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Public Health Insurance and the Labor Market: *Evidence from China's Urban Resident Basic Medical Insurance* ☆

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Abstract

This paper provides empirical evidence on the labor market effects of public health insurance using evidence from China. In 2007, China launched a national public health insurance program, Urban Resident Basic Medical Insurance (URBMI), targeting residents in urban areas who were not insured by the pre-existing employment-based health insurance system. Using panel data from the China Health and Nutrition Survey 2004, 2006, 2009, and 2011, I employ an instrumental variable strategy that exploits the time variation in URBMI implementation at the city level to overcome self-selection issues. I find that URBMI did not have a significant average causal effect on employment for the sample as a whole. However, after the program was implemented, job lock declined, and job flexibility increased, especially among women, the less educated, and individuals with good health status. The results also suggest increased labor supply for unhealthy workers, indicating a direct health improvement effect.

Keywords Public health insurance, Labor supply, Job mobility, Informality, Urban China

JEL classification: I13, I38, J21, J62

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1 Introduction

Universal health coverage has become one of the leading priorities of policymakers in many countries in recent years, especially in the developing world. Many developing countries are actively engaged in efforts to establish a national health insurance (NHI) system, including Mexico, Colombia, Thailand, China, India, Vietnam, Jamaica, and Ghana (Bitran et al., 2014). Public health insurance not only directly affects people's healthcare and health status but also plays an influential role in the labor market outcomes of individuals. Therefore, the potential impact of public health insurance programs warrants exploration.

In this paper, I explore the effects of China's Urban Resident Basic Medical Insurance (URBMI) on the labor market. I estimate whether adopting this public health insurance has had an impact on the labor market decisions and outcomes of individuals in a developing and transition economy. Empirical evidence from developing and transition economies is relatively scarce compared to that from developed countries, and this paper provides some insights from China.

This paper contributes to the existing literature on the labor market effects of public health insurance in at least two respects. First, it adds to the literature on the effects of health insurance on labor supply, labor mobility ("job lock") and labor market flexibility. Previous studies have examined the effects of health insurance on job choice, working hours, and wages, but most have focused on evidence from the US. Moreover, the results on the direction and magnitude are mixed and vary across different populations and time periods studied (e.g., Baicker et al., 2014; Borjas, 2003; Moffitt and Wolfe, 1992; Winkler, 1991; Yelowitz, 1995).

Second, this paper complements the literature on crowding out in developing countries by examining the effects of public health insurance on informality. Recently, there has been an increasing number of studies on the labor market effects of health insurance in developing countries, with a particular focus on the effect of expanded healthcare coverage on labor force participation and labor flows between the formal and informal sectors. As Levy (2008) notes, in the case of Mexico, public health insurance and other social programs expand social insurance such as healthcare benefits from the formal sector to the informal sector. This expansion may decrease the incentives to work in the formal sector and consequently impede long-run economic growth in developing countries. Non-contributory or less-contributory public insurance schemes can create incentives for workers to reallocate away from formal jobs, especially in countries with large informal labor markets. Reallocation toward small and inefficient informal jobs may potentially generate a loss of tax revenue for states and a welfare loss for workers in the long run, such as reduced pensions. This unintended side effect has attracted the attention of researchers and policymakers in developing countries. Is this a universal concern in the developing world? This study of URBMI, which primarily targets the unemployed and informal sector workers, provides new evidence from China.

The expansion of healthcare insurance in developing countries follows a general pattern that starts with formal sector employees, followed by informal sector workers, the unemployed, and economically disadvantaged individuals with government-subsidized enrollment (Bitran et al., 2014). China is no exception. Prior to the launch of URBMI, two public health insurance programs were established: Urban Employee Basic Medical Insurance (UEBMI) for formally employed residents in urban areas, which was established in 1998, and the New Cooperative Medical Scheme (NCMS) for rural residents, initiated in 2003. In an effort to establish a universal health insurance system, the Chinese government introduced the URBMI program in 2007 in urban areas, and by the end of 2009, almost all cities in the country had implemented this program (Barber and Yao, 2010). URBMI is designed to provide healthcare coverage to urban residents who are not covered by the employment-based UEBMI, including the unemployed, the self-employed and informally employed workers, the elderly, children and college students. Enrollment in URBMI is voluntary, and the premium is heavily subsidized by the government. URBMI covered 221 million urban residents in 2011, and the total number of recipients had increased to 299 million by the end of 2013.[1]

To estimate the potential labor market effects of URBMI, I use panel data from the China Health and Nutrition Survey (CHNS), specifically from the 2004, 2006, 2009 and 2011 waves. The main identification challenge when estimating the causal effect of URBMI on labor market outcomes arises from potential self-selection bias due to the voluntary enrollment scheme of the program. To overcome this endogeneity issue, I employ an instrumental variable (IV) strategy that exploits the time variation in URBMI implementation at the city level. The results show that URBMI does not have a significant average causal effect on employment and income for the sample as a whole, except for an increased trend toward self-employment. By exploring the heterogeneous effects by gender, education, and previous health and employment status, I find that formal sector employees are more likely to become self-employed compared to before program implementation, indicating a reduction in job lock. This inflow from long-term formal employment to self-employment is likely attributable to the less educated and individuals with good health status. Women enhance their job flexibility by leaving long-term employment and working for fixed-term contracts or other jobs in the informal sector, and men exhibit a transition to self-employment from other informal jobs. The findings are consistent with the fact that URBMI reduces the medical expenditure risks associated with informal sector employment and enhances labor market flexibility. The results also indicate increased self-employment and fixed-term contract workers for those who were previously in poor health status, indicating a direct health improvement effect of the insurance scheme. Additionally, the availability of URBMI may result in decreased labor costs for small business employers, and thus their labor demand increases, ultimately resulting in more job opportunities in the formal sector.

The remainder of this paper is organized as follows. The next section briefly reviews

[1] Data source: China Public Health Statistical Yearbook, 2014.

the theory and related literature on the effects of public health insurance on labor market outcomes. Section 3 introduces the public health insurance system and the labor market in urban China and the institutional setup of the URBMI program. Section 4 describes the data and the identification strategy for the empirical analysis. Section 5 presents the results, and the final section discusses the results and concludes the paper.

2 Theory and Related Literature

The standard static labor supply model assumes that individuals maximize their well-being by consuming market goods and leisure, which depend on their wages, their non-labor incomes, and other factors (Killingsworth, 1983). Health insurance could affect labor force participation for at least two reasons (Currie and Madrian, 1999). First, health insurance could generate a direct health improvement effect for workers, such that better health conditions increase work productivity. Second, health insurance may change a (risk-averse) person's utility associated with leisure, since spending more time on leisure and less on working may generate greater uncertainty about healthcare expenditures. Hence, if health insurance is tied to formal sector employment, then labor force participation in the formal sector is likely to increase. However, public health insurance, which is not directly linked to employment, would likely have the opposite effect on labor supply, since it detaches healthcare coverage from employment. Such a benefit reduces the opportunity cost of leisure and in some cases provides a positive income transfer to recipients, especially for those with low incomes or high medical costs; therefore, individuals' incentives for working may decrease. Moreover, employment-based health insurance may create a labor market distortion and reduce job mobility (so-called "job lock") if workers have to remain in less-preferred or less-productive jobs to avoid losing their health insurance (Madrian, 1994). Several studies have demonstrated that delinking insurance availability from the employer-employee relationship could decrease job lock and encourage self-employment and entrepreneurship (Boyle and Lahey, 2010; Fairlie et al., 2011; Heim and Lurie, 2015; Holtz-Eakin et al., 1996; Liu and Zhang, 2018).

Previous studies of various public healthcare programs in the US and other developed countries have provided mixed results. Many studies find evidence that public health insurance programs create disincentives to work (Boyle and Lahey, 2010; Dague et al., 2014; Moffitt and Wolfe, 1992; Winkler, 1991) or increase labor supply after reductions in insurance eligibility (Borjas, 2003; Yelowitz, 1995) and observe the phenomenon of "employment lock"; i.e., people join the labor force mainly for insurance reasons (Garthwaite et al., 2014). Gruber and Hanratty (1995) find that employment rose in Canada after the introduction of NHI, and their findings suggest that NHI caused a systematic increase in labor demand across all sectors as a result of increased job mobility, worker health, and productivity. Moreover, several studies find no significant labor market effects of public health insurance (Baicker et al., 2014; Leung and Mas, 2016; Strumpf, 2011).

Evidence from developing countries also provides interesting results and implications. Both Aterido et al. (2011) and Azuara and Marinescu (2013) examine Mexico's *Seguro Popular (SP)*, which expands health insurance beyond formal sector workers. The former finds that *SP* reduces the inflow of workers into formal employment and lowers labor force participation, while the latter shows that *SP* has no effect on informality in the overall population but increases informal employment for less-educated workers. Similarly, in Colombia, the *Subsidized Regime* provides public health insurance to the unemployed poor, and Camacho et al. (2014) find that the program is associated with an increase in informal employment. Beuermann and Pecha (2016) examine Jamaica's free universal public healthcare and find that there is no effect on employment at the extensive margin but an increase in the labor supply at the intensive margin due to improved worker health. Moreover, Wagstaff and Manachotphong (2012) show that informal sector employment increased among married women and formal sector employment decreased among married men after the introduction of universal healthcare coverage in Thailand.

3 Institutional Background

3.1 The Public Health Insurance System in Urban China

The public health insurance system in China currently consists of three major parts: UEBMI and URBMI in urban areas and NCMS in rural areas.[2] The evolution of health insurance in urban China followed economic reform and transition. Before 1978, under the country's centrally planned economic system, two major health insurance schemes operated in urban areas: the Labor Insurance Scheme (LIS) and the Government Employee Insurance Scheme (GIS), which covered almost all urban workers and their dependents (Barber and Yao, 2010). Since the 1980s, with market-oriented economic reforms, many workers from state-owned-enterprises were laid off and lost their eligibility for their original health insurance. Moreover, problems such as over-utilization and inefficient resource allocation hampered the old health insurance schemes. In 1998, following a reform of health insurance for urban formal sector workers, a new public insurance scheme, UEBMI, was established. UEBMI replaced the original LIS and GIS systems and expanded to the private sector; it was designed to cover all formally employed urban workers. UEBMI is a salary-oriented social insurance program with annual premiums amounting to 8% of payroll, which are paid by employers (6%) and employees (2%); 70% of employers' contributions enter a social pooled account, and the remaining 30% and employees' 2% share are deposited into individual medical

[2] Urban and rural households are specified according to the general household registration system in China (called the *"hukou"* system). Because only the urban part of the health insurance system is relevant to this study, the following presentation will focus on urban China.

savings accounts (Barber and Yao, 2010; Huang and Gan, 2015). In 2010, for instance, the average individual contribution to UEBMI was approximately 494 to 741 Chinese yuan (CNY) per person, and the average employer contribution was approximately 1483 to 1977 CNY per person (Yip et al., 2012).[3] The new scheme for formal sector employees no longer covered workers' dependents; hence, urban residents without formal employment were left uncovered by any public healthcare program from 1998 to 2006, and the total number of individuals in the urban population that was left behind was estimated at 420 million (Lin et al., 2009; Yip and Hsiao, 2009).[4] To provide health insurance coverage to uncovered urban residents, a new public health insurance program, URBMI, was introduced in 2007. Starting in 79 pilot cities in 2007, with an additional 229 cities joining in 2008, the program was rapidly rolled out nationwide. By the end of 2009, almost all cities in the country had implemented the URBMI program. Figure 1 illustrates the number of both URBMI and UEBMI recipients in each year from 2007 to 2013.

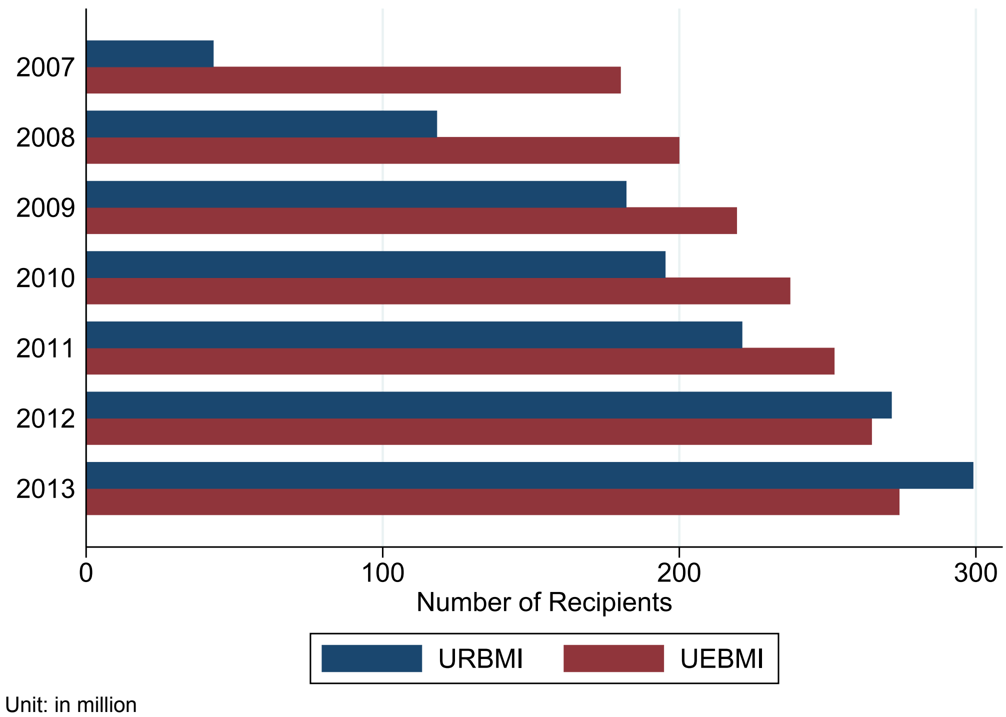


Figure 1: Number of URBMI and UEBMI Recipients, 2007-2013
Source: China Public Health Statistical Yearbook (from 2008 to 2014).

[3]The exchange rate is approximately 6.5 CNY = 1 USD. According to the National Bureau of Statistics, the average per capita annual disposable income of urban households in 2010 was CNY 19109.4.

[4]Apart from public health insurance, commercial insurance plans are available in the market. However, private insurance is rather expensive in China and thus not affordable to the majority.

3.2 Urban Resident Basic Medical Insurance

URBMI is a large-scale public insurance program operated by the government and managed at the city level. The targeted groups are urban residents who do not have UEBMI, including the unemployed and informally employed adults, the elderly, children and college students. Individuals participate in the program on a voluntary basis. The program is jointly financed by government subsidies and individual contributions. Individuals pay less than 50% of the premium, and the local and central government together subsidize the rest. The premiums vary slightly across cities and years. In 2010, for instance, the local and central government subsidy per person was on average 180 CNY, while individuals contributed approximately 20 to 170 CNY in the central and western provinces and 40 to 250 CNY in the eastern provinces (Yip et al., 2012). Poor households and the disabled are additionally financed by the Medical Finance Assistance program, which covers their individual share of contributions (Barber and Yao, 2010). Enrollment is on an annual basis, and participants can freely choose to continue or quit the following year. Reimbursements include medical expenditures on inpatient services and outpatient care for chronic and fatal diseases, and some cities have a larger coverage range of outpatient services (Liu and Zhao, 2014).

There have only been a few studies of URBMI; considering the large-scale population under the public program's target and influence, the effects of URBMI warrant further study. Lin et al. (2009) conduct the first economic analysis of URBMI on healthcare using household surveys from nine representative cities in 2007. They find that extremely rich or poor households and individuals with recent inpatient treatments or chronic diseases are more likely to participate. URBMI significantly benefits the poor individuals who are in need of inpatient care by reducing the financial pressure they face from medical expenditures. Liu and Zhao (2014) estimate the impact of URBMI on healthcare utilization and expenditure using CHNS data for 2006 and 2009. Their results show that the program increases the utilization of formal medical services, especially for children, low-income individuals, and residents in less-developed areas; however, it does not reduce total out-of-pocket health expenses. A recent paper by Liu and Zhang (2018) investigates the impact of URBMI on promoting entrepreneurship by individuals with urban *hukou* compared to those with rural *hukou*. They find that URBMI increases self-employment, which is similar to one of the key results of my paper. However, in this paper, I examine the labor market impact of URBMI in greater detail by exploring broader labor market outcomes and exploit IV as the identification strategy to control for unobservable characteristics.[5]

[5] Another difference is that, unlike Liu and Zhang (2018), I do not include rural *hukou* residents in the sample used for analysis. Under the current *hukou* policy in China, individuals with urban *hukou* and rural *hukou* not only face distinct circumstances in the labor market but are subject to completely different social programs. Regarding concerns that the group with rural *hukou* may not serve as a valid control group for those with urban *hukou* in this study, I deliberately exclude individuals with rural *hukou* from my sample to avoid systematic bias in the results.

3.3 Labor Market in Urban China and Expected Effects of URBMI

The labor market in China has become increasingly market-oriented since the economic reform of the 1980s. In urban areas, state-owned enterprises have downsized, and the private sector has been increasing steadily. Meanwhile, the informal sector has grown rapidly in recent decades (Liang et al., 2016; Wang et al., 2016).[6] Studies report that informal employment accounted for approximately 45% to 60% of urban employment in the 2000s (Wang et al., 2016).

In this study, I examine the potential effects of URBMI on the labor market decisions and outcomes of individuals. The following outcome variables are measured: employment, formal sector employment, and informal sector employment. Employment is defined as whether an individual is currently working. Formal sector employees include both open-ended contracts and fixed-term contracts. An open-ended employment contract is a long-term type of formal employment contract, while fixed-term contract workers usually have specific, short-term labor contracts. Informal sector workers include the self-employed and informal workers who lack formal employment contracts, for instance, temporary workers and family workers.[7] Moreover, to further explore the potential impact of URBMI on individuals' welfare, I check whether URBMI affected household income.[8]

Since URBMI is intended to provide health insurance to urban residents who were not covered by the pre-existing UEBMI, it could affect an individual's labor market decisions in the following ways. First, although it is subsidized by the government, URBMI is not a premium-free program, and Liu and Zhao (2014) show that total out-of-pocket health expenses were not reduced for the insured. Therefore, unlike free public healthcare programs in other countries, income effects are not likely to occur in the case of URBMI, and thus, labor market participation is potentially unaffected. The probability of working may even have increased for some marginal workers due to improved health. Moreover, since URBMI decouples health insurance eligibility from formal employment, transitions out of formal employment may increase, resulting in reduced job lock and increased job flexibility. By contrast, jobs in the informal sector, especially self-employment, may become more attractive than before, since URBMI reduces the healthcare expenditure risks that were formerly associated with informal sector employment. Furthermore, from the labor demand side, after the launch of URBMI, small employers were allowed to provide this new type of health insurance to their employees as an alternative to UEBMI, since the latter is more costly. Thus,

[6] Several factors account for the growth of informal employment in China, such as mass layoffs from state-owned enterprises, increased rural-urban migration, and the emergence of online businesses as opportunities for small business owners and freelancers to build careers.

[7] There is a very small fraction (0.85%) of working individuals in the data with employment type unknown, and I include them in the category of informal sector workers. The results are unchanged if I exclude them from the entire sample used for analysis.

[8] I use household income as a proxy for individual income because of missing value problems affecting the latter in the data.

their labor costs decrease, which may increase their labor demand.[9]

4 Data and Methodology

4.1 Data

I use data from the *CHNS*, which is an ongoing survey project jointly conducted by the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute of Nutrition and Food Safety at the Chinese Center for Disease Control and Prevention. CHNS contains longitudinal datasets with survey data collected every two to four years since 1989. Longitudinal samples of the survey are from nine provinces in China varying in geography, public resources, and socioeconomic development.[10] A multi-stage, random cluster sampling process is applied to sample six cities (two more developed cities and four counties) from each province. The survey collects information from individuals and households on demographic characteristics, socioeconomic status, basic physical conditions, and health-related behaviors.[11]

As URBMI was launched in 2007, I use four waves of data from the CHNS datasets; the 2004 and 2006 waves are included as the pre-program period, and the 2009 and 2011 waves are included as the post-program period. Information about individuals' health insurance, employment status, and basic demographic characteristics in each wave can be obtained from the CHNS' household and individual surveys. The sample includes a total of 54 cities across nine provinces.[12] After identifying the exact location of each city and combining the information with the list of the URBMI pilot cities, which implemented the program during the period 2007-2008, I find that of the 54 sample cities, 12 cities launched the program in 2007, 36 cities implemented it in 2008, and six cities did so in 2009. Considering the cities that implemented URBMI during 2007 and 2008 as pilot cities and the cities that implemented the program in 2009 as non-pilot cities, my sample for analysis includes 48 pilot cities and six non-pilot cities.

To examine the labor market outcomes, the sample used in the analysis is limited to men aged 18 to 60 and women aged 18 to 55, as the statutory retirement age in China is 60 years

[9]Note that even for formal sector employees, the coverage rate of the pre-existing UEBMI is not 100%, especially for fixed-term contract workers. This is probably because providing UEBMI to employees is costly for small employers, and due to a lack of supervision or market irregularities in some areas, not all employers provide UEBMI to their employees.

[10]These nine provinces are Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, and Guizhou, which are shown on the map of China in Figure A.1. In the 2011 wave, three municipalities, Beijing, Shanghai, and Chongqing, were added to the surveys for the first time. I do not include these municipalities in the sample used for analysis.

[11]Further information about the CHNS can be found on its website: http://www.cpc.unc.edu/projects/china

[12]The CHNS does not release the exact names of the cities contained in the surveys. I identified the exact location of each city by comparing the reported total area and population of each city and year in the CHNS Community Data with various yearbooks in China, following the same strategy used by Chyi and Zhou (2014) and Liu and Zhao (2014).

for males and 55 years for females.[13] Moreover, as URBMI is part of the urban healthcare system and the local urban *hukou* is required when individuals take up insurance in each city, I only include individuals with urban *hukou*. Therefore, the sample used for analysis consists of an unbalanced panel of 7868 observations, including 2582 in 2004, 2483 in 2006, 1542 in 2009 and 1261 in 2011.[14]

Table 1 presents summary statistics for the main variables, including URBMI enrollment status, individual characteristics, and labor market outcome variables, for the pilot and non-pilot cities. The pilot cities have a higher URBMI enrollment rate (26.0%) than the non-pilot cities (19.7%). The individual characteristics are quite similar in the pilot and non-pilot cities.

4.2 Empirical Strategy

To estimate the causal effect of URBMI on labor market outcomes, the following equation presents the relation of interest:

$$Y_{ict} = \beta_0 + \beta_1 URBMI_{ict} + \beta_2 X_{ict} + \mu_c + \nu_t + \epsilon_{ict} \tag{1}$$

where Y_{ict} denotes a labor market outcome for individual i in city c at time t. The variable $URBMI_{ict}$ is an indicator of i's URBMI enrollment status in city c at time t. The effect of interest is captured by β_1. X_{ict} is a vector of individual characteristics, including age, gender, marital status, education status, and household size. μ_c is a set of city fixed effects, and ν_t controls for year fixed effects. ϵ_{ict} is an error term.

Since people did not enroll in URBMI at random, estimating Eq.(1) by OLS would yield biased results for the average causal effects of URBMI. Because URBMI is a voluntary program, endogeneity issues would arise from the fact that individuals self-select into the program. To overcome this identification challenge, I employ an IV strategy that exploits the time variation in URBMI implementation at the city level. Specifically, I instrument $URBMI_{ict}$ using an indicator variable for whether the city where individual i lived had implemented URBMI at time t. The first-stage regression is then given by

$$URBMI_{ict} = \alpha_0 + \alpha_1 URBMI\_city_{ct} + \alpha_2 X_{ict} + \mu_c + \nu_t + \eta_{ict} \tag{2}$$

where $URBMI\_city_{ct}$ is an indicator for city c having implemented URBMI at time t. The indicator is coded as follows. All cities are coded as 0 in 2004 and 2006. The 48 pilot cities launched URBMI between 2007 and 2008; they are coded as 1 in 2009. The six non-pilot cities

[13] The results are similar if I expand the sample to include older cohorts up to age 70.

[14] I retain individuals that have at least one pre-treatment observation for the sake of analyzing their labor market transitions and assessing the direct health effect of the program given previous health status. The main results are equivalent if I use all observations from each year in the sample. Moreover, to check whether there is potential sample attrition bias, I apply the inverse probability weighting (IPW) method under the assumption that the attrition is based on observable characteristics (Wooldridge, 2002). The results of the main analysis are similar when IPW is used to correct for panel attrition. These results are available upon request.

Table 1: Summary Statistics

	Full Sample	Pilot Cities		Non-Pilot Cities	
		Pre (2004 & 2006)	Post (2009 & 2011)	Pre (2004 & 2006)	Post (2009 & 2011)
URBMI Enrollment	0.0904	0	0.260	0	0.197
	(0.287)	(0)	(0.439)	(0)	(0.399)
Individual Characteristics:					
Age	42.47	41.05	45.02	40.87	45.47
	(10.11)	(10.51)	(9.054)	(9.589)	(8.120)
Male	0.521	0.512	0.545	0.490	0.527
	(0.500)	(0.500)	(0.498)	(0.500)	(0.500)
Married	0.842	0.825	0.868	0.836	0.885
	(0.365)	(0.380)	(0.339)	(0.371)	(0.319)
Primary school	0.0806	0.0861	0.0761	0.0566	0.0753
	(0.272)	(0.281)	(0.265)	(0.231)	(0.264)
Middle school	0.324	0.322	0.339	0.289	0.287
	(0.468)	(0.467)	(0.473)	(0.454)	(0.453)
High school	0.227	0.246	0.227	0.123	0.115
	(0.419)	(0.430)	(0.419)	(0.329)	(0.319)
Technical school	0.165	0.154	0.168	0.223	0.201
	(0.371)	(0.361)	(0.374)	(0.416)	(0.401)
College or above	0.140	0.122	0.144	0.225	0.251
	(0.347)	(0.328)	(0.351)	(0.418)	(0.434)
Years of schooling	10.50	10.37	10.55	11.05	11.13
	(3.248)	(3.258)	(3.137)	(3.403)	(3.593)
Current student	0.0273	0.0373	0.00990	0.0352	0.00717
	(0.163)	(0.190)	(0.0990)	(0.184)	(0.0845)
Household size	2.607	2.622	2.672	2.316	2.290
	(0.938)	(0.912)	(0.981)	(0.890)	(0.897)
Labor Market Outcome:					
Current working	0.651	0.628	0.674	0.695	0.746
	(0.477)	(0.483)	(0.469)	(0.461)	(0.436)
Formal sector jobs	0.442	0.416	0.455	0.537	0.573
	(0.497)	(0.493)	(0.498)	(0.499)	(0.495)
Informal sector jobs	0.209	0.212	0.218	0.158	0.172
	(0.406)	(0.408)	(0.413)	(0.365)	(0.378)
Long-term employee	0.357	0.339	0.340	0.508	0.530
	(0.479)	(0.473)	(0.474)	(0.500)	(0.500)
Contract worker	0.0853	0.0773	0.116	0.0293	0.0430
	(0.279)	(0.267)	(0.320)	(0.169)	(0.203)
Self-employed	0.124	0.123	0.132	0.0957	0.111
	(0.329)	(0.329)	(0.338)	(0.294)	(0.315)
Other informal job	0.0850	0.0883	0.0864	0.0625	0.0609
	(0.279)	(0.284)	(0.281)	(0.242)	(0.240)
Household annual income	52980.4	44338.1	70573.4	38258.6	61121.5
	(67338.4)	(51232)	(89363.3)	(43321.8)	(68985.5)
Observations	7868	4553	2524	512	279

Notes: Standard deviations in parentheses.

had launched the program by the end of 2009; hence, it is reasonable to code them as 0 in 2009. All cities had URBMI in 2011, so all are coded as 1 in 2011. The coefficient α_1 on the IV captures the effect of an individual living in a city that had implemented URBMI on his or her probability of taking up the insurance. City fixed effects μ_c and year fixed effects ν_t absorb the effects of time-invariant city characteristics and the influence of aggregate time-series trends. In the following tables, I also show results from models that add linear, city-specific time trends, which account for city characteristics that change smoothly over time and are correlated with the timing of URBMI implementation.

As the strategy is to exploit the time variation in URBMI implementation at the city level, the reduced form is a difference-in-differences regression:

$$Y_{ict} = \gamma_0 + \gamma_1 URBMI\_city_{ct} + \gamma_2 X_{ict} + \mu_c + \nu_t + \zeta_{ict} \tag{3}$$

where γ_1 captures the "intent-to-treat" effects of living in a city that had implemented URBMI on an individual's labor market outcome. In all regressions, standard errors are clustered at the city level.

According to the administration scheme of the URBMI program, residents enroll in the program in the local city where their household registered, so an individual can only have had the insurance after his or her city implemented the program. Therefore, an individual's probability of having URBMI should be highly correlated with the introduction of the program at the city level. Moreover, the timing of URBMI roll-out and the selection of pilot cities were determined by the central and provincial governments, so the setup of the program is exogenous to individuals. Thus, the IV should be relevant and plausibly exogenous. Additional empirical checks on the validity of the instrument can be found in the next section.

Furthermore, I conduct a balancing test for individual characteristics on the instrument to check whether there is a selection of individuals and to what extent this selection is eliminated by the models, following the procedure proposed by Pei et al. (2017). Table 2 presents the results of balancing regressions of different individual characteristics on the instrument. Panel A shows coefficients from regressions with the instrument, city fixed effects, and year fixed effects. Panel B repeats the balancing regressions with a set of individual characteristics except for the respective dependent variable. Panel C also adds city-specific linear trends. The results show that estimates are insignificant in all cases in Panel B, suggesting that the model controlling for individual characteristics, city fixed effects, and year fixed effects effectively eliminates concerns about selection issues for individuals. In the following analysis, I rely on the model that controls for individual characteristics, city fixed effects, and year fixed effects as the main empirical model.

Table 2: Balancing Test of Individual Characteristics on the Instrumental Variable

Dependent Variable:	Age	Student	Married	Household Size	Primary Schl	Middle Schl	High Schl	Tech Schl	College
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Individual characteristics on instrument + City fixed effects + Year fixed effects:									
URBMI-city	−1.031	0.010	−0.019	0.049	−0.052	0.063	−0.018	0.020	0.001
	(0.452)**	(0.007)	(0.017)	(0.085)	(0.030)*	(0.036)*	(0.030)	(0.029)	(0.045)
B. Individual characteristics on instrument + Baseline controls + City fixed effects + Year fixed effects:									
URBMI-city	−0.262	0.008	−0.007	0.033	−0.047	0.061	−0.018	0.016	−0.004
	(0.415)	(0.006)	(0.017)	(0.076)	(0.031)	(0.037)	(0.030)	(0.030)	(0.045)
C. Individual characteristics on instrument + Baseline controls + City fixed effects + Year fixed effects + City-specific linear trends:									
URBMI-city	−0.065	0.009	−0.015	−0.031	−0.050	0.057	−0.036	0.012	0.005
	(0.300)	(0.007)	(0.013)	(0.064)	(0.027)*	(0.027)**	(0.032)	(0.026)	(0.037)
Observations	7862	7862	7862	7862	7862	7862	7862	7862	7862

Notes: Robust standard errors in parentheses are clustered at the city level. The dependent variable of each model in Column (1) is the individual's age. The dependent variable of each model in Column (2) is whether the respondent is currently a student (including part-time study and on-the-job training). The dependent variable of each model in Column (3) is whether the respondent is married. The dependent variable of each model in Column (4) is household size. The dependent variable of each model in Columns (5) to (9) is an individual's education level: elementary school, middle school, high school, technical school, and college graduate, respectively. The baseline controls are individual characteristics (unless chosen as the dependent variable), which include gender, age, education dummies, marital status, and household size. *significant at 10 percent, **significant at 5 percent, ***significant at 1 percent.

5 Results

5.1 URBMI Enrollment

First, I estimate an individual's probability of taking up URBMI if he or she lived in a city where the program had been implemented. Table 3 reports estimates of the first-stage regression Eq. (2), where $URBMI_{ict}$ is regressed on $URBMI\_city_{ct}$ and controls. Column (1) presents the most basic model that controls for city fixed effects and year fixed effects, Column (2) also controls for individual characteristics, and Column (3) adds city-specific linear trends. The results show that the first-stage coefficients are statistically significant at the 1% level in all models. Living in cities where the program has been implemented increases an individual's probability of taking up URBMI by approximately 12.4 percentage points. The first-stage F-statistic is above 10 in all specifications, indicating that the first-stage relationship is not weak.

5.2 Validity of the Instrument

The key identifying assumption of the empirical strategy is that cities with and without the URBMI program should not differ in observable and unobservable characteristics that are correlated with individual labor market outcomes, except for the URBMI program. One

Table 3: First-stage Regressions

Dependent Variable:	URBMI Enrollment		
	(1)	(2)	(3)
URBMI-implemented city	0.123	0.124	0.124
	$(0.031)^{***}$	$(0.030)^{***}$	$(0.038)^{***}$
Mean of Dep. Variable	0.090	0.090	0.090
City fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Individual characteristics	No	Yes	Yes
City-specific linear trends	No	No	Yes
IV F-stat	16.23	17.06	10.52
Observations	7868	7868	7868

Notes: Robust standard errors in parentheses are clustered at the city level. The set of individual characteristics includes gender, age, education dummies, marital status, and household size. *significant at 10 percent, **significant at 5 percent, ***significant at 1 percent.

concern that may arise is that the pilot cities and non-pilot cities may have different pre-program trends and that they may exhibit different trajectories in labor market development. To rule out this potential threat, I conduct a placebo test using the 2004-2006 panel data only and assuming that the program had already been launched in 2006 in the pilot cities. The test is performed on reduced-form estimates, where each labor market outcome is regressed on "placebo" $URBMI\_city_{ct}$. The results in Table 4 Panel A show that there are no significant differences in each labor market outcome in the pre-program period between the pilot and non-pilot cities, which eliminates the concern of different time trends of unobservable characteristics between the pilot and non-pilot cities.

Moreover, there might be other time-varying differences during the period from 2004 to 2011 between cities with and without the URBMI program that affected people's labor market decisions. For instance, different cities may have had different labor market policies, regulations, and environments, which may have affected all residents in each city. To check whether this threat exists, I run the reduced-form analysis on the "non-targeted" individuals, that is, those who had free medical insurance before URBMI was launched according to their reports in the survey.[15] These individuals should, in principle, not be affected by the URBMI program. The results in Table 4 Panel B show that there are no significant differences in each labor market outcome for the non-targeted group during the period from 2004 to 2011 in cities with and without the URBMI program. Therefore, it is reassuring to see that the test does not refute the validity of the instrument, which strengthens the key identifying assumption.[16]

[15] A few state-owned enterprises or government departments that maintained the old health insurance system, which provides free medical insurance to their employees.

[16] Additional results on other labor market outcomes are presented in Table A.1, which further confirm the validity of the instrument.

Table 4: Test of the Validity of the Instrumental Variable

Dependent Variable:	Working	Formal Sector Employees	Informal Sector Jobs
	(1)	(2)	(3)
A. Pre-existing trend:			
URBMI-city	−0.012	−0.020	0.008
	(0.040)	(0.021)	(0.038)
Mean of Dep. Variable	0.635	0.429	0.206
Observations	5065	5065	5065
B. Non-targeted group:			
URBMI-city	0.006	−0.103	0.036
	(0.066)	(0.072)	(0.037)
Mean of Dep. Variable	0.789	0.670	0.119
Observations	1015	1015	1015
City fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Individual characteristics	Yes	Yes	Yes

Notes: Robust standard errors in parentheses are clustered at the city level. Panel A presents estimates using the 2004-2006 panel data. Panel B presents estimates using the non-targeted sample (individuals who had free medical insurance before URBMI was implemented) in the 2004-2011 panel data. The key regressor of each model is the instrumental variable. The dependent variable of each model in Column (1) is an individual's probability of working. The dependent variable of each model in Column (2) is an individual's probability of being a formal sector employee. The dependent variable of each model in Column (3) is an individual's probability of working in the informal sector. The set of individual characteristics includes gender, age, education dummies, marital status, and household size. *significant at 10 percent, **significant at 5 percent, ***significant at 1 percent.

5.3 Labor Market Outcomes

As defined in Section 3.3, the main labor market outcome variables in this empirical analysis are an individual's probability of working and whether he or she works in the formal or informal sector. Table 5 Panel I reports estimates of the effect of URBMI on an individual's probability of working. Columns (1) to (3) report the IV estimates of Eq.(1), columns (4) to (6) show estimates of the reduced-form regression, Eq.(3), and the OLS results are listed in columns (7) to (9). The OLS estimates of Eq.(1) show that URBMI is significantly and negatively associated with an individual's probability of working by 5.8 to 9.2 percentage points. However, the IV results, although giving similar estimates in columns (2) and (3) as the OLS, are statistically insignificant. Consistent with the IV results, the reduced-form estimates are small and insignificant. The results indicate that having URBMI has no statistically significant causal effect on an individual's probability of working on average for the whole sample.

Table 5 Panel II presents estimates of the effect of URBMI on an individual's probability of being a formal sector employee. The IV and reduced-form estimates are insignificant, showing that URBMI does not affect an individual's average probability of working as a formal sector employee. The OLS estimates, on the other hand, show a significantly negative relationship between URBMI enrollment and formal sector employment of approximately −16.8 to −19.3 percentage points. The downward bias of the OLS estimates relative to the IV estimates could be attributed to self-selection in that formal sector employees usually have UEBMI and are therefore less likely to enroll in URBMI.

The results of the effect of URBMI on an individual's probability of working in the informal sector are reported in Table 5 Panel III, including the self-employed, temporary workers, and family workers. The IV estimates and reduced-form estimates suggest that there are no average treatment effects of URBMI on an individual's probability of working in the informal sector. The OLS estimates show that URBMI is significantly and positively associated with informal sector employment by 10.1 to 11.0 percentage points. Once again, self-selection bias is highly likely, since informal sector workers are more in need of the healthcare coverage provided by URBMI.

Table A.2 presents the results for more specific labor market outcomes, including an individual's probability of being a long-term (open-ended contract) employee, a fixed-term contract worker, or self-employed or having other informal jobs, i.e., temporary workers and family workers. The former two types of jobs belong to the formal sector, while the latter two consist of informal sector jobs. Although insignificant or weakly significant, the estimates imply that URBMI is negatively associated with an individual's probability of being a long-term employee and informal employment as a temporary or family worker but positively associated with one's probability of working for a fixed-term contract and being self-employed. In each broad category, the two outcomes with opposite directions may offset

Table 5: Effects of URBMI on Labor Market Outcomes

	IV			Reduced Form			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:									
I. Probability of Working									
URBMI	−0.010	−0.082	−0.095				−0.112	−0.058	−0.092
	(0.254)	(0.244)	(0.181)				(0.032)***	(0.032)*	(0.028)***
URBMI-city				−0.001	−0.010	−0.012			
				(0.032)	(0.030)	(0.024)			
Mean of Dep. Variable	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651	0.651
II. Probability of Being Formal Sector Employees									
URBMI	−0.033	−0.102	−0.053				−0.243	−0.168	−0.193
	(0.247)	(0.272)	(0.219)				(0.027)***	(0.028)***	(0.030)***
URBMI-city				−0.004	−0.013	−0.007			
				(0.031)	(0.034)	(0.028)			
Mean of Dep. Variable	0.442	0.442	0.442	0.442	0.442	0.442	0.442	0.442	0.442
III. Probability of Working in the Informal Sector									
URBMI	0.023	0.020	−0.042				0.131	0.110	0.101
	(0.128)	(0.147)	(0.136)				(0.024)***	(0.024)***	(0.020)***
URBMI-city				0.003	0.002	−0.005			
				(0.016)	(0.019)	(0.017)			
Mean of Dep. Variable	0.209	0.209	0.209	0.209	0.209	0.209	0.209	0.209	0.209
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
City-specific linear trends	No	No	Yes	No	No	Yes	No	No	Yes
Observations	7868	7868	7868	7868	7868	7868	7868	7868	7868

Notes: Robust standard errors in parentheses are clustered at the city level. The dependent variable of each model in Panel I is an individual's probability of working. The dependent variable of each model in Panel II is an individual's probability of being a formal sector employee. The dependent variable of each model in Panel III is an individual's probability of working in the informal sector. The set of individual characteristics includes gender, age, education dummies, marital status, and household size. *significant at 10 percent, **significant at 5 percent, ***significant at 1 percent.

one another, which leads to small and insignificant average effects.

Moreover, I estimate whether URBMI has an impact on household income. This outcome variable is defined as household annual gross income, which is converted to 2011 prices using the Chinese CPI. The results of the effect of URBMI on the logarithm of household income are presented in Table A.3. The estimates are positive but insignificant, suggesting that the average treatment effect of URBMI on household income is negligible. The OLS estimates are significant and negative, which similarly indicate a self-selection issue, as the majority of URBMI insurers are unemployed or informally employed and are likely to come from disadvantaged households.[17]

Overall, the results suggest that URBMI does not have a significant average causal effect on employment for the sample as a whole. Since enrollment is voluntary, self-selection is a major issue, which makes the OLS estimates biased. The examination of more detailed job categories suggests that the effects on different labor market outcomes may have opposition directions, which generate small and insignificant average effects. To further explore whether any potential heterogeneous effect exists and to attempt to understand the mechanism, in the following section, I conduct a reduced-form analysis on subgroups with differences in gender, education background, previous health and employment status using more specified employment categories as outcome variables.

5.4 Heterogeneous Effects and Labor Market Transitions

5.4.1 Heterogeneous Effects by Gender

Issues of gender discrimination and a gender earnings gap exist in the labor markets of many countries, and China is no exception (Gustafsson and Li, 2000). To assess whether URBMI differently affects the labor market outcomes of men and women, I report the reduced-form estimates by gender in Table 6.[18] For men, there is a transition within the informal sector. Men are more likely to become self-employed and less likely to perform other informal jobs. For women, the program is significantly associated with a decrease in long-term formal sector employment of 12.0 percentage points and an increase in fixed-term contract jobs and other informal jobs of 4.5 and 3.1 percentage points, respectively. The results suggest that the reduced job lock is more evident for women, resulting in an increase

[17]Furthermore, to determine whether there is any disproportionate effect over the income distribution, I estimate the quantile treatment effects (Abadie et al., 2002) and plot the results of log household income in Figure A.2. The quantile effect plot shows that the estimated effect of URBMI is larger for the lower tail of the income distribution, indicating that relatively disadvantaged households may benefit more than the most advantaged (in terms of household income) from the URBMI program.

[18]Table 6, Table 7, Table 8, and Table 9 present reduced-form results as main outcomes. The first-stage estimates and first-stage F statistics are also reported. The instrument becomes weak for some subgroups, so the subgroup analyses in this section focus on reduced form-results to estimate intent-to-treat effects. I report estimates from the main regressions, which control for individual characteristics, city fixed effects, and year fixed effects. The results are mostly unchanged if I also add city-specific linear trends and are available upon request.

Table 6: Heterogeneous Effect by Gender

Dependent Variable:	Working	Long-term Employees	Fixed-term Contract	Self-employed	Other Informal	Log HH Income
	(1)	(2)	(3)	(4)		
A. Men:						
URBMI-city	−0.033	−0.029	0.033	0.057	−0.094	−0.021
	(0.033)	(0.043)	(0.023)	(0.031)*	(0.044)**	(0.148)
1st-stage estimates	0.135	0.135	0.135	0.135	0.135	0.134
	(0.029)***	(0.029)***	(0.029)***	(0.029)***	(0.029)***	(0.030)***
1st-stage F stat.	22.33	22.33	22.33	22.33	22.33	19.55
Mean of Dep. Var.	0.719	0.410	0.087	0.136	0.086	10.366
Observations	4103	4103	4103	4103	4103	4041
B. Women:						
URBMI-city	−0.004	−0.120	0.045	0.040	0.031	0.108
	(0.050)	(0.038)***	(0.020)**	(0.029)	(0.016)*	(0.156)
1st-stage estimates	0.115	0.115	0.115	0.115	0.115	0.112
	(0.035)***	(0.035)***	(0.035)***	(0.035)***	(0.035)***	(0.034)***
1st-stage F stat.	10.96	10.96	10.96	10.96	10.96	10.61
Mean of Dep. Var.	0.577	0.300	0.084	0.110	0.084	10.315
Observations	3765	3765	3765	3765	3765	3704
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Ind. char.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses are clustered at the city level. Panel A presents estimates using the sample of males. Panel B presents estimates using the sample of females. The dependent variable of each model in Column (1) is an individual's probability of working. The dependent variable of each model in Column (2) is an individual's probability of being an open-ended contract employee. The dependent variable of each model in Column (3) is an individual's probability of being a fixed-term contract worker. The dependent variable of each model in Column (4) is an individual's probability of being self-employed. The dependent variable of each model in Column (5) is an individual's probability of having other informal jobs. The dependent variable of each model in Column (6) is the logarithm of an individual's household annual gross income (inflation-adjusted). The key regressor of each model is the instrumental variable. The set of individual characteristics includes gender, age, education dummies, marital status, and household size. *significant at 10 percent, **significant at 5 percent, ***significant at 1 percent.

in their labor market flexibility. Compared to men, women usually take more responsibility for the household and child care and face dilemmas between career and family, especially in traditional societies such as China. When URBMI delinks insurance availability from long-term employment, women have more choices of other types of jobs with greater flexibility to achieve a balance between work and family.

5.4.2 Heterogeneous Effects by Education

Education has always played an important role in an individual's labor market outcome. Hence, I examine whether there is any heterogeneous effect on subgroups with different education levels. Based on the 9-year compulsory schooling law in China, the less educated are defined as individuals whose years of schooling are nine or below, i.e., individuals with lower secondary schooling or below. The better educated are those with years of schooling

Table 7: Heterogeneous Effect by Education Levels

Dependent Variable:	Working	Long-term Employees	Fixed-term Contract	Self-employed	Other Informal	Log HH Income
	(1)	(2)	(3)	(4)		
A. Lower Education Level:						
URBMI-city	0.013	−0.086	0.040	0.104	−0.046	0.153
	(0.052)	(0.033)**	(0.026)	(0.037)***	(0.044)	(0.202)
1st-stage estimates	0.162	0.162	0.162	0.162	0.162	0.159
	(0.047)***	(0.047)***	(0.047)***	(0.047)***	(0.047)***	(0.047)***
1st-stage F stat.	11.71	11.71	11.71	11.71	11.71	11.57
Mean of Dep. Var.	0.531	0.167	0.079	0.172	0.113	10.066
Observations	3446	3446	3446	3446	3446	3377
B. Higher Education Level:						
URBMI-city	−0.011	−0.038	0.043	0.013	−0.029	0.024
	(0.028)	(0.046)	(0.023)*	(0.020)	(0.024)	(0.209)
1st-stage estimates	0.089	0.089	0.089	0.089	0.089	0.088
	(0.026)***	(0.026)***	(0.026)***	(0.026)***	(0.026)***	(0.027)***
1st-stage F stat.	11.28	11.28	11.28	11.28	11.28	11.03
Mean of Dep. Var.	0.745	0.505	0.090	0.086	0.063	10.554
Observations	4422	4422	4422	4422	4422	4368
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Ind. char.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses are clustered at the city level. Panel A presents estimates using the sample of less-educated individuals whose years of schooling are nine or less (individuals with a lower secondary schooling level or below). Panel B presents estimates using the sample of individuals whose years of schooling are above nine. The dependent variable of each model in Column (1) is an individual's probability of working. The dependent variable of each model in Column (2) is an individual's probability of being an open-ended contract employee. The dependent variable of each model in Column (3) is an individual's probability of being a fixed-term contract worker. The dependent variable of each model in Column (4) is an individual's probability of being self-employed. The dependent variable of each model in Column (5) is an individual's probability of having other informal jobs. The dependent variable of each model in Column (6) is the logarithm of an individual's household annual gross income (inflation-adjusted). The key regressor of each model is the instrumental variable. The set of individual characteristics includes gender, age, education dummies, marital status, and household size. *significant at 10 percent, **significant at 5 percent, ***significant at 1 percent.

above nine. In Table 7, the estimates by education levels show that for the less educated, the probability of working in a long-term formal job decreases by 8.6 percentage points, while the probability of being self-employed increases by 10.4 percentage points. The results suggest that the effect on reducing job lock and promoting entrepreneurship is likely to originate from less-educated people. For better-educated people, URBMI is positively associated with working for a fixed-term contract in the formal sector.

The results of heterogeneous effects by gender and by education are inspiring. In the current labor market in urban China, which features gender disparity, women and undereducated workers are relatively less advantaged in the labor market than men and the well-educated. The program has a statistically significant employment impact on those vulnerable groups. In particular, by reducing the medical expenditure risks associated with informal sector employment, URBMI encourages marginal workers' labor force participation. In line with the findings in Liu and Zhang (2018), the effect on promoting self-employment and entrepreneurship is more evident for men and people with lower levels of education.

5.4.3 Heterogeneous Effects by Previous Health Status

As public health insurance, URBMI could have a direct, positive effect on people's health status, thereby enhancing worker productivity or labor supply. Moreover, the incentives to take up insurance might differ between people with good or poor health status. Based on their self-reported health status before the program was implemented, I divide the sample into healthy and unhealthy groups.[19] The estimates in Table 8 show that for healthy people, the availability of URBMI is negatively associated with long-term employment in the formal sector but positively associated with self-employment. These results indicate that there is a reduced job lock effect. For previously unhealthy individuals, the availability of URBMI increases their probability of working for fixed-term contracts by 3.8 percentage points and the probability of being self-employed by 5.3 percentage points. The results show an increased trend of labor supply for previously unhealthy individuals, indicating that a health-improving effect may be at work.

5.4.4 Effects of URBMI on Labor Market Transitions

The impact of URBMI may be heterogeneous across subgroups with different employment backgrounds. Moreover, the introduction of the program may lead to changes in labor market dynamics by inducing labor flows from one sector to another. To explore the heterogeneous effects and potential labor market transitions caused by URBMI, Table 9 reports the reduced-form estimates separately for individuals who were not working, who were formal sector employees, and who were working in the informal sector before URBMI was implemented. The results show that for those who were not working previously, the probability of becoming fixed-term contract workers increases by 7.5 percentage points after URBMI was implemented. For formal sector employees, URBMI is significantly associated with an increase in self-employment of 2.3 percentage points. There are no significant effects for those who were working in the informal sector.

The results for the previously non-employed are most likely to be attributed to the increase in labor demand due to reduced labor costs. After the introduction of URBMI, small business employers in many cities were allowed to pay for URBMI instead of the more expensive UEBMI for their employees; thus, labor demand may have increased due to decreased labor costs, which is particularly the case for employers of fixed-term contract workers.

[19] Based on the information in the 2004 and 2006 survey waves, an individual is considered unhealthy if he or she was diagnosed with one of the following conditions: hypertension, diabetes, myocardial infarction, apoplexy, bone fracture, asthma, stroke, cancer, whistling in the chest, goiter, angular stomatitis, blindness in one or both eyes, and loss of one or both arms or legs or if their self-reported health status is not healthy.

Table 8: Heterogeneous Effect by Previous Health Status

Dependent Variable:	Working	Long-term Employees	Fixed-term Contract	Self-employed	Other Informal	Log HH Income
	(1)	(2)	(3)	(4)		
A. Previously Healthy:						
URBMI-city	−0.045	−0.086	0.037	0.057	−0.053	0.057
	(0.039)	(0.032)**	(0.025)	(0.025)**	(0.029)*	(0.135)
1st-stage estimates	0.126	0.126	0.126	0.126	0.126	0.122
	(0.035)***	(0.035)***	(0.035)***	(0.035)***	(0.035)***	(0.036)***
1st-stage F stat.	13.19	13.19	13.19	13.19	13.19	11.74
Mean of Dep. Var.	0.679	0.366	0.091	0.138	0.085	10.396
Observations	5059	5059	5059	5059	5059	4989
B. Previously Unhealthy:						
URBMI-city	0.029	−0.060	0.038	0.053	−0.001	0.011
	(0.036)	(0.045)	(0.016)**	(0.019)***	(0.037)	(0.277)
1st-stage estimates	0.124	0.124	0.124	0.124	0.124	0.125
	(0.057)**	(0.057)**	(0.057)**	(0.057)**	(0.057)**	(0.056)**
1st-stage F stat.	4.82	4.82	4.82	4.82	4.82	4.90
Mean of Dep. Var.	0.601	0.341	0.074	0.099	0.086	10.242
Observations	2809	2809	2809	2809	2809	2756
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Ind. char.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses are clustered at the city level. Panel A presents estimates using the sample of healthy individuals before the launch of URBMI. Panel B presents estimates using the sample of unhealthy individuals before the launch of URBMI. The dependent variable of each model in Column (1) is an individual's probability of working. The dependent variable of each model in Column (2) is an individual's probability of being an open-ended contract employee. The dependent variable of each model in Column (3) is an individual's probability of being a fixed-term contract worker. The dependent variable of each model in Column (4) is an individual's probability of being self-employed. The dependent variable of each model in Column (5) is an individual's probability of having other informal jobs. The dependent variable of each model in Column (6) is the logarithm of an individual's household annual gross income (inflation-adjusted). The key regressor of each model is the instrumental variable. The set of individual characteristics includes gender, age, education dummies, marital status, and household size. *significant at 10 percent, **significant at 5 percent, ***significant at 1 percent.

Table 9: Effects of URBMI on Labor Transitions

Dependent Variable:	Working	Long-term Employees	Fixed-term Contract	Self-employed	Other Informal	Log HH Income
	(1)	(2)	(3)	(4)	(5)	(6)
A. Not working previously:						
URBMI-city	0.020	−0.039	0.075	0.010	−0.026	0.195
	(0.061)	(0.028)	(0.020)***	(0.041)	(0.040)	(0.233)
1st-stg estimates	0.120	0.120	0.120	0.120	0.120	0.121
	(0.044)***	(0.044)***	(0.044)***	(0.044)***	(0.044)***	(0.042)***
1st-stage F stat	7.63	7.63	7.63	7.63	7.63	8.17
Mean of Dep. Var.	0.197	0.060	0.032	0.058	0.048	10.020
Observations	2723	2723	2723	2723	2723	2626
B. Formal sector employees previously:						
URBMI-city	−0.039	−0.078	0.024	0.023	−0.007	−0.045
	(0.049)	(0.054)	(0.027)	(0.010)**	(0.016)	(0.172)
1st-stg estimates	0.091	0.091	0.091	0.091	0.091	0.093
	(0.019)***	(0.019)***	(0.019)***	(0.019)***	(0.019)***	(0.020)***
1st-stage F stat	22.74	22.74	22.74	22.74	22.74	22.05
Mean of Dep. Var.	0.922	0.732	0.143	0.019	0.028	10.702
Observations	3436	3436	3436	3436	3436	3432
C. Working in the informal sector previously:						
URBMI-city	−0.081	−0.036	0.009	0.066	−0.120	0.016
	(0.081)	(0.060)	(0.064)	(0.061)	(0.093)	(0.233)
1st-stg estimates	0.198	0.198	0.198	0.198	0.198	0.179
	(0.072)***	(0.072)***	(0.072)***	(0.072)***	(0.072)***	(0.072)**
1st-stage F stat	7.54	7.54	7.54	7.54	7.54	6.16
Mean of Dep. Var.	0.830	0.076	0.054	0.441	0.259	10.107
Observations	1709	1709	1709	1709	1709	1687
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Ind. char.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses are clustered at the city level. Panel A presents estimates using the sample of individuals who were not working before the launch of URBMI. Panel B presents estimates using the sample of individuals who were formal sector employees before the launch of URBMI. Panel C presents estimates using the sample of individuals who were working in the informal sector before the launch of URBMI. The dependent variable of each model in Column (1) is an individual's probability of working. The dependent variable of each model in Column (2) is an individual's probability of being an open-ended contract employee. The dependent variable of each model in Column (3) is an individual's probability of being a fixed-term contract worker. The dependent variable of each model in Column (4) is an individual's probability of being self-employed. The dependent variable of each model in Column (5) is an individual's probability of having other informal jobs. The dependent variable of each model in Column (6) is the logarithm of an individual's household annual gross income (inflation-adjusted). The key regressor of each model is the instrumental variable. The set of individual characteristics includes gender, age, education dummies, marital status, and household size. *significant at 10 percent, **significant at 5 percent, ***significant at 1 percent.

The increased probability of being self-employed for formal sector employees indicates a reduction in job lock. In other words, the availability of URBMI eliminates the healthcare expenditure risks associated with self-employment, and thus some formal sector employees become more inclined to be self-employed if they find that self-employment is a better match than formal employment. This finding suggests that URBMI increases job matches and job flexibility. Moreover, the coefficient estimates of household income for women in Table 6, the less educated in Table 7 and the previously non-employed in Table 9 are large and positive although insignificant, which provides suggestive evidence that the program is pro-poor and has a positive impact on disadvantaged households, in line with the implications of the quantile effect plot in Figure A.2. Correspondingly, the positive impact on household incomes may be due to the increased labor market participation of economically disadvantaged individuals.

6 Discussion and Conclusion

In this study, I examine whether the URBMI public health insurance program introduced in China in 2007 affected individuals' labor market outcomes. The aim of URBMI is to provide healthcare to the unemployed and informally employed and other urban residents who lack pre-existing employment-based health insurance. To address the self-selection bias resulting from the voluntary enrollment in the program, I employ an IV strategy that exploits the time variation in URBMI implementation at the city level. The sample data for analysis is drawn from the CHNS datasets, specifically the 2004, 2006, 2009, and 2011 waves.

I find that URBMI did not have a significant average causal effect on labor market outcomes for the sample as a whole. However, the results of subgroup analyses show that URBMI encouraged inflows from long-term formal employment into self-employment, indicating reduced job lock. This inflow is significantly evident among the less educated and individuals with good health. Within the informal sector, relative to other informal jobs, self-employment becomes more attractive among men and healthy individuals. Women increase their job flexibility by leaving long-term jobs and taking fixed-term contracts and informal jobs other than self-employment. Unhealthy individuals increase their labor supply in fixed-term employment and self-employment, potentially thanks to a direct health-improving effect and reduced medical expenditure risks. The better educated and non-employed residents also show increased inflows into fixed-term employment. Furthermore, there is suggestive evidence that the program may benefit economically disadvantaged households as measured by household income.

One potential explanation for the increased labor supply of the previously non-employed to become contract workers is that the availability of URBMI provides some small business employers with a cheaper alternative to UEBMI to pay for their employees' health insurance; thus, labor costs decrease, and labor demand consequently increases. Increased labor demand gives marginal workers more opportunities to become employed in the formal sector. Therefore, the URBMI program has served as a supplement to the employment-based health insurance system in urban China. The evidence of increased employment in the informal sector of women, the less educated, and less healthy individuals, who belong to, comparatively speaking, vulnerable groups in the labor market, could be attributed to the reduced medical expenditure risks associated with informal sector employment and labor market transitions that provided more job opportunities for vulnerable workers after the introduction of URBMI. The finding of increased informal employment, especially for vulnerable groups in the labor market, is in accordance with studies on the labor market impact of public health insurance in many developing countries (Aterido et al., 2011; Azuara and Marinescu, 2013; Wagstaff and Manachotphong, 2012). Moreover, women may benefit from increased labor market flexibility due to the availability of URBMI when confronting trade-offs between family and career. Note that the discrepancy between the IV estimates and the OLS estimates reflects heavy self-selection of program enrollment by people without jobs or working in the informal sector.

However, unlike the findings of many previous studies that public health insurance is usually negatively associated with labor force participation, there is no generally significant evidence of decreased labor supply in the case of URBMI. Notably, labor supply actually appears to increase for some individuals. There are likely two reasons for this result. First, the URBMI program is not a free program; although it is subsidized by the government, individuals have to pay for a share of the premium to receive the insurance, so income effects for socio-economically disadvantaged participants are unlikely. More importantly, China lacks a well-functioning social safety net, and the welfare system is still under construction; thus, working might be an indispensable means of maintaining self-sufficiency, especially for people with low family income. Therefore, the more financially disadvantaged an individual is, the less likely it is that working incentives decrease, even though the availability of URBMI helped reduce medical expenditure risks in daily life.

In conclusion, this paper sheds light on the impacts of public health insurance on labor market decisions and outcomes in the context of a developing and transition economy. China is not a singular case, as many countries are on the path to creating a well-functioning national health insurance system. The empirical evidence from China provides insightful policy implications for understanding the labor market effects of public health insurance, especially on job mobility and informality.

References

Abadie, A., Angrist, J., Imbens, G., 2002. Instrumental variables estimates of the effect of subsidized training on the quantiles of trainee earnings. Econometrica 70, 91–117.

Aterido, R., Hallward-Driemeier, M., et al., 2011. Does expanding health insurance beyond formal-sector workers encourage informality? Measuring the impact of Mexico's Seguro Popular. World Bank Policy Research Working Paper No. 5785 .

Azuara, O., Marinescu, I., 2013. Informality and the expansion of social protection programs: Evidence from Mexico. Journal of health economics 32, 938–950.

Baicker, K., Finkelstein, A., Song, J., Taubman, S., 2014. The impact of Medicaid on labor market activity and program participation: Evidence from the Oregon health insurance experiment. American Economic Review 104, 322–28.

Barber, L., Yao, L., 2010. Health insurance systems in China: a briefing note. World health report Background Paper, No. 37.

Beuermann, D., Pecha, C., 2016. Healthy to Work: The Impact of Free Public Healthcare on Health Status and Labor Supply in Jamaica. Inter-American Development Bank IDB Working Paper Series; 756.

Bitran, R., et al., 2014. Universal health coverage and the challenge of informal employment: lessons from developing countries. Health, Nutrition, and Population (HNP) discussion paper. Washington DC: World Bank Group .

Borjas, G.J., 2003. Welfare reform, labor supply, and health insurance in the immigrant population. Journal of Health Economics 22, 933–958.

Boyle, M.A., Lahey, J.N., 2010. Health insurance and the labor supply decisions of older workers: Evidence from a US Department of Veterans Affairs expansion. Journal of public economics 94, 467–478.

Camacho, A., Conover, E., Hoyos, A., 2014. Effects of Colombia's social protection system on workers' choice between formal and informal employment. The World Bank Economic Review 28, 446–466.

Chyi, H., Zhou, B., 2014. The effects of tuition reforms on school enrollment in rural China. Economics of Education Review 38, 104–123.

Currie, J., Madrian, B.C., 1999. Health, health insurance and the labor market. Handbook of labor economics 3, 3309–3416.

Dague, L., DeLeire, T., Leininger, L., 2014. The effect of public insurance coverage for childless adults on labor supply. National Bureau of Economic Research Working Paper, No. 20111.

Fairlie, R.W., Kapur, K., Gates, S., 2011. Is employer-based health insurance a barrier to entrepreneurship? Journal of Health Economics 30, 146–162.

Garthwaite, C., Gross, T., Notowidigdo, M.J., 2014. Public health insurance, labor supply, and employment lock. The Quarterly Journal of Economics 129, 653–696.

Gruber, J., Hanratty, M., 1995. The labor-marker effects of introducing national health insurance: Evidence from Canada. Journal of Business & economic statistics 13, 163–173.

Gustafsson, B., Li, S., 2000. Economic transformation and the gender earnings gap in urban China. Journal of Population Economics 13, 305–329.

Heim, B.T., Lurie, I.Z., 2015. The impact of health reform on job mobility: Evidence from Massachusetts. American Journal of Health Economics .

Holtz-Eakin, D., Penrod, J.R., Rosen, H.S., 1996. Health insurance and the supply of entrepreneurs. Journal of Public Economics 62, 209–235.

Huang, F., Gan, L., 2015. Impact of China's urban employee basic medical insurance on health care expenditure and health outcomes. National Bureau of Economic Research Working Paper, No. 20873.

Killingsworth, M., 1983. Labor Supply. Cambridge Surveys of Economic Literature, Cambridge University Press.

Leung, P., Mas, A., 2016. Employment Effects of the ACA Medicaid Expansions. National Bureau of Economic Research Working Paper, No. 22540.

Levy, S., 2008. Good intentions, bad outcomes: Social policy, informality, and economic growth in Mexico. Washington, D.C.: Brookings Institution Press.

Liang, Z., Appleton, S., Song, L., 2016. Informal Employment in China: Trends, Patterns and Determinants of Entry. IZA Discussion Paper .

Lin, W., Liu, G.G., Chen, G., 2009. The urban resident basic medical insurance: a landmark reform towards universal coverage in China. Health Economics 18, S83–S96.

Liu, H., Zhao, Z., 2014. Does health insurance matter? Evidence from China's urban resident basic medical insurance. Journal of Comparative Economics 42, 1007–1020.

Liu, L., Zhang, Y., 2018. Does non-employment based health insurance promote entrepreneurship? Evidence from a policy experiment in China. Journal of Comparative Economics 46, 270–283.

Madrian, B.C., 1994. Employment-based health insurance and job mobility: Is there evidence of job-lock? The Quarterly Journal of Economics 109, 27–54.

Ministry of Health of the People's Republic of China, Various years from 2008-2014. China Public Health Statistical Yearbook. Beijing: Peking Union Medical College Publishing House.

Moffitt, R., Wolfe, B., 1992. The effect of the Medicaid program on welfare participation and labor supply. The Review of Economics and Statistics , 615–626.

National Bureau of Statistics (NBS), Various years from 2004-2012. China Statistical Yearbook. Beijing: China Statistical Press.

Pei, Z., Pischke, J.S., Schwandt, H., 2017. Poorly measured confounders are more useful on the left than on the right. National Bureau of Economic Research Working Paper, No. w23232.

Strumpf, E., 2011. Medicaid's effect on single women's labor supply: Evidence from the introduction of Medicaid. Journal of health economics 30, 531–548.

Wagstaff, A., Manachotphong, W., 2012. Universal health care and informal labor markets: the case of thailand. World Bank Policy Research Working Paper .

Wang, J., Cooke, F.L., Lin, Z., 2016. Informal employment in China: Recent development and human resource implications. Asia Pacific Journal of Human Resources 54, 292–311.

Winkler, A.E., 1991. The incentive effects of Medicaid on women's labor supply. Journal of Human Resources , 308–337.

Wooldridge, J.M., 2002. Inverse probability weighted M-estimators for sample selection, attrition, and stratification. Portuguese Economic Journal 1, 117–139.

Yelowitz, A.S., 1995. The Medicaid notch, labor supply, and welfare participation: Evidence from eligibility expansions. The Quarterly Journal of Economics , 909–939.

Yip, W., Hsiao, W., 2009. China's health care reform: A tentative assessment. China economic review 20, 613–619.

Yip, W.C.M., Hsiao, W.C., Chen, W., Hu, S., Ma, J., Maynard, A., 2012. Early appraisal of China's huge and complex health-care reforms. The Lancet 379, 833–842.

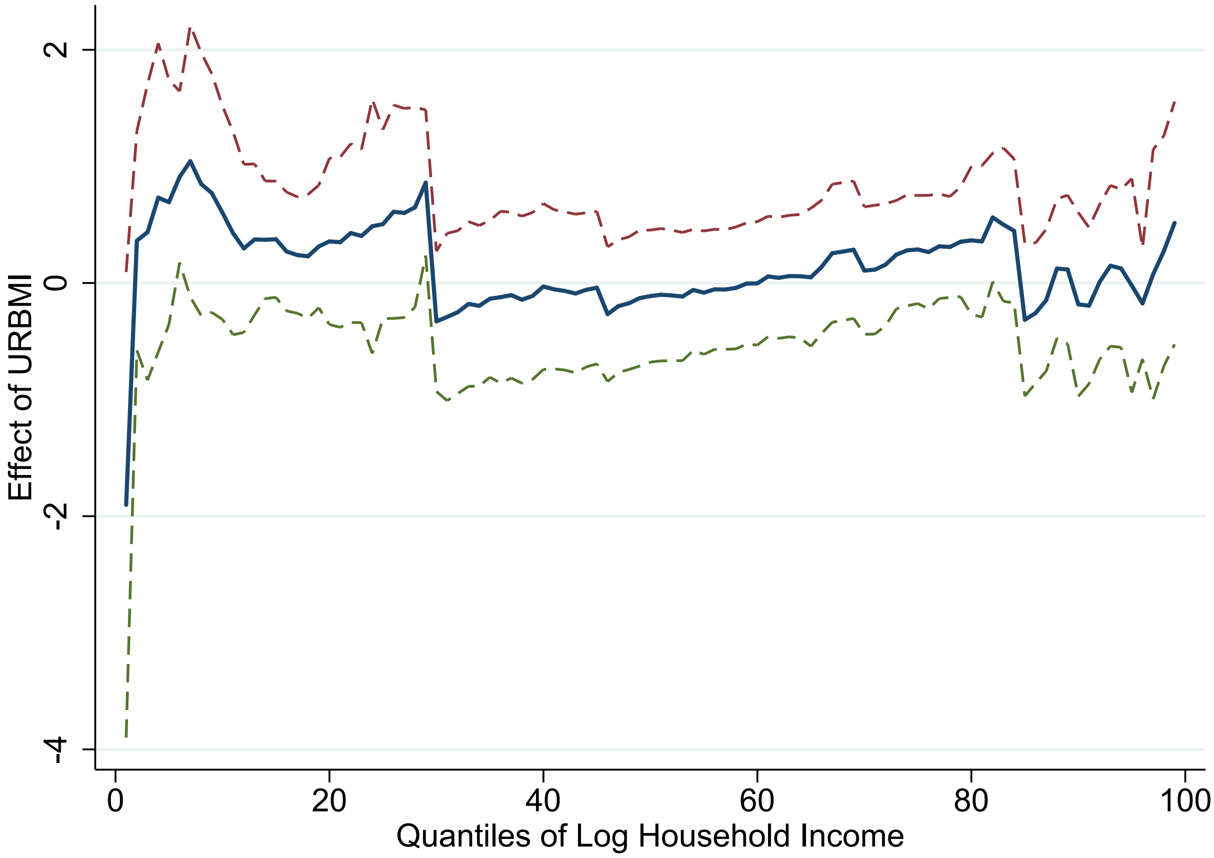
Zhou, Y., 2013. The State of Precarious Work in China. American Behavioral Scientist 57, 354–372.

Appendix A

Figure A.1: Map of China with Survey Regions Shaded

Note: The nine survey provinces are marked in grey shading on the map of China.

Figure A.2: Quantile Effect for Log Household Income



Note: The figure plots quantile treatment effects using the estimator proposed by Abadie, Angrist, and Imbens (2002) for the 1st to 99th percentiles. The dotted lines above and below the thick line plot the 95% confidence intervals for each coefficient.

Table A.1: Test of the Validity of the Instrumental Variable

Dependent Variable:	Long-term Employees	Fixed-term Contract	Self-employed	Other Informal	Log Household Income
	(1)	(2)	(3)	(4)	(5)
A. Pre-existing trend:					
URBMI-city	0.001	−0.021	−0.005	0.013	−0.068
	(0.020)	(0.017)	(0.029)	(0.029)	(0.154)
Mean of Dep. Var.	0.356	0.072	0.120	10.086	10.160
Observations	5065	5065	5065	5065	4977
B. Non-targeted group:					
URBMI-city	−0.106	0.003	0.013	0.049	−0.433
	(0.073)	(0.020)	(0.030)	(0.030)	(0.280)
Mean of Dep. Var.	0.592	0.078	0.059	0.060	10.613
Observations	1015	1015	1015	1015	1014
City fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Ind. char.	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses are clustered at the city level. Panel A presents estimates using the 2004-2006 panel data. Panel B presents estimates using the non-targeted sample (individuals who had free medical insurance before URBMI was implemented) in the 2004-2011 panel data. The key regressor of each model is the instrumental variable. The dependent variable of each model in Column (1) is an individual's probability of being self-employed. The dependent variable of each model in Column (2) is an individual's probability of being an open-ended contract employee. The dependent variable of each model in Column (3) is an individual's probability of being a fixed-term contract worker. The dependent variable of each model in Column (4) is the logarithm of an individual's household annual income (inflation-adjusted). The set of individual characteristics includes gender, age, education dummies, marital status, and household size. *significant at 10 percent, **significant at 5 percent, ***significant at 1 percent.

Table A.2: Effects of URBMI on Other Labor Market Outcomes

	IV			Reduced Form			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:									
I. Probability of Being a Long-term Employee									
URBMI	−0.363	−0.390	−0.392				−0.240	−0.165	−0.185
	(0.223)	(0.267)	(0.239)				(0.022)***	(0.018)***	(0.019)***
URBMI-implemented city				−0.045	−0.048	−0.049			
				(0.026)*	(0.030)	(0.024)*			
Mean of Dep. Variable	0.357	0.357	0.357	0.357	0.357	0.357	0.357	0.357	0.357
II. Probability of Being a Fixed-term Contractor									
URBMI	0.330	0.288	0.339				−0.003	−0.003	−0.007
	(0.182)*	(0.165)*	(0.258)				(0.019)	(0.019)	(0.021)
URBMI-city				0.041	0.036	0.042			
				(0.020)**	(0.018)*	(0.022)*			
Mean of Dep. Variable	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.085
III. Probability of Self-employment									
URBMI	0.275	0.276	0.319				0.096	0.082	0.070
	(0.153)*	(0.155)*	(0.187)*				(0.021)***	(0.020)***	(0.019)***
URBMI-city				0.034	0.034	0.040			
				(0.016)**	(0.017)**	(0.023)*			
Mean of Dep. Variable	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124	0.124
IV. Probability of Doing Other Informal Jobs									
URBMI	−0.252	−0.257	−0.362				0.036	0.028	0.031
	(0.210)	(0.208)	(0.235)				(0.019)*	(0.019)	(0.019)
URBMI-city				−0.031	−0.032	−0.045			
				(0.023)	(0.023)	(0.026)*			
Mean of Dep. Variable	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.085	0.085
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
City-specific linear trends	No	No	Yes	No	No	Yes	No	No	Yes
Observations	7868	7868	7868	7868	7868	7868	7868	7868	7868

Notes: Robust standard errors in parentheses are clustered at the city level. The dependent variable of each model in Panel I is an individual's probability of being an open-ended contract employee. The dependent variable of each model in Panel II is an individual's probability of being a fixed-term contract worker. The dependent variable of each model in Panel III is an individual's probability of being self-employed. The dependent variable of each model in Panel IV is an individual's probability of having other informal jobs except for self-employment. The set of individual characteristics includes gender, age, education dummies, marital status, and household size. *significant at 10 percent, **significant at 5 percent, ***significant at 1 percent.

Table A.3: Effects of URBMI on Log Household Annual Income

Dependent Variable:	Log Household Annual Income								
	IV			Reduced Form			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
URBMI	0.403	0.176	0.992				−0.271	−0.164	−0.197
	(0.935)	(1.118)	(1.089)				(0.095)***	(0.089)*	(0.090)**
URBMI-city				0.049	0.021	0.120			
				(0.118)	(0.139)	(0.132)			
Mean of Dep. Variable	10.341	10.341	10.341	10.341	10.341	10.341	10.341	10.341	10.341
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
City-specific linear trends	No	No	Yes	No	No	Yes	No	No	Yes
Observations	7745	7745	7745	7745	7745	7745	7745	7745	7745

Notes: Robust standard errors in parentheses are clustered at the city level. The dependent variable of each model is the logarithm of an individual's household annual gross income (inflation-adjusted). The set of individual characteristics includes gender, age, education dummies, marital status, and household size. *significant at 10 percent, **significant at 5 percent, ***significant at 1 percent.