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Abstract

Migrant workers form a very important part of the labor force in the economic development of many countries. Their turnover decisions may affect the stability of the performance of manufacturing industries. It is important to understand what kind of individual behavioral preferences may affect their job changing frequency. This study conducts a lab-in-the-field experiment through a large online-to-offline job-matching platform to elicit manufacturing migrant workers' preferences, such as uncertainty attitudes, intertemporal choices and social preferences, especially difference aversion. The study also surveyed their demographic characteristics and other factors related to their job choices. We find that subjects who are more risk seeking change jobs more frequently. We also use the job record data from the platform and conduct empirical analysis to investigate one explanation of this result: risk-seeking subjects possess more optimistic expectations of potential job opportunities and they are more likely to sample different jobs and thus generate higher job changing frequency. Our findings may help policy-makers and employers design policies or mechanisms to prevent exorbitant job-changing behavior.

Key words: migrant worker, preference, job turnover, job search, experiment

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1. Introduction

Internal migration has become a worldwide phenomenon, which is especially evident in developing countries such as China (Gui et al. 2012). In China's context, the influx of rural–urban migrant workers guaranteed the supply of inexpensive labor needed to fuel the decades-long manufacturing boom (Lu and Song, 2006; Imbert et al.,2022). There were 290.77 million migrant workers in China by 2020[2] who moved away from their ancestral home (mainly in less developed inland areas, including many rural regions) to manufacturing factories in more developed cities in coastal regions and the Yangtze River Delta region (Lu and Song, 2006; Hao et al., 2016). One issue of considerable interest for those who study migrant workers is their high job changing frequencies[3]: they voluntarily quit jobs frequently.[4,5,6] A study on rural–urban migrant workers in Guangdong Province, China, shows that on average, they change jobs more than once per year (Wu and Xie, 2006), which is more frequent than any other general population in China[7].

High frequencies of job change may be harmful to both rural–urban migrant workers and manufacturing industries. For migrant workers, the instability of their employment status may make them more economically vulnerable, potentially aggravating their probability of committing crimes and susceptibility to mental health problems.[8] Lack of job stability may increase financial vulnerability, which would adversely affect the sense of security and decrease wellbeing (Huang et al. 2020). For manufacturing industries, a higher turnover rate may negatively affect product reliability, hurt the efficiency of employee coordination, and jeopardize the production competitiveness of all manufacturing industries.[9]

It is a puzzle why migrant workers change jobs frequently. The literature has confirmed many external and socioeconomic factors affecting migrant workers' job stability, such as domicile discrimination, public vocational training (Li et al., 2015; Bi and Yang, 2008), despotic factory regimes (Zhang, 2011; Zhu and Liu, 2020), and substandard living conditions (Lu and Song, 2006).

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[2] The data are released by the National Bureau of Statistics (NBS) of China, http://www.stats.gov.cn/tjSj/zxfb/202004/t20200430_1742724.html. According to Chinese NBS, the population of Chinese migrant workers in 2020 increased by 2.41 million compared to 2019.

[3] We use "Job Changing Frequency" in our paper instead of "Job Turnover Rate" because the later represents the turnover rate of a manufacturing factory, and it is a ratio, whereas Job Changing Frequency in our study refers to how many times a worker changed his job during a period of time, and it is a count variable.

[4] According to the "Report on employment trends of migrant workers in China" released by the Department of Sociology of Tsinghua University in 2012, 25% of migrant workers changed their jobs in the past seven months, and 50% of migrant workers changed their jobs in the past 1.8 years. The survey also found that the trend of "short working duration" is increasing year by year.

[5] According to research on the new generation of migrant workers in China launched by the Chinese Labor Movement Research Institute in 2010 on the state of the migrant workers all over China, those who were born in or after the 1980s change jobs 2.89 times more often than those who were born before the 1980s.

[6] According to Liu et al. (2020), compared to their urban peers, migrants born after 1980 have poorer job stability.

[7] The employee turnover rate was 26% in Guangdong from 2015 to 2016, with rates higher for migrant workers (30%), according to the Chinese Employer-Employee Survey (CEES), which surveyed a representative sample of 573 manufacturing firms in Guangdong Province in 2015, and 1122 firms in Guangdong and Hubei provinces. Source: https://iems.ust.hk (accessed on Sep.8, 2021)

[8] Please see Cameron et al.,2019; Meng and Xue, 2019; Giles et al., 2021.

[9] Please see Moon et al., 2022a; Moon et al., 2022b; Michele et al., 2006.

However, all the literature focuses on the social factors that may impact migrant workers' job changing decisions, and few studies focus on the attributes of the migrant workers themselves. Only a couple of research papers on field behaviors involving job stability, for instance, Burks et al. (2009), correlate cognitive skills (CS)[10] of the U.S. truck drivers with their preferences and behavior in the field, such as employment stability, and van Huizen and Alessie (2019) study the correlation between risk aversion and job mobility using a large Dutch dataset of the general population. To the best of our knowledge, it is unexplored how individual preferences in migrant workers may relate to the frequency of job change. Many behavioral studies find that individual preferences are related to various field behaviors, such as smoking and alcohol consumption, risk-taking behavior, and loan repayment.[11] When people make decisions to change jobs, they need to face uncertainty, intertemporal choices and consideration for others. It is natural to think that migrant workers' high job changing frequencies may also be related to their risk, ambiguity, time preference and social preference, especially difference aversion.[12] Therefore, we examine the relationship between migrant workers' individual preferences and job changing frequencies to fill the gap in the literature.

In this paper, we conduct the study in two steps. First, we recruit migrant workers as subjects from a large job-matching platform and perform a lab-in-the-field experiment to elicit their individual preferences[13], such as risk attitudes and time preferences. We also conducted an in-experiment survey immediately after they completed the experimental tasks as well as a postexperiment survey four months later. Second, we explore their recorded employment histories on the platform to find possible explanations of the link between their job changing frequencies and individual preferences.

From the lab-in-the-field study, we find that, compared with the individual preferences of general adults or student subjects, migrant workers are more risk seeking, more ambiguity seeking, more impatience in both the short term and long term, and greater fairness concerns.[14] Furthermore, we find that migrant workers who are more tolerant of risk or ambiguity change their jobs more frequently.

In the second part of the study, to investigate why more risk-seeking migrant workers would change jobs more frequently, we conducted a follow-up survey and obtained subjects' employment histories from the job-matching platform. From the recorded employment histories, we observe that some migrant workers prefer to perform "job sampling". They usually work on a job for a few days

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[10] Burks et al. (2009) find that the association of time and risk preferences on economic behaviors is unmediated by cognitive ability.

[11] Please see Chabris et al.,(2008); Khwaja et al.(2006); Weller et al. (2008); Charness et al.,(2020), and Karlan, (2005).

[12] First, uncertainty arising from employment conditions may be particularly salient among migrants (Rousseau and Frounfelker, 2019) since decisions to leave relate to the uncertainty in cash flow as well as career outlook. Second, migrant workers usually have jobs requiring a high tolerance for tedium and might obtain a rush from quitting. On the one hand, patient migrant workers may be more tolerant of boring jobs and thus work for longer durations; on the other hand, patient people may be better at restraining their desire for consumption and have better financial security. Third, working involves dealing with other people.

[13] We elicited migrant workers' individual preferences in three aspects: uncertainty preference (including risk and ambiguity preference), time preference (including short-term and long-term intertemporal choices) and social preference (concerns for others).

[14] Please see Croson and Gneezy, 2009; van Huizen and Alessie, 2019; Holt and Laury, 2002; and Chew et al., 2021.

and then hop onto another one, accumulating first-hand work experience before they find a more suitable job where they can work for a relatively long period. Based on the analysis of survey data, we find that more risk-seeking subjects possess more optimistic expectations of potential job opportunities, which is consistent with the literature (McCall, 1970; Weinstock and Sonsino, 2014). Thus, they may conduct more job sampling while searching for appropriate jobs and are more likely to quit when the work does not meet their expectations. After analyzing the data from the platform, we find that these more risk-seeking migrant workers conduct more job sampling and have a higher job changing frequency. Therefore, it explains the path between risk seeking and job changing frequency[15].

The contributions of this study are threefold. The first is that we illustrate the general pattern of migrant workers' elicited preferences through a lab-in-the-field experiment and their relations to ones' job changing frequency in the real world. The second contribution of this paper is that we offer a detailed explanation of the link between the risk preference of migrant workers and their job changing frequencies in the field. Although the aggerate migrant inflow is well studied in previous literature (Imbert et al., 2022), individual migrant workers changing jobs across firms via a job-matching platform are unexplored. The third contribution is that, to the best of our knowledge, this study is among the first to externally validate the experimentally elicited individual preferences that explain the field behavior of migrant workers. This study may also shed light on understanding the decision-making patterns and behaviors of people who are relatively low-educated and work in labor-intensive industries, and it would help managers, researchers and policy-makers take workers' internal behavioral tendencies into consideration when they design mechanisms or policies.

The rest of the paper is organized as follows. Section 2 presents the related literature and behavioral predictions. In Section 3, we describe the experimental design and implementations. Section 4 provides the results of the data analysis. Section 5 provides an explanation of the results in Section 4. Section 6 concludes.

2. Related literature and behavioral predictions

The literature has confirmed that people's lived experiences, including the experience of migration, may shape their individual preferences (Heckman and Kautz, 2012; and Gibson et al., 2020), and risk-tolerant people are more likely to become migrants (Conroy and Hector, 2009). Both empirical and experimental studies have shown that migrants are generally more risk-seeking than other populations

[15] We also conducted the same experiment on 96 MBA students. All MBA subjects had at least 3-5 years of experience working in a variety of industries, including manufacturing, finance, pharmaceuticals, energy, and consulting. We display the results in the Online Appendix A1.6. Compared to migrant workers, MBA students are more risk averse, ambiguity averse, patient, and demand less MAO in Ultimatum game. There is no correlation between MBA students' individual preferences and their JCF. Additionally, expectations do not influence their decision to change jobs.

in developing countries such as China.[16] Chinese migrant workers in the manufacturing industry have many homogeneous characteristics; for instance, the majority of them are male[17], with a proportion of 44% working in the manufacturing sector. By 2019, the average monthly wage of migrant workers in the manufacturing sector was 3958 CNY (approximately 615 USD). Migrant workers' lived experiences, psychological status, and economic behaviors are different from those of locals (Hao et al., 2016; Lin et al., 2011; Chu and Hail, 2014). Due to the restrictions of China's household registration (*hukou*) system (Afridi et al., 2015), migrant workers commonly tend to work longer hours and earn less than locals and live in substandard conditions (Lu and Song, 2006).

Migrants who work in the industrial sector tend to be engaged in physically demanding, low-income work (Lu and Song, 2006), which may create a cognitive burden to resist the temptation of changing jobs (Banerjee and Duflo, 2011). Migrant workers are segmented in their employment and social and residential lives, and they have difficulties accessing key services in cities, such as education, health care, and social security (Cadsby et al., 2020). Their children are more likely to be enrolled in lower quality public schools compared with local students (Chen and Feng, 2017, 2019). Thus, they may suffer from psychological problems due to discrimination and inequity (Lin et al., 2011).

Much behavioral research has shown that people's economic behaviors are correlated with their individual preferences, for example, in investment, borrowing, health-related behaviors such as exercise, son preference through sex selection, and cooperation in the workplace.[18] The external validation of experimentally elicited preferences in the domain of economic decision making in the field remains critical (Levitt and List, 2007; Sutter et al., 2013; and Charness et al., 2020). In this paper, we extend the research on the external validity of experimentally elicited preferences to job changing frequencies.

Much research has found that job stability is currently in the key interests of manufacturing factories (Cai and Wang, 2020). For migrant workers, stable employment provides flexibility to build personal savings and facilitates decent settlement in cities (UNDP, China, 2007). Migrant workers may be economically vulnerable after leaving a job and are less likely to obtain job promotion. Thus, leaving a job can be considered a decision that increases uncertainty. Therefore, the preference or tolerance for uncertainty may have an effect on their job changing frequencies. Researchers have found that uncertainty aversion (including risk aversion and ambiguity aversion) may lead to conservative behavior (Chabris et al., 2008; Charness et al., 2020). Additionally, previous studies have

[16] Please see: Hao et al., (2016); Akgüç et al.,(2016); Zhang et al., (2011).
[17] The data comes from Chinese NBS: stats.gov.cn. "Sixty-five percent" refers to the proportion of males among all rural urban migrant workers, including those work in the manufacturing sector and the service sector. There are no official statistics for male workers exclusively in the manufacturing sector. However, the sex ratio in the population of migrant workers is unbalanced in general.
[18] Please see Meier and Sprenger, (2010); Chabris et al., (2008); Sutter et al., (2013); Kosfeld and Rustagi, (2015); and Chew et al(2018)

found that risk seeking can increase one's likelihood of leaving a job through multiple channels (Hatton et al., 2001; Allen and Weeks 2005; Allen et al., 2007; Vardaman et al., 2008). Combining the two streams of behavioral patterns, we make the following prediction:

H1: *Migrant workers with more uncertainty aversion have lower job-changing frequencies.*

Another individual behavioral factor that may be related to job changing frequencies is time preference. Intertemporal choices are often related to field behavior involving persistence and restricting transient desires (Chabris et al., 2008; Sutter et al., 2013). Such field behavior often includes smoking[19], gambling[20], alcohol consumption[21], etc. For migrant workers, the financial gain of employment at manufacturing factories is far more attractive than farming at home. For the sake of a relatively high salary, migrant workers may want to work in factories rather than going back home, but there are also many factors that cause them to dislike manufacturing jobs, such as long working hours and repetitive tasks (Lu and Song, 2006). In this sense, patience may induce more tolerance of boring jobs. Thus, we have the following behavioral prediction:

H2: *Migrant workers who are more patient have lower job-changing frequencies.*

Since working in a factory involves getting along with leaders and colleagues, difference aversion and fairness may play a role in their social life in factories and thus affect their decision to stay in the job. According to Luo et al. (2019), the mandatory hukou system in China (Afridi et al., 2015) institutionally assigns individuals to either rural or urban hukou and favors urban areas through many social resources, such as housing and education. To seek compensation for their less favorable social identity, rural hukou proposers decrease the amount offered regardless of their responder's hukou type, and rural hukou responders expect higher offers from their urban hukou proposers. Previous news on Chinese migrant workers showed that fairness and equality are highly relevant to their job-changing decisions.[22] Thus, we make the following behavioral prediction:

H3: *Migrant workers who are more difference averse have greater job-changing frequencies.*

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[19] Please see; Kirby and Petry (2004); Ohmura, Takahashi and Kitamura (2005); Reynolds et al. (2004).

[20] Please see Petry and Casarella (1999); Dixon et al.(2003).

[21] Please see Bjork et al. (2004).

[22] On September 5, 2020, the supervisors of a factory in Kunshan threw ID cards on the ground inadvertently when distributing them to new employees (mainly migrant workers). The new employees felt they were not treated fairly, so a large number of them voluntarily left the company. For the corresponding news report, please see http://finance.sina.com.cn/chanjing/cyxw/2020-09-06 (accessed on May 4th, 2022）.

3. The experiment

3.1 Experiment and implementation

The experiment was conducted in an offline meeting site for a job-matching platform. This job-matching platform focuses on providing job-matching services for migrant workers and manufacturing firms in the Yangtze River Delta region. The migrant workers are recruited to work at assembly lines in labor-intensive electronics manufacturing factories. Low-skilled jobs and repetitive work limit workers' competitiveness and promotions in their careers. Every morning, thousands of job seekers come to the offline meeting site to apply for jobs. The application procedure involves filling in a job application, taking photos, and traveling to the hiring firm for a job interview by a prearranged bus. Before the job interview, applicants typically need to wait in the offline meeting site for two to three hours. We recruited them to participate in our study during their wait. We conducted a lab-in-the-field study from August 18th to 20th, 2020, after a pilot study in July. The timeline of the experiment, survey and data collection are depicted in Figure 1. We recruited 205 job seekers to participate in our study. For each participant, we first elicited his or her individual preferences using incentivized choice lists. Specifically, we designed six experimental tasks and tested for participants' risk aversion, ambiguity aversion, near-term time preferences, far-term time preferences, decision to be a proposer in the Ultimatum game (Proposal_UG), and decision to be a responder in the Ultimatum game (MAO_UG, where MAO stands for minimum acceptable offer).[23][24][25] Our experimenter also requested participants' contact information so that we could make online cash transfers via WeChat to compensate them for their participation and conduct follow-up studies with them in the future.[26]

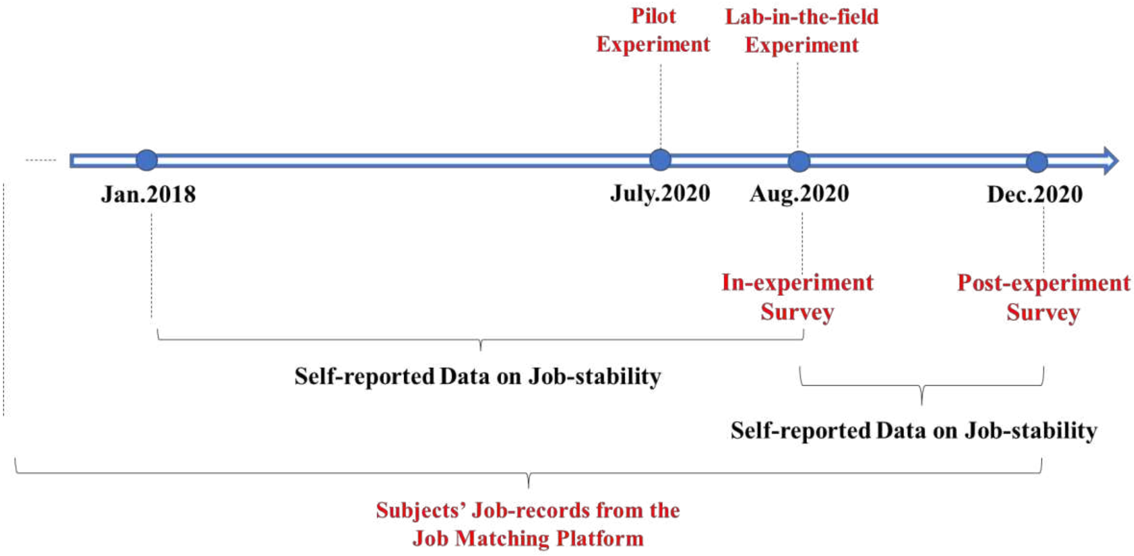
[23] Among all the method eliciting uncertainty preference, we use incentivized choice list. According to Tasoff and Zhang (2022), most methods of eliciting preferences are highly correlated with each other.

[24] Among all the social preference games, including the dictator game, ultimatum game, trust game and public game, we use result of ultimatum game to represent social preference because of the following two reasons: firstly, according to Galizzi and Navarro-Martinez (2019), there was a relatively high degree of consistency in the decisions that the participants made in each of the social preference games; secondly, the difference-aversion or reciprocity (Charness and Rabin,2002; Croson and Gneezy, 2009; Fehr et al., 2013) which is especially addressed in ultimatum game, is more relevant to migrant workers' job changing decision.

[25] The detailed experimental methods are displayed in the Online Appendix A2.1. The decision sheet is translated into English, and displayed in Online Appendix A2.2. The implementation is described in the Online Appendix A2.3, and the collection of demographic and job-related information is introduced in Online Appendix A2.4. The survey questions are shown in the Online Appendix A2.5.

[26] Wechat is the most popular messaging app with a monthly user base of more than 1 billion people. (https://www.cnbc.com/2019/02/04/what-is-wechat-china-biggest-messaging-app.html, accessed on April 29, 2022). This identifying information is removed from the main datasets.

Figure 1 Timeline of Experiment and Surveys



All tasks were designed through incentive-compatible methods (e.g., Holt & Laury, 2002; Sutter et al., 2013; Chew et al., 2021), and subjects were compensated on the basis of choices made or answers provided. In line with Sutter et al. (2013), we investigated risk, ambiguity, and time preference and their effects on job-related behavior by using raw switching points to avoid confounding effects due to (arbitrary) parametric assumptions. By defining certainty equivalents for uncertainty tasks and future equivalents for time preference tasks, we can relate them directly to demographics and field behavior in a model-free way.

We obtained the subjects' demographic characteristics (i.e., gender, age, education level, etc.) and past experience in the job market by survey. We performed two waves of surveys. The first was conducted immediately after subjects completed the experiment, and the follow-up survey was conducted via WeChat four months after the experiment (in December 2020). In the first wave survey, we asked the subjects how many times they had changed jobs since 2018, as well as basic demographic information such as gender, age, education level and marital status. In the follow-up survey, we asked how many times they had changed jobs since the experiment in August 2020. We also asked subjects about their reasons for changing jobs in the follow-up survey. Eighty-two participants did not answer our follow-up survey. We obtained 123 subjects with complete data (i.e., on experimental decisions and surveys).[27]

[27] There were 205 subjects who participated in the first-wave experiment. Since we could not meet them in person after they started to work in factories, we conducted the follow-up visit on WeChat. The data for 123 samples were eventually obtained. We performed Wilcoxon rank sum test on individual preference and demographical variables and found no significant difference between the subjects who did not answer our second survey and those who continued to participate in the second survey. A majority of the subjects in our sample have rural hukou, making up 86.18% of the total.

3.2 Data summary on demographics and job changing frequency (JCF)

Table 1 shows the subjects' demographics, including age, gender, and educational level. In our sample, more than 90% of migrant workers were under 35 years old. Workers between the ages of 21 and 30 made up the largest proportion of the sample. Male workers dominated each age group.[28] A majority of the subjects in our sample had rural hukou, making up 86.18% of the total. We divide subjects into subgroups according to whether they received more than 9 years of education. Because China has a nine-year compulsory education policy,[29] the completion of nine years of schooling provides a basic benchmark for the educational level and cognitive abilities of workers.

To evaluate whether our sample is representative of the populations of urban migrants and migrants in general, we compare our dataset with the 2005 census data on urban migrants, the 2010 census data on all migrants,[30] and the sample of migrant workers from Hao et al. (2016). We assess the representativeness of our sample along education level and occupation dimensions. The percentage of educational achievement below junior high school (9th grade) was 38% in the 2005 census, 22% in the 2010 census, 35% in Hao et al. (2016), and 38% in our sample. Thus, the general education level of our sample is comparable to that in the 2005 census and the sample in Hao et al. (2016). According to the 2005 and 2010 censuses, the two main industries to hire rural–urban migrants were the manufacturing and service industries: the proportion of migrant workers working in the manufacturing sector was 54% and 45.66% of the population in the 2005 and 2010 censuses, respectively. Since our sample contains only migrant workers in the manufacturing sector, our findings may more closely represent this group of migrant workers.

Table 1 Demographic statistics of migrant workers in the study

Age	Total	Males	Years of education		Having at least one child
			<9 years	≥9 years	
16-20	8	7	3	5	0
21-25	47	41	13	34	5

[28] It is common in manufacturing factories located along the coast of China to see an imbalance in gender representation, since the tedious work or physical labor at manufacturing factories is extremely challenging for women. Female migrant workers usually choose to work in the service industry (such as shop assistants) instead.

[29] We divide subjects into subgroups according to whether they received more than 9 years of education. Because China has had a policy of nine years of compulsory education since 1986, the designation of nine years of schooling provides a basic benchmark for the educational level and cognitive abilities of migrant workers.

[30] To explore how well our migrant sample represented the migrant population in China, we especially focus on the results from three studies: Meng and Zhang (2010), Liang et al. (2014), and Hao et al.(2016). Meng and Zhang's (2010) Table 2 offers detailed distributional information of rural–urban migrants on two attributes: education and occupation, using 1990, 2000, and 2005 censuses in China. In addition, Liang et al. (2014) 's Online Appendix A2 offers detailed comparisons of education and occupations of migrant workers in the Yangtze River Delta using census data from 2000-2010. Hao et al. (2016) recruited a sample of 48 migrants in 2010. They randomly recruited rural–urban migrant workers in restaurants.

26-30	36	34	17	19	7
31-35	23	22	10	13	12
36-40	6	6	4	2	3
41-45	3	1	0	3	3
SUM	123	111	47	76	31

We used two different measurements to capture job changing frequency (JCF). The first one, *JCF1*, represents the number of times a migrant worker quit his job from Jan 1, 2018 to Aug 19-20, 2020 (i.e., 32 months). That is, the JCF of migrant workers from Jan 1, 2018 to the date we conducted the experiment. The second one, *JCF2*, represents how many times a migrant worker left his job between Jan 2018 and Dec 2020 (i.e., 36 months). That is, the JCF of migrant workers from Jan 1, 2018 to the time we conducted the follow-up survey. The regression results for *JCF2* provide a robustness check of the results over a longer period. Table 2 below shows the descriptive statistics for JCF.[31,32]

Table 2 Summary statistics of job changing frequency (JCF)

job changing frequency	Mean	SD	Min	Max
JCF1	6.62	6.83	1	32
JCF2	9.06	7.65	2	36

Note.

1. *JCF1*: the frequency with which a migrant worker quit his job from Jan 1st 2018 to Aug 19-20, 2020. That is, the JCF of migrant workers from Jan 1, 2018 to the time we conducted the experiment.
2. *JCF2*: the frequency of the times that a migrant worker left his job during Jan 2018 – Dec 2020. That is, the JCF of migrant workers from Jan 1, 2018 to the time we conducted the follow-up survey.

4. Analysis and main results

In this section, we first report findings on individual preferences from a lab-in-the-field study. Second, we analyze the correlation between experimental decisions and JCF to examine which individual preferences may be related to migrant workers' job changing frequency. In the third part of this

[31] Due to the prevalence of small-scale farming in China, it is possible that migrant workers need to spend several months every year at home to manage family agricultural production. For this reason, when calculating the job changing frequency, only the length of time migrant workers spend on the job market is considered. For example, migrant worker A is on the labor market for an average of 8 months per year and has held 2 jobs in 32 months (Jan. 2018-Aug. 2020). The migrant worker B is usually on the labor market 12 months each year and has worked 3 jobs in 32 months (from Jan. 2018-Aug. 2020). Since A is not in the labor market for the whole year, we can compare A and B's JCF1 only after we adjust their job changing frequency according to the time they are active in the labor market. Consequently, A and B have the same job changing frequency. The JCF1 for A is $\frac{2}{8/12}$, and The JCF1 for B is $\frac{3}{12/12}$. Thus, the JCF1 s of A and B are the same. We apply the same method when deriving JCF2.

[32] There were 11 subjects who started to look for jobs in the manufacturing job market after Jan. 1, 2018. The youngest was 19 years old, and the oldest 42. As we studied migrant workers' labor experiences in the manufacturing market for the whole period of Jan. 2018 to 2020, these subjects did not satisfy our working period requirement, so we dropped them when analyzing the correlation between job changing frequency and individual preferences in all our subsequent studies.

section, we use the data from the second wave survey and the employment history data from the job-matching platform to investigate a possible explanation for the correlation we find in the second part of this section.

4.1 Findings on individual preferences

Table 3 displays the overall decision patterns among our subjects. First, contrary to previous findings that people are generally risk averse (Dohmen et al., 2011; Chew et al., 2021), subjects in our sample tend to be risk seeking. The average risk-aversion measure is 0.30.[33] Moreover, we do not find any evidence indicating more ambiguity aversion than risk aversion. In our sample, the ambiguity attitude is not significant away from ambiguity neutrality (T test: p=0.4451), indicating that subjects may not perceive a significant difference between the risk and ambiguity scenarios. This pattern is mainly driven by the male manufacturing migrant workers in the sample[34].

Second, subjects show impatience in the short term,[35] as they prefer getting a lower amount of money tomorrow than more money 31 days later. This pattern is consistent with the findings documented in the literature (e.g., Frederick et al., 2002; Sutter et al., 2013; and Chew et al., 2018). Since the extent of impatience in the long term is significantly lower than that in the short term,[36] the general pattern of present bias (e.g., hyperbolic discounting) is still observed.

Finally, the average proposal in the ultimatum game is 49%, and the average MAO is 36%[37]. In particular, 77.24% of the "proposers" divided the pie exactly in half. In addition, 43.09% of "responders" demanded exactly half. There is no evidence that the amount proposed in the UG and the MAO in the UG are significantly correlated.[38]

We also conducted the same experiment on 96 MBA students in a variety of industries. Migrant workers are more risk seeking, ambiguity seeking, impatient, and more difference averse compared to MBA subjects (see the details in the Online Appendix. A1.6). Compared with the general population or student subjects' game elicited behavior preferences in the previous literature, migrant workers are also more risk seeking, ambiguity seeking, impatient, and more difference averse (Frederick et al.2002; Dohmen et al. 2011; Sutter et al. 2013; Chew

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[33] Risk aversion measure>0.5 indicates risk aversion.

[34] See Table A3 in the Online Appendix for the separate description for the decision patterns of the male and female manufacturing migrant workers

[35] In average, comparing with getting 1 amount of money tomorrow, subjects would like to receive money 30 days later only if the amount is larger or equal to 1.21.

[36] T test: p=0.01.

[37] The Proposal and MAO of student subjects in Chew et al., 2021 are 46% and 32%, respectively. Oosterbeek et al.(2004) performs a meta-analysis of 37 papers with 75 results from ultimatum game experiments. The subjects are from different countries with cultural differences. They find that on average the proposer offers 40% of the pie to the responder, and on average 16% of the offers are rejected.

[38] The correlation coefficient between Proposal (UG) and MAO (UG) is 0.02. In addition, the P value of the simple OLS regression of Proposal (UG) on MAO (UG) is 0.83.

et al. 2021).

Table 3 Subjects' individual preferences

Panel A: Summary of the individual preferences of migrant workers

	Mean	**SD**	**Min**	**Max**
Attitudes toward uncertainty				
Risk aversion index	0.30	0.25	0.1	0.95
Ambiguity aversion index[39]	-0.01	0.20	-0.89	0.71
Future equivalent (￥)				
Short-term: 1 days vs. 31 days	1.21	0.12	0.995	1.295
Present bias: Short-term/Long-term	1.07	0.14	0.77	1.29
Ultimatum Game (UG)				
Proposal	0.49	0.12	0.01	1
MAO	0.36	0.17	0	0.7

Panel B: The decision patterns of migrant workers

		The characteristics of manufacturing migrant workers
Uncertainty attitudes	Risk Tolerance	Risk Seeking
	Ambiguity Tolerance	Ambiguity Seeking
	Ambiguity Aversion vs. Risk Aversion	Neutral
Intertemporal choices	Impatience (near)	Impatient
	Impatience (far)	Impatient
	Present bias	Yes
Difference aversion	Ultimatum game (Proposal)	49.5% of the pie
	Ultimatum game (MAO)	36.4% of the pie

From the above findings, we find that migrant workers are more uncertainty seeking, more impatient both in the near term and far term and have more concerns over fairness. We provide a summary of the comparison results in Table 3. These findings also speaks to the literature studying the characteristics of migrant workers in the sense that migrant workers are more uncertainty seeking (Gibson et al., 2020) and tend to value fairness (Yang et al., 2012).

4.2 Correlation between experimental decisions and JCF

Table 4 reports the regression results of subjects' individual preferences on their job changing frequency. Since leaving a job could be viewed as a random event that occurs with some intensity, we

[39] Following Sutter et al(2013), the risk aversion index ranges from 0(extreme risk seeking) to 1(extreme risk averse), and the ambiguity aversion index ranges from -1 (extreme ambiguity seeking) over 0 (ambiguity neutrality) to 1 (extreme ambiguity averse).

use Poisson regression as our main method of analysis.[40] Columns (1) and (2) include only experimental decisions as independent variables. Columns (3) and (4) add control variables for age, education level, family status, self-reported average wage of the last three jobs, and consumption of entertainment.

[40] To perform the Poisson regressions, we round the measure of job changing frequency into its closest integer in order. In addition, we also use the upper closest and lower closest integer as alternative measures. Both alternative measures show largely the same patterns of significant correlations, so we simply display the rounded measure in the following tables.

Table 4 Preferences and job changing frequency (Poisson regression)

Dependent variable: job changing frequency	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	JCF1	**JCF2**	**JCF1**	**JCF2**	**JCF1**	**JCF2**	**JCF1**	**JCF2**	**JCF1**	**JCF2**
Risk aversion	-.462**	-.238	-.493**	-.329**	-.462**	-.333**	-3.231***	-2.353***	-3.249***	-2.353***
	(.18)	(.152)	(.193)	(.162)	(.192)	(.161)	(.475)	(.395)	(.475)	(.397)
Ambiguity aversion	-.767***	-.67***	-.324	-.341*	-.24	-.33*	-2.599***	-2.078***	-2.502***	-2.04***
	(.248)	(.205)	(.238)	(.207)	(.232)	(.2)	(.603)	(.495)	(.608)	(.493)
Impatience (short)	-.974***	-.612*	-.163	-.019	-.171	-.028	-1.577**	-.455	-.283	-.01
	(.352)	(.32)	(.359)	(.34)	(.363)	(.343)	(.688)	(.64)	(.369)	(.354)
Present bias	.065	.486*	-.223	.16	-.24	.087	-.21	.14	-1.415**	-.079
	(.299)	(.256)	(.326)	(.284)	(.325)	(.281)	(.336)	(.289)	(.653)	(.55)
Proposal (UG)	.733***	-.215	.266	-.159	.411	-.027	.688**	.273	.613**	.269
	(.275)	(.285)	(.269)	(.29)	(.269)	(.294)	(.269)	(.292)	(.264)	(.292)
MAO (UG)	-.348*	.236	-.916***	-.283	-.909***	-.34*	-.736***	-.301	-.647***	-.301
	(.208)	(.192)	(.216)	(.203)	(.217)	(.204)	(.225)	(.21)	(.229)	(.213)
Risk_aversion *Edu_group							2.562***	1.993***	2.394***	1.943***
							(.463)	(.387)	(.448)	(.38)
Ambiguity_aversion *Edu_group							3.415***	2.414***	3.199***	2.351***
							(.603)	(.492)	(.595)	(.486)
Risk_aversion *Age_group							2.359***	1.655***	2.449***	1.68***
							(.451)	(.387)	(.455)	(.39)
Ambiguity_aversion *Age_group							1.327**	1.029**	1.269**	1.03**
							(.584)	(.485)	(.587)	(.485)
Age			0	-.021***						
			(.009)	(.008)						
Age_group					.156*	-.074	-.311**	-.409***	-.338**	-.42***
					(.087)	(.077)	(.142)	(.127)	(.143)	(.127)
Education			-.161***	-.204***						
			(.055)	(.049)						

Edu_group					-.134*	-.227***	-.7***	-.671***	-.665***	-.657***
					(.081)	(.071)	(.144)	(.123)	(.141)	(.121)
Male			.449**	.046	.427**	.045	.6***	.196	.607***	.198
			(.184)	(.146)	(.184)	(.147)	(.187)	(.15)	(.187)	(.15)
In_relation			.217**	-.126	.245**	-.121	.349***	-.021	.322***	-.026
			(.094)	(.091)	(.095)	(.093)	(.102)	(.097)	(.101)	(.097)
Boy			-.862***	-.414**	-.911***	-.459***	-.889***	-.445***	-.836***	-.431***
			(.193)	(.162)	(.193)	(.161)	(.201)	(.168)	(.2)	(.167)
No_child			-.073	-.101	-.063	-.063	.074	.027	.099	.035
			(.151)	(.132)	(.15)	(.131)	(.153)	(.133)	(.153)	(.134)
Avg_wage			-.082	-.054	-.107**	-.074*	-.118**	-.077*	-.106**	-.07
			(.05)	(.041)	(.051)	(.041)	(.054)	(.044)	(.052)	(.043)
Consumption			-.373***	-.246***	-.377***	-.259***	-1.294***	-.553*	-1.032***	-.387*
			(.038)	(.031)	(.038)	(.03)	(.408)	(.329)	(.287)	(.232)
Imp_consump							.76**	.234		
							(.342)	(.276)		
Pre_consump									.607**	.105
									(.27)	(.22)
Observations	112	110	106	104	106	104	106	104	106	104
Pseudo R^2	.036	.018	.256	.182	.253	.169	.312	.212	.312	.212

Note.

1. *Male*=1 if the subject is male; *Male*=0 if the subject is female.
2. *Education*=1 means primary school, *Education*=2 means junior high/middle school, *Education*=3 means senior high/technical school, *Education*=4 means some college education and *Educatio*n=5 means bachelor's degree or above.
3. *In_relation* is a dummy variable measuring subjects' relationship status. If *In_relation*=1, the subject is married or has a partner; if *In_relation*=0, the subject is single or divorced.
4. If *Boy*=1, the subject has at least one boy, while if *Boy*=0, it means the subject has no boy.
5. If *No_child*=1, the subject has no child, while if *No_child*=0, the subject has at least one child. Thus, with *Boy* and *No_child*, we can have a simple overview of the family composition: whether they have children and, if yes, whether they have at least one boy.
6. *Consumption* means how much income the subject usually spends on entertainment. *Consumption* varies between 1 and 7. *Consumption*=1 means "almost none of my income", and consumption=7 means "almost all of my income". *Imp_consump* is the interaction between *Impatience* and *Consumption*, and *Pre_consump* is the interaction between *Present_bias* and *Consumption*,
7. Asterisks indicate significance at 10% (*), 5% (**), and 1% (***)

The results show that participants' preference for uncertainty (risk and ambiguity) is significantly negatively correlated with their job changing frequencies. Both measurements of JCF (*JCF1* and *JCR2*) reveal the same pattern of results. For instance, from Column (1), Table 4, we find that on average, a risk-averse person's probability of changing jobs is 46.2% less than a risk-seeking person.[41]

Age and education levels are significantly correlated with job changing frequency (see Table 4)[42]. In addition to age and education, we find another factor that is related to job change: those who have at least one son change jobs with significantly less frequency, which is consistent with the empirical studies that show an increased tendency to save for sons (Chen et al. 2019; Wei and Zhang ,2011; Lu et al. 2017).[43] [44] Migrant workers' self-reported monthly wage of their last three jobs, *Avg_wage*, has a negative and significant coefficient, suggesting that a higher wage may increase job stability in general. As a robustness check, we replace *Age* and *Education* with two dummy variables: *Age_group* and *Edu_group* in Columns (5) to (10).[45] We used 25 years old as a cutoff point for different age levels after conducting interviews with migrant workers. Chinese migrant workers usually regard 25 years old as "time to settle down" for a stable life and carry more family responsibility. Due to compulsory education laws (including elementary and junior high school education) in China, 9 years of schooling provides a benchmark for the baseline educational level. Even though the factories do not require a minimum level of education, extremely inadequate education (such as not knowing the 26 letters of the English alphabet) will hinder the migrant workers from passing the interviews organized by the factories and affect their job prospects. Thus, in the context of Chinese migrant workers, 25 years old and 9 years of education are two important cutoffs for demographic characteristics. We further include the interactions between uncertainty attitude and demographic backgrounds in Columns (7) to (10) since we find a consistent significant influence of risk and ambiguity aversion on job changing frequency, as shown in columns (1) to (6).

From columns (7)-(10), we find that for different age levels, there are differences in the influence of risk or ambiguity aversion on job changing frequency. The regression coefficients for

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[41] The variable "risk aversion" = 1 for a completely risk-averse person, and = 0 for a completely risk-seeking person.

[42] In the Online Appendix A1.1, we explored whether individual preferences are related to demographical characteristics. We find significant correlation between Age_group or Education_group, with individual preferences. The regressions in Table A1 and A2 show negative correlation between proposal_UG and age group, and positive correlation between present bias and education group.

[43] This finding speaks to those of Chen et al. (2019) and Wei and Zhang (2011), which confirm that parents with sons may save more to increase their sons' future competitiveness in the marriage market. The result also echoes the findings of Lu et al. (2017). They find that sons bring parents significantly less happiness than daughters, and the difference becomes even more apparent when the children are ready for marriage.

[44] The hometowns of Chinese migrant workers are usually middle/West provinces in China. In the Online Appendix A4.2, we include the economic developing level of migrant workers' hometowns (*trainkilo*), their hometown's distance to Kunshan (*gdpper*), and their total working years till 2018 (*Work_year*) in the control variables. We conduct the same regression analysis in Table 4, Table 6, Table 9, and Table 10 in the paper. The results are displayed in the Online Appendix, see Table A4-A7. After controlling these variables, all our main findings in this paper still hold. Moreover, none of the coefficients of *trainkilo*, *gdpper* and *Work_year* are significant. This indicates that these factors do not play a role in migrant worker's JCF decisions.

[45] The variable "Age_group" = 1 for age older than 25, and variable "Education_group" = 1 for education more than 9 years.

Risk_aversion and *Ambiguity_aversion* are significantly negative. This shows that for migrant workers who are younger than 25 years old, the more risk averse or ambiguity averse they are, the less likely they are to change jobs. However, the negative correlation between risk/ambiguity aversion and turnover frequency is less pronounced for migrant workers who are older than 25, as the coefficients of the interaction terms *Risk_aversion*Age_group* and *Ambiguity_aversion*Age_group* are positive.

Similarly, the negative correlations between risk/ambiguity aversion and turnover frequency are less pronounced for migrant workers who receive more than 9 years of education, since the coefficients of the interaction terms of the uncertainty preferences and the education level, *Risk_aversion*Edu_group* and *Ambiguity_aversion*Edu_group,* are positive.

Consumption is a variable describing migrant workers' consumption of entertainment. Each migrant worker was asked, "How much of your income do you usually spend on entertainment, including gaming, dining out, going to KTV, and other types of entertainment?" They chose to enter a number in 1-7, with 1 representing "almost none of my income" and 7 representing "almost all of my income".

We included *Consumption* as a control variable and run the regression in Columns (3)-(10) Table 4. Because a less patient migrant worker may be less likely to restrain temptations and may spend more on entertainment, we further include the interaction between subjects' time preferences and *consumption* in columns (7)-(10) of Table 4. In columns (7) and (8), the control variables include *Imp_consump*, the interaction between *Impatience* and *Consumption*, and in columns (9) and (10), we include *Pre_consump*, the interaction between *Present_bias* and *Consumption*.

The variable Consumption is negatively and significantly correlated with JCF, indicating that the more income spent on entertainment, the less likely migrant workers are to change jobs. This is probably because spending more on entertainment will lead to increased economic vulnerability. Thus, migrant workers who consume entertainment more may be less able to afford temporary zero-income status if they change jobs, so their JCFs are lower.

The regressions from columns (1)-(10) on the correlation between individual preferences and job changing frequency support the same conclusion that risk/ambiguity attitudes may predict job changing frequency strongly and significantly. We do not find a consistent pattern of correlation between time presence (or difference aversion) and job changing frequency.

From the above analysis, we find robust evidence supporting H1 but less supportive evidence for H2 or H3. In sum, risk aversion or ambiguity aversion is negatively correlated with the job changing frequencies of migrant workers.

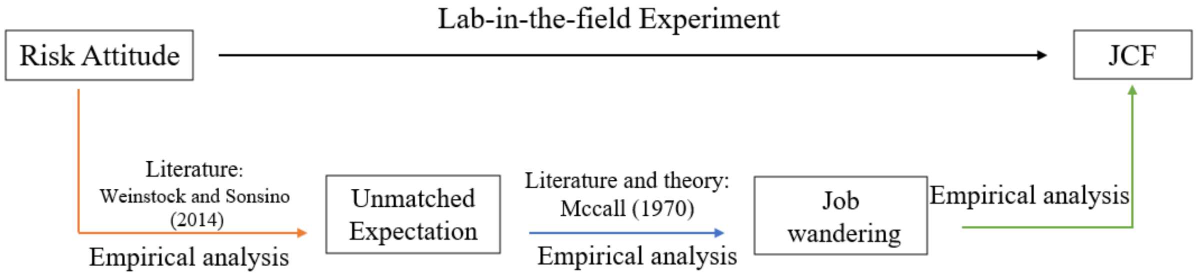
4.3 Possible explanations of the experimental findings

4.3.1 The path of a possible explanation

To explain the above findings from the lab-in-the-field experiment (i.e., that more risk-seeking migrant workers have higher JCF), we start from the literature to find a possible path of explanation and then combine theoretical modeling and empirical analysis by using data from the second wave survey as well as the employment history data provided by the job-matching platform to verify the explanation.

Figure 2 illustrates the flow of logic in our entire study. The top path in black represents our findings from the lab-in-the-field about the correlation of risk attitude and JCF. The bottom path in various colors represents possible explanations, consisting of three links. First, risk attitudes may be correlated with unmatched expectations (Weinstock and Sonsino, 2014), as more risk-seeking migrant workers make more optimistic expectations of the value of a potential job offer. By analyzing the survey data we collected, we find evidence to support this view. Second, we build a theoretical model based on McCall (1970) and predict that those who have higher expectations from a job are more likely to perform job sampling. By using the survey data and employment history data from the platform, we find supporting evidence. Finally, we find empirical evidence that those who have more job sampling experience are more likely to change their jobs frequently.

Figure 2 The logic of the explanation analysis



4.3.2 The first link: risk attitude and job expectations

In the literature, several papers find correlations between risk preferences and expectations. For instance, Weinstock and Sonsino (2014) confirm the predictive power of personal risk preference for forecast optimism. They elicit the risk preference of subjects randomly recruited at dining areas of shopping centers by incentivized binary choice lists. Through survey questions, they find personal optimism with respect to economic or financial uncertainties, such as predicting the performance of volatile stocks. The correlational study of Weinstock and Sonsino (2014) reveals that the experimentally elicited risk attitude significantly correlates with optimism in economic forecasts. In addition, Bucciol and Miniaci (2011) confirm the correlation between risk preference and the variance of returns of American households' asset portfolios. Since the job-changing decisions of migrant workers also contain economic uncertainty (van Huizen and Alessie, 2019), it is natural to predict that the more risk-seeking migrant workers make more optimistic expectations of a potential job offer's value.

Gathering data on migrant workers' expectations of the available job opportunities is unrealistic, since it is difficult to form a proper and coherent measure. To avoid this problem, we asked the subjects what reasons led them to leave a job in our follow-up survey. If the migrant workers with different preferences of risk face the same available job opportunities in the labor market, those migrant workers with more optimistic expectations of the value of jobs may be more likely to leave if the jobs turn out to fail their expectations.

In the follow-up survey, we asked subjects why they left a job and gave them several options for answers, as shown in Table 5. The choices are coded into 4 dummy variables in Table 5, depicting the aspects that may influence migrant workers when they decide to quit a job. It turns out that most migrant workers left their jobs because of job-related characteristics or because the jobs did not match expectations, chosen by 77% and 63% of the subjects, respectively. Less than 30% of migrant workers in our sample left a job because of other people in the job or for other reasons.

Then, we empirically investigate whether more risk-seeking migrant workers are more likely to leave because the jobs do not match their expectations.

In Table 6, we report the results of the relationship between individual preferences and *leave_expectation* (i.e., whether the subject has ever left a job because it did not match expectation). We find that risk aversion is negatively and significantly correlated with *leave_expectation*. This reveals that more risk-seeking migrant workers are more likely to leave if their jobs turn out to be below their expectations.

Table 5 The dummy variables representing the reason(s) migrant workers quit a job

The variables	Which reason(s) have led you quit a job?	Mean	Std. Dev.	Min	Max
leave_expectation	Leave because the job did not match expectation	.626	.486	0	1
leave_job	Leave because of job-related characteristics	.772	.421	0	1
leave_people	Leave because of people (colleague, leaders, etc.)	.285	.453	0	1
leave_other	Leave because of other reasons not mentioned above	.065	.248	0	1

Note.
We collected the data in Table 5 via the follow-up survey. The question in the follow-up survey asked subjects: Have you ever left a job for one or more of the following reasons? It contained four possible answers:
1. I left because I found the job was worse than I had expected after I came into the factory.
2. I left because of job-related characteristics (i.e., tiring jobs, low income, tedious work, noise or potential physical harm on the job).
3. I left because of a people-related issue (i.e., social relationships with colleagues, roommates in the factory dormitory, or leaders).
4. I left because of other reasons (i.e., family, friend…)

Table 6 The relationship between individual preference and the factors causing migrant workers to leave

Linear Regression (OLS)	The dependent variable: leave_expectation		
Risk_aversion	-.586***	-.729***	-.769***
	(.169)	(.199)	(.217)
Ambiguity_aversion		-.32	-.328
		(.247)	(.264)
Impatience		.331	.292
		(.417)	(.457)
Present_bias		-.23	-.282
		(.348)	(.393)
Proposal_UG		-.033	-.029
		(.36)	(.381)
MAO_UG		.072	.048
		(.248)	(.268)
Control Variable	No	No	Yes
Observations	123	123	116
R-squared	.091	.11	.144

We conduct probit and logit regressions in the Online Appendix (see Table A8) to check the robustness of the result. We also examine the relationship between risk attitude and the other reason causing migrant workers to quit a job, including *leave_job*, *leave_people*, and *leave_other* (see Table A9 in the Online Appendix). We find that none of these factors correlate with migrant workers' risk attitudes.

4.3.3 The second link: job expectation and job sampling

In this subsection, we attempt to explain how expectations of a job are positively related to the tendency to conduct job searches by adjusting the model developed by McCall (1970). We predict that migrant workers who are more risk-seeking benefit more from job search, which will drive them to search for jobs more frequently.[46] From the model, we predict that migrant workers who have more optimistic expectations of working opportunities prefer searching for jobs more.

Chinese migrant workers have different ways to search for jobs than ordinary job seekers who may interview for several jobs and pick an offer. Since migrant workers can only apply and interview for one position at a time, they usually stay in the factory right after they conduct interviews. They may even have no chance to go to the workplace to look at the working environment. Therefore, they use job sampling to perform the job search. Job sampling means that they try to work in the factory for several days and then leave if they find it unsuitable. The labor-intensive jobs available for those migrant workers have a similar wage level[47], which is about or slightly higher than 20 CNY/hour

[46] Please see our detailed theoretical analysis in the Online Appendix A3.

[47] We did interviews and obtained job ads from the job-matching platform and observed that despite seasonal variations in

(approximately $2.99), so there is not much difference in possible income. What matters to them might be the detailed aspects of the job, such as the working and living environment, the work hours, whether the leader or colleagues are easy to get along with, etc. They need to work in the factory for a few days to evaluate these factors by themselves. These multiple short working experiences may help migrant workers find a more appropriate job where they will work for a longer duration afterward. The process of job sampling is similar to product sampling. While in product sampling, a customer is able to try out a product, assessing its worthiness before purchasing it, migrant workers try to work in the factory for several days and then leave if they find it unsuitable.

It is a challenge to directly provide an empirical verification of the theoretical prediction provided above, since it is not easy to obtain data about the migrant workers' job search[48]. With the assistance of the job-matching platform, we obtained the employment history of the subjects on the platform.[49] Thus, we can observe part of the subject's past work experience: jobs that migrant workers found through the job-matching platform. The dataset includes the factories they worked in, the durations they were employed for each job, and the total wages they received during each work experience. Figure 3 displays the distribution of job duration and daily wages from the dataset we obtained from the job-matching platform. We observe that many work durations are less than 7 days. Meanwhile, average daily wages mostly range from 160-240 CNY (i.e., approximately $24-$36).[50] Therefore, we are able to observe and define migrant workers' tendency to perform job sampling.

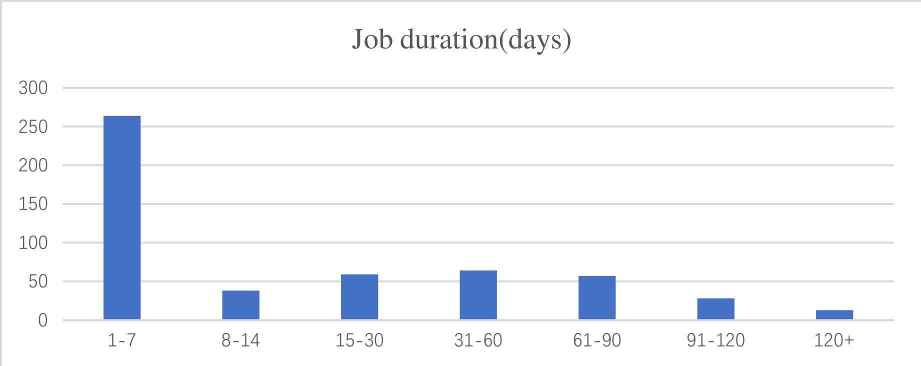
Figure 3 The distribution of job duration and daily wages

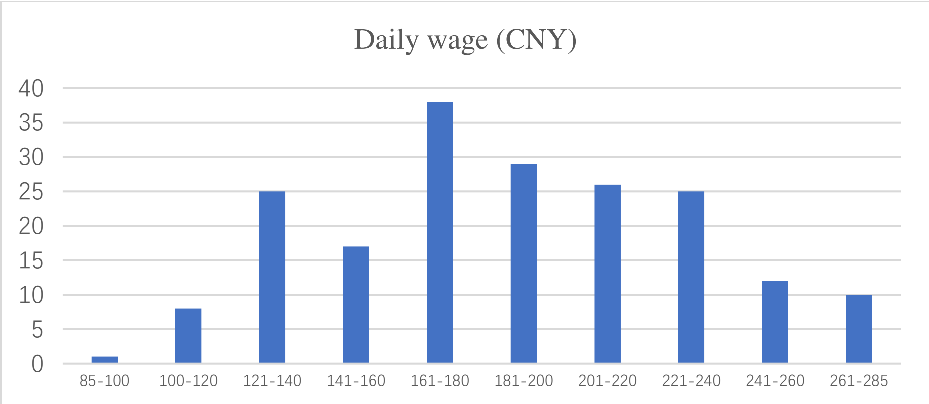
the overall wage level, the job opportunities posted on the market during the same period reflect the same wage levels.

[48] He et al. (2022) conduct a large randomized experiment on a large online job board to study how job search is affected by varying salaries, distinguishing the directed search model from the random search model. Our paper also studies job search through an intermediary, but differs with He et al. (2022) in the following three aspects. First, we want to study how risk attitude affect job search of migrant workers. Thus, we need to acquire each subject's detailed job searching experience, instead of the overall job applications on the job matching platform. Second, He et al. (2022) find that higher wage offers attract more job applications. However, in the context of Chinese migrant workers, wage is not a dominant factor in job search. According to our interview on the migrant workers, except from the wage, other aspects (the working and living experiment, etc.) are also important. Third, Chinese migrant workers search for job in the "job sampling "manner: not only search through the intermediary for wage offers, they also work for a few days for direct working experiences.

[49] Since the platform can only identify 86 of the 123 subjects of our study in their database, we only use these subjects' job histories for the analysis in this subsection.

[50] In Figure 3, we display the average daily wage of each job of each subject in the dataset provided by the job-matching platform. However, the dataset does not cover exactly how many hours a migrant worked per day during one job experience. We are not able to estimate the hourly wage of each experience from the dataset, but by interviewing the migrant workers, executives and employers on the job-matching platform, we confirm that the hourly wage of migrant workers is approximately 20 CNY/hour (about $2.99)





We display a typical job record of a migrant worker who conducts job sampling in Table 7. The record is drawn randomly from the real empirical data provided by the job-matching platform. The durations of jobs A and E are very short: only 2 days. However, each of the other jobs this migrant worker engaged in (Jobs B, C, D) lasted for at least a month.

Table 7 A typical job record of a migrant worker who conducts job sampling

Working experience	Date of Interview	Job duration
A	2019/10/14	2
B	2019/12/08	93
C	2020/06/02	72
D	2020/08/20	31
E	2020/10/26	2

Because the migrant worker cannot be paid for so little time worked, the fact that there are job durations less than a week (such as A and E in Table 7) indicates that it may be difficult for the migrant worker to identify an unsuitable job until he has first-hand experience in the factory. Then, the migrant worker can work for longer periods (such as B, C, and D in Table 7).

Since migrant workers are only able to be paid if they work for more than 7 days,[51] working durations less than or equal to 7 days can naturally be regarded as a job searching process. This unpaid, short-term employment—which we define below as job sampling—is consistent with the intent of migrant workers to search for a job and is a good indicator of their tendencies in job-seeking.

According to the dataset we obtained from the job-matching platform, the median and mean of job durations less than or equal to 7 days are both 4 days. The median of job durations longer than 7 days is 43 days, and the mean of job durations longer than 7 days is 53 days. The average of all working records in the dataset is 34 days.

We define *job_sampling_1* as a dummy variable indicating whether the subject has had such an experience from Jan 2018 to Dec 2020: the subject worked for less than or equal to 7 days at one job and then worked for more than 53 days at another. According to this definition, for the migrant worker depicted in Table 7, working experience A can be considered one experience of job sampling since the migrant worker for only 2 days and was not paid from A but may have gained enough work experience to proceed to work at another job for 93 days afterward.

For the robustness check, we tried 6 different definitions of job sampling, as shown in Table 8, according to the statistical characteristics mentioned above. For instance, we replace 7 days with 4 days, 53 days with 43 or 34 days, the time span with the duration of Jan. 2018-Aug. 2020, or the dummy variable with a quantitative variable. Columns (1) and (2) of Table 8 present the names and definitions of these job sampling variables, respectively.

Table 8 Definition of *job_sampling*

Variable name	**The definition of variables representing job sampling. (Using bold fonts, we indicate the difference between the definition of this variable and that of *job_sampling_1*.)**
job_sampling_1	● Dummy variable. ● Time dimension: 2018.1-2020.12. ● Definition: If a subject has two working experiences: they worked for less than or equal to 7 days, then they worked for more than 53 days (the latter experience does not need to occur immediately after the former experience), *job_sampling_1*=1; otherwise, *job_sampling_1*=0.
job_sampling_2	● **Discrete quantitative variable.** ● Time dimension: 2018.1-2020.12. ● Definition: *job_sampling_2* equals the number of times that *job_sampling_1* equals 1.
job_sampling_3	● Dummy variable. ● Time dimension: 2018.1-**2020.8**. ● Definition: If a subject has two working experiences: they worked for less than or equal to 7 days, then they worked for more than 53 days (the latter experience does not need to occur immediately after the former experience), *job_sampling_3*=1; otherwise, *job_sampling_3*=0.
job_sampling_4	● Dummy variable. ● Time dimension: 2018.1-2020.12. ● Definition: If a subject has two working experiences: they worked for less than or equal to

[51] According to the wage schedule of the manufacturing factories in Kunshan, China, migrant workers can only get their weekly wage on the following week. In other words, a migrant worker starts to be paid by the factory only after they have worked for at least 7 days.

	7 days, then they worked for more than **34** days (the latter experience does not need to occur immediately after the former experience), *job_sampling_4*=1; otherwise, *job_sampling_4*=0.
job_sampling_5	• Dummy variable. • Time dimension: 2018.1-2020.12. • Definition: If a subject has two working experiences: they worked for less than or equal to **4** days, then they worked for more than 53 days (the latter experience does not need to occur immediately after the former experience), *job_sampling_5*=1; otherwise, *job_sampling_5*=0.
job_sampling_6	• Dummy variable. • Time dimension: 2018.1-2020.12. • Definition: If a subject has two working experiences: they worked for less than or equal to 7 days, then they worked for more than **43** days (the latter experience does not need to occur immediately after the former experience), *job_sampling_6*=1; otherwise, *job_sampling_6*=0.

In Table 9, we show the relationship between *job_sampling* and whether migrant workers leave a job because of unmatched expectations. Columns (1) to (5) of Table 9 study the correlation between *job_sampling_1*, our first indicator of job sampling, and *leave_expectation*. We apply OLS regression in Columns (1)-(4) and probit regression in Column (5) as a robustness check. The regressions reveal that migrant workers suffering from unmatched expectations are more likely to engage in job sampling.

Columns (6)-(10) of Table 9 replace the dependent variables with other indicators of job sampling, from *job_sampling_2* to *job_sampling_6*. The regressions largely confirm the findings we draw above in terms of *job_sampling_1*.

Table 9 Relationship between job sampling and expectation

The relationship between job_sampling, expectation, and risk attitude	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: job_sampling_1					job_sampling_2	job_sampling_3	job_sampling_4	job_sampling_5	job_sampling_6
	OLS				Probit	OLS	Probit			
Leave_expectation	.381***	.243**	.266**	.249*	.789*	.392**	.778	.932**	.392	.94**
	(.105)	(.12)	(.127)	(.137)	(.411)	(.172)	(.483)	(.416)	(.43)	(.416)
Risk_aversion		-.486**	-.423	-.448	-1.481	-.424	-1.208	-.826	-2.38**	-.858
		(.22)	(.277)	(.295)	(.903)	(.37)	(.993)	(.904)	(.972)	(.902)
Ambiguity_aversion			.104	.09	.417	-.09	1.854*	.336	-1.133	.345
			(.268)	(.282)	(.913)	(.354)	(1.081)	(.886)	(.957)	(.889)
Impatience			-.193	-.242	-.83	.559	.163	-1.206	.509	-1.188
			(.48)	(.513)	(1.643)	(.643)	(1.84)	(1.64)	(1.532)	(1.642)
Present_bias			.061	.074	.327	-.284	1.392	-.144	.088	-.021
			(.433)	(.487)	(1.547)	(.611)	(1.785)	(1.545)	(1.548)	(1.521)
Proposal_UG			.655	.669	2.508*	.865	3.369**	2.521*	-.014	2.558*
			(.396)	(.417)	(1.465)	(.523)	(1.642)	(1.475)	(1.427)	(1.474)
MAO_UG			.143	.248	1.015	.368	2.611*	.936	1.17	1.002
			(.304)	(.332)	(1.119)	(.416)	(1.361)	(1.126)	(1.062)	(1.119)
Age				-.002	0	-.007	0	-.011	.019	-.009
				(.013)	(.042)	(.016)	(.052)	(.042)	(.038)	(.042)
Male				.114	.422	.204		.606	.013	.611
				(.204)	(.665)	(.256)		(.657)	(.664)	(.659)
Education				.082	.288	.079	.015	.347	-.045	.352
				(.074)	(.236)	(.093)	(.264)	(.235)	(.222)	(.236)
In_relation				-.218	-.78*	-.159	-.932	-.518	-.456	-.521
				(.132)	(.436)	(.165)	(.63)	(.415)	(.427)	(.416)
Boy				.197	.587	.328	-1.21	.735	-.522	.746
				(.254)	(.768)	(.319)	(1.235)	(.766)	(.762)	(.767)
No_child				.065	.099	.24	.247	.297	-.405	.308
				(.205)	(.616)	(.258)	(.723)	(.616)	(.599)	(.616)
Avg_wage				-.022	-.145	-.035	-.565*	-.188	-.17	-.205
				(.072)	(.232)	(.09)	(.298)	(.232)	(.22)	(.229)
Consumption				-.037	-.1	-.046	-.124	-.094	-.078	-.09
				(.033)	(.111)	(.041)	(.12)	(.109)	(.106)	(.109)
Observations	86	86	86	81	81	81	71	80	81	81
Pseudo R^2	.125	.184	.216	0.143	.257	0.105	.331	.235	.178	.240

4.3.4 The third link: job sampling and JCF

Finally, if we can find that migrant workers' JCFs are positively correlated with their tendency to engage in job searching, we will confirm a potential mechanism for the correlation between risk seeking and JCF: migrant workers who are more risk-seeking have higher job expectations and are more likely to perform job sampling, resulting in higher JCFs.

More job sampling does not necessarily correlate with more job changing frequency. One may argue that the preference to perform job sampling would mean more short-duration job experiences (e.g., less than seven days or even less than four days), which may result in more job changing frequency within a certain period of time. However, on the other hand, the tendency to conduct more job sampling indicates that job seekers want to find suitable jobs, which may encourage migrants to stay in one place for a longer period after they find a job they are satisfied with, thus resulting in lower JCF. To test whether job sampling is positively correlated with JCF (*JCF1* and *JCF2*),[52] we perform regression analysis on *JCF1/JCF2* on the six job sampling variables and display the regression coefficients of each in Table 10.

We find that most job sampling variables are positively and significantly correlated with JCF. For example, the regression coefficient of *JCF1* on *job_sampling_1* is 0.851 ($p<0.01$), meaning that when controlling for individual preferences, the migrant workers who have sampled jobs before are 85.1% more likely to change jobs than those without job sampling experience.

We also include the demographic characteristics of migrant workers as control variables and show each regression coefficient in Columns (3)-(6) of Table 10. The significant positive relationship between job sampling and JCF remains consistent in most of the regression results. Therefore, job sampling leads to higher JCFs.

To conclude, by the three steps of the analysis above, we offer a possible explanation for the correlation between risk attitude and higher job changing frequency: migrant workers who are willing to tolerate greater risk often have higher expectations for their job prospects, so they are more likely to quit when their expectations are not met. Consequently, these migrant workers tend to sample more between jobs: they may work for a few days (even if they cannot be paid) to learn and gain experience before committing to the job for a long time. Due to this, more risk-seeking migrant workers change jobs more frequently.

[52] It might be a concern that when migrant workers self-reported JCF, they might regard jobs with extremely short working durations (less than 7 days or 4 days) as informal work experiences and not report them. We compared the self-reported JCF and the employment history data from the platform, and find that for any migrant worker, the JCF they reported is greater than or equal to the number of jobs recorded on the platform during the same period of time. This shows that migrant workers did not intentionally exclude short-duration jobs. In addition, the reason why some JCF is larger than the actual number of turnovers on the platform is that migrant workers not only look for jobs through the platform but also find jobs through other channels. Therefore, the JCF is representative.

Table 10 Regression coefficients of job sampling variables and JCFs

	With individual preferences as control		With demographics as control		With individual preferences and demographics as control	
	(1)	(2)	(3)	(4)	(5)	(6)
	JCF1	JCF2	JCF1	JCF2	JCF1	JCF2
job_sampling_1	.851***	.679***	.695***	.41***	.782***	.527***
	(.112)	(.092)	(.109)	(.09)	(.123)	(.101)
job_sampling_2	.648***	.419***	.335***	.142**	.418***	.227***
	(.084)	(.071)	(.073)	(.068)	(.089)	(.077)
job_sampling_3	.702***	.489***	.352***	.138	.555***	.272***
	(.107)	(.09)	(.105)	(.09)	(.125)	(.105)
job_sampling_4	.728***	.593***	.618***	.359***	.629***	.429***
	(.111)	(.091)	(.111)	(.092)	(.121)	(.099)
job_sampling_5	.582***	.323***	.286***	.039	.291***	.062
	(.098)	(.086)	(.094)	(.085)	(.108)	(.097)
job_sampling_6	.724***	.587***	.61***	.351***	.628***	.426***
	(.111)	(.091)	(.111)	(.092)	(.121)	(.099)

Note.
1. We display only the regression coefficients of JCF on job sampling variables in Table 10. The regression method is Poisson regression.
2. In Columns (1) and (2), we include individual preferences as control variables.
3. In Columns (3) and (4), we include demographical variables, average wage, and consumption on entertainment as control variables.
4. In Columns (5) and (6), we include individual preferences, demographical variables, average wage, and consumption on entertainment as control variables.

In sum, we find that the expectations of migrant workers who are more risk seeking are likely to be higher. Thus, they prefer to engage in job sampling and experience turnover more frequently because the jobs do not meet their expectations. Their job changing frequency is higher than that of risk-averse workers

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5. Conclusion

Through a lab-in-the-field experiment at the offline meeting site of an online-to-offline job-matching platform, we elicited subjects' individual preferences by incentive-compatible economic experiments. We first examined the individual preferences of migrant workers; then, we studied which individual preferences could be related to their job changing frequency. Finally, we offered an explanation for the relationship between individual preference and job change frequency.

Migrant workers show a higher degree of uncertainty-seeking patterns, more impatience in both the near and far term, and greater concerns with fairness. These preferences are significantly correlated with JCFs. Specifically, risk or ambiguity aversion is significantly negatively correlated with JCF. We further investigate the durations of subjects' past jobs as recorded on the platform and offer a possible explanation: those who seek more risk are more likely to form higher expectations of potential job opportunities, so they are more likely to quit when their expectations are not met. It is this tendency that drives migrant workers to engage in job sampling: they are more likely to work for a few days (even if they cannot be paid) for learning and searching purposes before settling down for a longer time. As a result, more risk-taking migrant workers have a higher job-changing frequency.

Our findings provide a new perspective on the puzzle of migrant workers' high job-changing frequency. The mechanism we uncover has implications for important public policy recommendations. First, migrant workers who leave their hometowns are generally risk-tolerant with high expectations for possible jobs as well as living conditions in developed areas. Public policies can be designed to set reasonable and achievable expectations for them. Second, the regulatory sectors can strongly suggest that factories disclose information about each aspect of the workplace and lifestyle in the factories.

This study investigate one possible explanation of why migrant workers change job frequently. There might exist other possible paths that need to further explore in the future. It is also worthy to investigate why migrant workers have difficulty securing jobs. More importantly, policy designs that use behavioral mechanisms to address migrant workers' job changing frequency are worth developing as well. Providing access to relevant information about job placement by intermediaries, fostering the unbiased expectations of migrant workers about future job positions, and incentivizing the intrinsic motivation of migrant workers in the workplace are major potential research avenues to help them earn a more stable income.

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