previously overlooked. An interesting question to follow up is how to better identify them from survey information, especially in the absence of direct measures of search intensity.[14]

Labor force status history and employment transition probability One way suggested in the literature to better capture the marginally attached workers in the NIF population is to exploit the observed labor force status histories, which capture information on the unobserved

[11]The joint test results are similar.

[12]The Online APPENDIX Section A.2 shows more heterogeneity results for NIF. In a nutshell, (1) the probabilities of using self-search, formal search, and informal search by female homemakers relative to a comparable U all increase in age for highly educated women, whereas the age profile of such relative probabilities are much flatter for less educated women; (2) the age profiles of relative probabilities of using the three search methods are downward sloping for male DI, OT and DG, regardless of education; (3) the age profiles are steeper for male DI and OT than for DG.

[13]Additionally, we investigate in the Online APPENDIX Section A.3 whether NIFs and U are different in the other labour market outcomes, revealing a more nuanced continuum between inactivity and unemployment than conventional statistics capture.

[14]For example, Brandolini, Viviano, and Cipollone (2006) proxy search intensity by the 'number of months since the last search action'. However, this information is rare in labour surveys. Furthermore, defining 'job search activities' in an allencompassing manner is also a practical challenge.

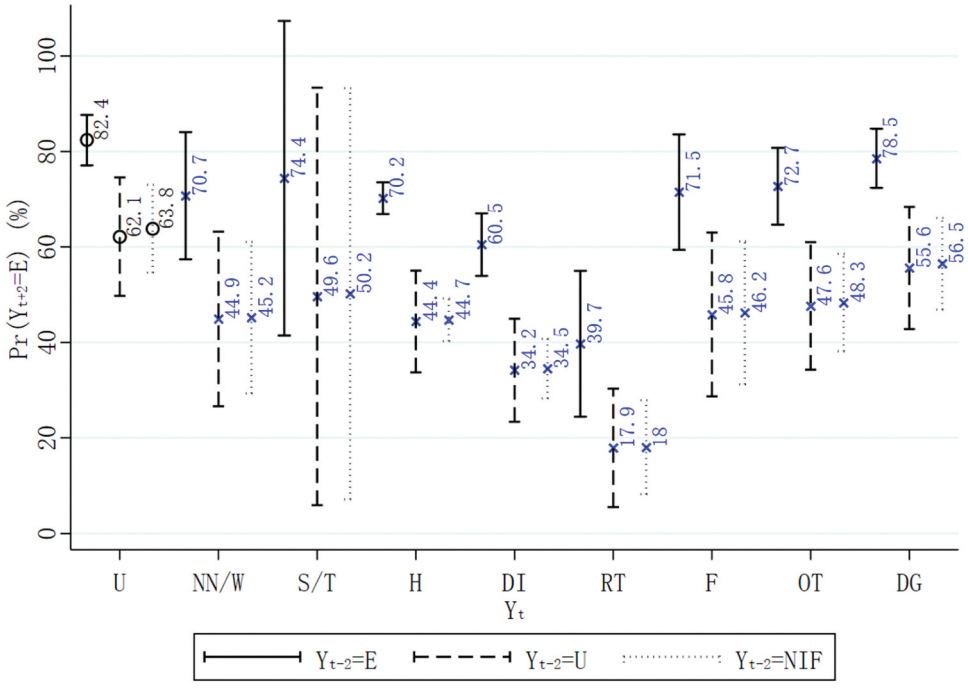


Figure 8. Probability of transition from U and NIF to employment in 2 years: by labor force status history. Sources: CFPS 2012–2022. Note: On the vertical axis is $p_{j,E}$, which denotes the probability of transition from status j (x-axis) to status E (employment) in the time frame of 2 years between t and t+2. Probabilities are estimated using multinomial logit model. Covariates include gender, age, education, urban, region, and year dummies. 95% confidence intervals are plotted as vertical spikes. Sample is restricted to men between 16 and 57 years of age and women between 16 and 52 years of age at time t. Panel weights are used. U: unemployed; NIF: not in labor force; NN/W: do not need/want to work; S/T: student/trainee; H: homemaker; DI: disabled/ill; RT: retired; F: physically feeble; OT: other; DG: discouraged. The first three hollow circle markers refer to $Y_t = U$, the second three "x" markers refer to Y_t = NN/W, and so on.

labor market attachment of a worker (Kudlyak and Lange 2014). In our data, this approach amounts to adding labor force status at time t − 2 as a predictor in estimating Equation (1). Figure 8 shows that past employment status significantly elevates the current employment transition probability for all U and NIF groups,[15] a pattern that is consistent with the U.S. evidence. Specifically, in the Chinese context, such difference is about 20% for those whose current status is U. Furthermore, all the current NIF groups (other than the disabled/ill and early retired) who have employment history are more than 70% likely to be employed in the next 2 years, exceeding that of the currently unemployed workers whose *t*-2 status was U or NIF. In other words, NIF workers with employment history are more attached to the labour market than those without, and similar to unemployed workers with employment history.

Alternative classification of NIF and unemployment statistics

The results above highlight the value of labour force status history in proxying the unobserved job search intensity. Consequently, classifying these NIFs as active job seekers seems reasonable for better measuring labour market attachment and worker's willingness to supply labour. To see the effect of doing so, we extend Sun (2024) to construct alternative unemployment statistics and examine their predictive power. Table 5 presents the standard unemployment rate (U3), the extended unemployment rate (U5, where DG and OT are included in U), and the variable-weight extended unemployment rate (U5_1, where all the NIFs are included in U according to their probability of transition to employment relative to standard U, and labour force status history is used in predicting the transition probabilities); see Section A.5 of the Online

[15]In comparison, the effects of household demographic and financial background are much less significant; see the Online APPENDIX Section A.3.

Table 5. Extended unemployment rates 2012–2022 (in percent).

	Urban			Rural			National		
	U3	U5	U5_1	U3	U5	U5_1	U3	U5	U5.1
2012	3.5	12.0	20.8	1.4	7.0	13.1	2.5	9.7	17.3
2014	2.9	6.6	13.2	1.5	4.2	9.8	2.4	5.7	12.1
2016	2.0	5.3	12.1	1.2	3.8	9.5	1.6	4.5	10.8
2018	1.8	4.7	10.1	1.1	3.5	8.5	1.4	3.8	8.6
2020	2.5	5.2	10.3	1.4	3.6	8.8	2.0	4.3	9.4
2022	2.3	4.3	9.3	1.8	3.9	8.5	2.1	4.1	9.0

Sources: CFPS 2012–2022.

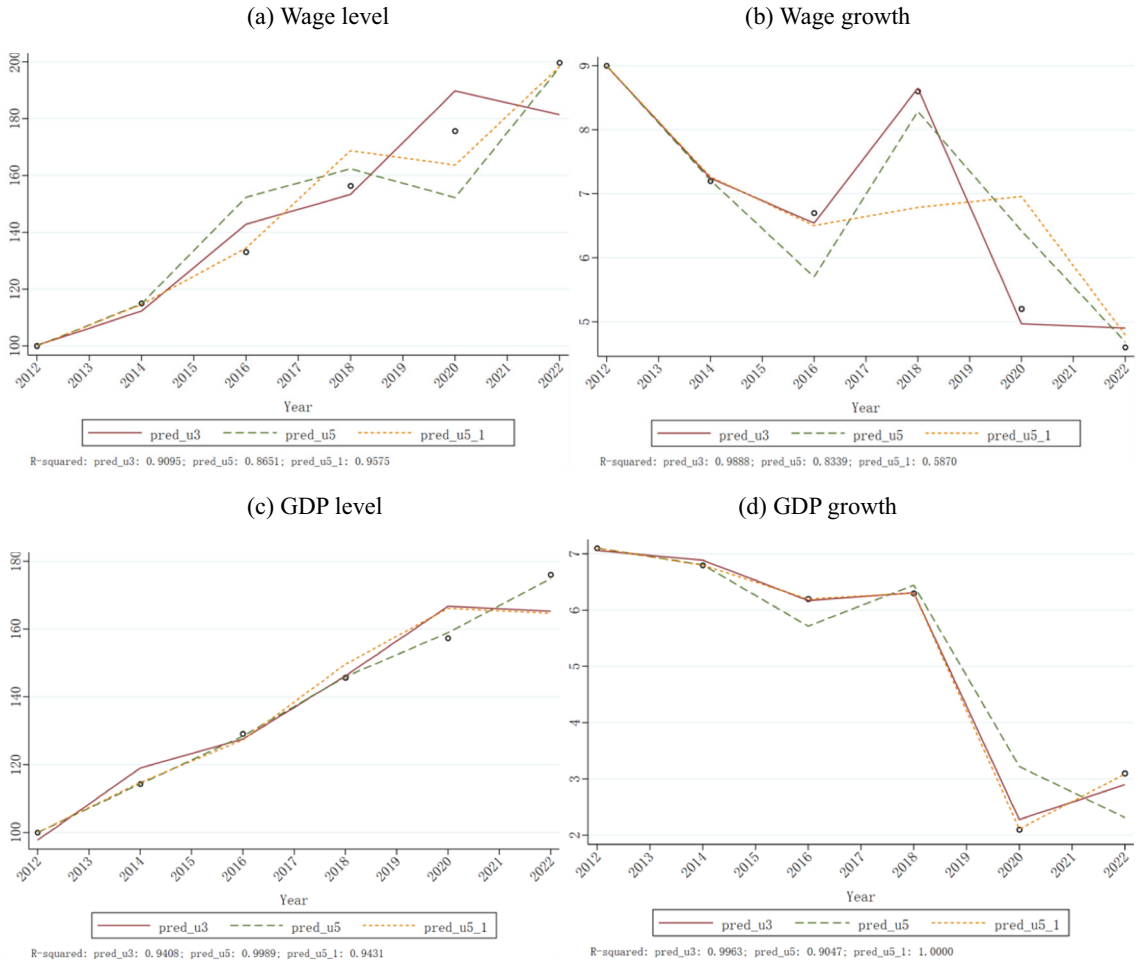


Figure 9. Goodness of fit for unemployment statistics predicting wage and GDP in China. Wage and GDP data: NBS; unemployment statistics: U3, U5, and U5_1 are calculated using CFPS (2012–2022). The hollow circle indicates data. "pred_x": predicted values from a regression of wage/GDP data on a constant and a quartic function of the respective unemployment statistic denoted by "x" in "_x". The wage/GDP level data are indices with year 2012 set as base year.

APPENDIX for details. Following Sun (2024), Figure 9 evaluates the effectiveness of alternative unemployment statistics in capturing labour market tightness and labour resource utilization by illustrating the predictive power of each statistic in forecasting wage and GDP dynamics. The figure shows that the variable-weight extended unemployment rates U5_1 exhibits superior predictive accuracy compared to both the U3 and U5 rates in most cases.[16] The U5 also shows superior predictive accuracy in some cases, for instance for predicting GDP level.

Figure 10 and 11 further explore the relationship between alternative unemployment statistics and

[16]The results are similar using provincial data; see Table A.5 in the Online APPENDIX.

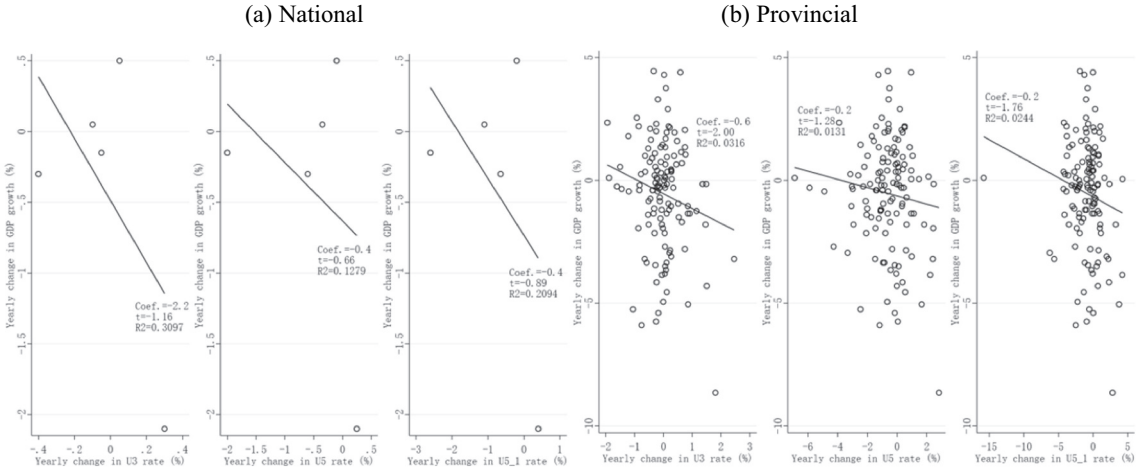


Figure 10. Okun's law in China.

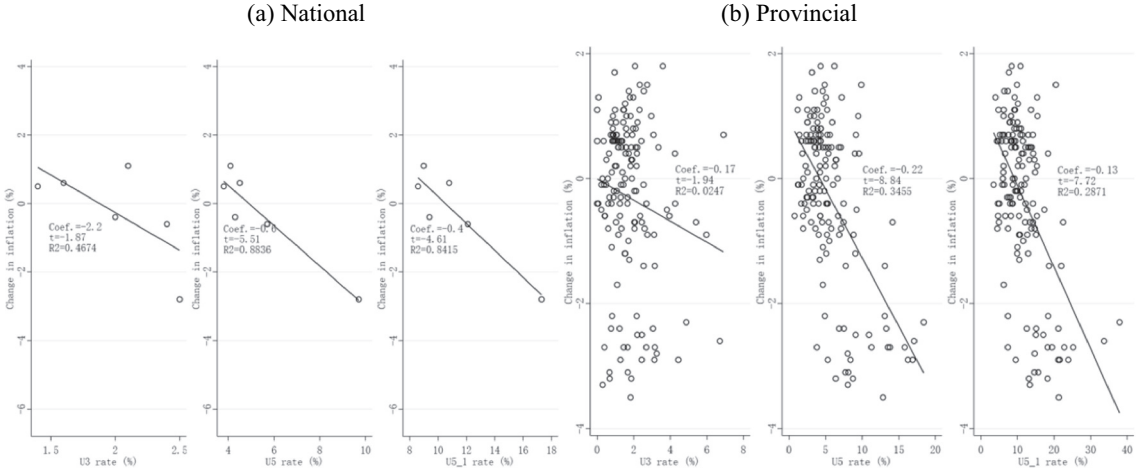


Figure 11. Phillips curve in China. $N = 150$ for Panel (b).

macroeconomic indicators.[17] Figure 10 illustrates the application of Okun's Law in China. Panel (a) shows that, on the national level, a one percentage point change in the standard unemployment rate U3 is associated with a −2.2% point change in real GDP growth, similarly to that in other countries such as the U.S (Okun 1962; Prachowny 1993). However, as found in previous research (Lu et al. 2015), the relationship is not statistically significant, which may be due to the small sample. Panel (b) shows the relationship using provincial data, where the relationship becomes statistically significant and economically less significant due to the sample. Furthermore, both Panel (a) and (b) show that the relationship between GDP growth change and alternative unemployment statistics U5 and U5_1 is smaller and less significant, suggesting that the alternative statistics capture a stronger relationship between the labour market tightness and cross-sector labour reallocation, a channel that can weaken the comovements between unemployment and GDP growth rates (Lu et al. 2015). Additionally, Figure 11 illustrates the Phillips curve in China, where the relationship is statistically more significant and the fit is better when alternative unemployment statistics are used.[18] These relationships merit further discussion and research in the future.

[17]Deleting outliers yields similar results to Panel (b) of Figure 10 and 11.
[18]The estimated coefficient using the U3 rate and the bigger provincial data sample is of the same magnitude as the estimate in previous research (Du and Zhang 2022).

Discussion: implication to labour policies

One natural question to follow is how to facilitate the transition from NIF to employment. One important factor that affects job search activity is the social safety net, in particular, the unemployment insurance (UI) system. UI benefits in China have long remained at a relatively low level. Existing studies show that the replacement rate is only between 13% and 30% (Tang, Xie, and Zhao 2024), which is substantially lower than the 50%–90% replacement rate observed in developed countries such as the U.S., France, Germany, and Denmark (Chetty 2008; Fredriksson and Söderström 2020; Nekoei and Weber 2017; Zheng and Wang 2011). Furthermore, more than half of China's urban workforce is still left uncovered by the UI system, and the eligibility criteria for UI benefits are stringent, resulting in a relatively low utilization rate (Tang, Xie, and Zhao 2024). These institutional arrangements are largely driven by policymakers' concern that overly generous payments could undermine incentives for re-employment, as suggested by some international evidence (Card et al. 2015; Chetty 2008). However, UI benefits can subsidize job search costs, thereby inducing more job search effort (Schwartz 2015). This channel is found to promote the job search effort of China's unemployed (Liang and Ji 2020). The effect of UI reform on the labour supply efforts and outcomes of NIFs merits further investigation.

Another policy with the potential to facilitate job search and re-employment is the provision of public employment services. Many developed countries, such as Austria, Denmark, France, Germany, Hungary, the U.K., the U.S. et al., have provided job placement services and vocational training to help job seekers improve their skills, gain information, and secure jobs that better match their qualifications (Caliendo and Schmidl 2016; DellaVigna et al. 2017; Fougère, Pradel, and Roger 2009; Gautier et al. 2018; Launov and Wälde 2016; Ziegler 2025). In this area, China's development began at a relatively late stage, starting only since 2020 to expand public programmes to promote job search and match by enhancing the skills of job seekers and subsidizing firms for hiring (Zhao and Hou 2025). The impact of this policy merits further examination and comparative analysis in the international context.

V. Conclusion

This paper studies the labour force attachment of the 'Not in the Labor Force' (NIF) population in China, which is traditionally considered inactive and irrelevant to labour supply. Using a two-year observation window, we show that some NIF subgroups – such as discouraged workers, individuals citing 'other reasons', and homemakers – have employment transition rates comparable to those of standard unemployed individuals, with homemakers representing a previously underexamined but substantial marginally attached group. Additional direct evidence suggests that some NIF individuals actively engage in job search behaviour similar to the unemployed. Furthermore, we propose an extended unemployment index that incorporates NIF individuals with variable weights based on their predicted probability of employment. This index offers a more accurate signal of labour market dynamics and outperforms traditional unemployment measures in predicting changes in wages and GDP in China, thereby providing a more comprehensive understanding of labour supply, market tightness, and resource utilization. There are many more interesting questions that warrant further exploration. An important question is what types of policies can better support NIF individuals in seeking and securing employment. We will explore this issue further in future research.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Table A1. Sample attrition rate.

	Attrition rate
Tracked 2 waves	
2012–2014	17.22%
2014–2016	19.02%
2016–2018	22.09%
2018–2020	37.37%
2020–2022	31.75%
Tracked all waves	
2010–2022	73.61%

Table A2. Regression of sample attrition on labor force status.

Dependent variable: sample attrition		
Labor force status	Coef.	S.E.
Unemployed (dummy)	0.013	(0.013)
NIF: NN/W (dummy)	0.013	(0.013)
NIF: S/T (dummy)	−0.039	(0.014)
NIF: H (dummy)	−0.005	(0.003)
NIF: DI (dummy)	0.004	(0.008)
NIF: RT (dummy)	−0.001	(0.003)
NIF: F (dummy)	0.000	(0.003)
NIF: OT (dummy)	0.005	(0.007)
NIF: DG (dummy)	−0.000	(0.006)
Observations	76,301	
F-statistic	1.54	
Prob>F-statistic	0.1278	
R-Squared	0.0360	

Notes: The dependent variable is an indicator of attrition, which equals one if an individual is attrited from the sample between t and t + 2 during 2012–2022, and zero otherwise. The omitted category of labour force status is "Employed". Covariates include demographic characteristics (gender, age, education) and regional characteristics (urban/rural, region) and year dummies. Panel weights are used. Standard errors are clustered at personal level. F-statistic is for the joint test of the null hypotheses of the coefficients of labour force status dummies.