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 employment-based health insurance. Using panel data from the China Health and Nutrition Survey, I identify the impacts of the program based on its staggered implementation across cities. I find that URBMI did not have a significant average causal effect on labor force participation. However, it did increase employment mobility, as evidenced by the decrease in long-term employment and expansion of fixed-term contract jobs and self-employment. 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 employment for unhealthy workers, indicating a direct health improvement effect.

Keywords Public Health Insurance, Medical Subsidy Programs, Employment, Job Lock, Labor Market Flexibility, Occupational Mobility, Labor Force Demographics, Urban China

JEL classification: H51, I13, I18, J21, J62

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1 Introduction

In recent years, universal health coverage has become a leading priority for policymakers in many countries, 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, 2014). Public health insurance not only directly affects people's healthcare and health status but also plays an influential role in individuals' labor market outcomes. First, public health insurance can generate a direct health improvement effect for workers such that improved health increases work productivity. Second, unlike employment-based health insurance, public health insurance detaches healthcare coverage from employment. Therefore, it may affect people's labor market decisions if they work primarily to maintain affordable health insurance ("employment lock") or if they remain in jobs that are less preferable or less productive to avoid losing their health insurance ("job lock") (Garthwaite et al., 2014; Madrian, 1994).

Previous studies have provided mixed results on the labor market impact of public health insurance when examining public healthcare programs in the US and other developed countries. Many studies have found evidence that public health insurance programs create disincentives to work (Boyle and Lahey, 2010; Dague et al., 2017; Moffitt and Wolfe, 1992; Winkler, 1991) or increase the labor supply after reductions in insurance eligibility (Borjas, 2003; Garthwaite et al., 2014; Yelowitz, 1995). Gruber and Hanratty (1995) found that employment rose in Canada after NHI system introduction because of a systematic increase in labor demand across all sectors as a result of increased job mobility, increased productivity, and improvements in worker health. Several studies have found no significant labor market effects from public health insurance (Baicker et al., 2014; Leung and Mas, 2018; Strumpf, 2011). Other studies have addressed whether public health insurance can alleviate job lock (Fairlie et al., 2011; Hamersma and Kim, 2009; Heim and Lurie, 2015). Empirical evidence from developing and transitional economies is relatively scarce, with studies focusing mostly on the effects on the informal sector (Aterido et al., 2011; Azuara and Marinescu, 2013; Camacho et al., 2014; Wagstaff and Manachotphong, 2012).

In this paper, I explore the effects of China's Urban Resident Basic Medical Insurance (URBMI) on the labor market. Established in 2007, URBMI filled a fundamental gap in China's NHI system, targeting a large share of the urban population not covered by employment-based health insurance. I estimate whether adopting this public health insurance system has impacted labor market decisions and the outcomes of individuals in China, a developing and transitional economy.[1] As the world's most populous country, and as one that is experiencing rapid economic growth, China faces many complex social issues, such as the misallocation of labor in the market, the perpetuation of gender and educational inequalities, and the

[1]The labor market effect refers to an equilibrium effect, as the empirical analysis cannot precisely distinguish between labor supply and labor demand.

widening of the gap between the rich and poor (Rudolph and Szonyi, 2018). Understanding the labor market impact of public health insurance in China is necessary not only for public policymakers in China who wish to address these challenging social problems but also for policymakers in other transitional economies who aim to establish NHI systems.

The expansion of healthcare insurance in developing countries follows a general pattern that starts with including formal sector employees and then informal sector workers, the unemployed, and economically disadvantaged individuals via government-subsidized enrollment (Bitran, 2014). China is no exception. Prior to the launch of URBMI, two public health insurance programs had already been 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, which was 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 it (Barber and Yao, 2010). URBMI is designed to provide healthcare coverage to urban residents not covered by employment-based UEBMI, including workers who are unemployed, self-employed and informally employed, along with the elderly, children and college students. Enrollment in URBMI is voluntary, and the premiums are heavily subsidized by the government. URBMI covered 221 million urban residents in 2011, and the total number of recipients had increased to 376 million by the end of 2015.[2]

Few studies have examined URBMI in China, despite it targeting and influencing a large population. Therefore, the effects of URBMI warrant further study. Lin et al. (2009) conducted the first economic analysis of the effects of URBMI on healthcare in 2007 using household surveys from nine representative cities. They found that extremely rich or poor households and individuals with recent inpatient treatments or chronic diseases were more likely to participate in the program. URBMI significantly benefits poor individuals who need inpatient care by reducing the financial pressure from their medical expenditures. Liu and Zhao (2014) estimated the impact of URBMI on healthcare utilization and expenditure and showed that the program increased the utilization of formal medical services, especially for children, low-income individuals, and residents in less-developed areas. However, the program did not reduce total out-of-pocket health expenses. Pan et al. (2016a) evaluated the effect of URBMI on health and found that the program significantly improved the health status of beneficiaries, especially those with disadvantages in terms of education and income. A recent paper by Liu and Zhang (2018) investigated the impact of URBMI on promoting entrepreneurship, and it showed that the program increased self-employment activities more for urban *hukou* residents than for rural *hukou* ones.[3]

[2]Data source: China Public Health Statistical Yearbook, 2016.

[3]Urban and rural households are specified according to the general household registration system in China (called the *"hukou"* system).

I address two new questions in this paper. First, I provide a comprehensive investigation of the labor market effects of URBMI. Compared to Liu and Zhang (2018), I examine the labor market impact of URBMI in greater detail by exploring broader labor market outcomes and performing an overall evaluation of the labor market impact. In this way, I am able to provide broader policy implications. The outcomes under investigation include the following: the level of employment (i.e., the probability of working); various types of employment (long-term employment, fixed-term contracts, self-employment, and other informal jobs); and employment mobility.[4] Second, I estimate separate effects for different subgroups depending on demographic and socioeconomic factors, such as gender, education level, and previous health and employment status. As the URBMI principally targets the relatively disadvantaged urban population not covered by the UEBMI, understanding the second question is essential for designing and improving policies to provide optimal healthcare solutions for vulnerable and marginalized populations.

To estimate the 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 a potential self-selection bias due to the program's voluntary enrollment scheme. To overcome this endogeneity issue, I exploit the staggered implementation of URBMI across cities in China between 2007 and 2009. As URBMI is part of the urban healthcare system, I study the program's impact across working-aged individuals in urban areas.

The results are summarized as follows. First, URBMI does not have a significant average causal effect on the overall employment level for the whole sample or subgroups. Second, URBMI increases employment mobility, as evidenced by a decline in long-term employment and by increases in fixed-term contract jobs and self-employment. Formal sector employees were more likely to become self-employed after URBMI implementation, indicating a reduction in job lock. This inflow from long-term formal employment to self-employment was likely attributable to less-educated workers and to individuals with favorable health status. Women enhanced their job flexibility by leaving long-term employment and working in fixed-term contracts or other informal sector jobs, while men transitioned from other informal jobs to self-employment. Third, the increased trends in self-employment and fixed-term contract employment for those who previously had poor health status indicate a direct health improvement effect from the insurance scheme. Additionally, the availability of URBMI may

[4]Another important difference is that, unlike Liu and Zhang (2018), I do not include rural *hukou* in the analysis sample. 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 also subject to completely different social programs. In addition, some cities have relaxed policies that include local residents with rural *hukou* in the URBMI program, while other cities strictly exclude rural *hukou* from the program (Pan et al., 2016a). In light of the concern that the group with the rural *hukou* may not serve as a valid control group for those with urban *hukou*, I deliberately exclude individuals with rural *hukou* from my sample to avoid systematic bias in the results.

have resulted in decreased labor costs for small business employers. Thus, their labor demand would have increased, ultimately creating more job opportunities in the formal sector.

These findings suggest that the URBMI has served as a supplement to employment-based health insurance. Rather than crowding out employment, URBMI enhanced the favorability of fixed-term contract jobs and self-employment. In other words, people were still working after URBMI implementation, but labor force participation became more flexible. Nevertheless, the URBMI's current coverage and reimbursement rates are not as generous as those of UEBMI, exacerbating disparities and inequalities in healthcare (Li et al., 2017; Pan et al., 2016b). Therefore, it is essential to refine the policy to guarantee equivalent benefits and coverage across different schemes of public insurance and to eliminate health care inequalities across different population groups. The finding that different subpopulations reacted differently to URBMI is consistent with contemporary China's underlying social inequalities and other developmental problems, such as gender gaps, inefficient labor allocation, and inequalities from labor market disparities (Guo and Cheng, 2010; Zhang and Wu, 2018). Analyzing separate subgroup effects and discussing the responsible mechanisms are critical for understanding the complexity of China's developing and transitional economy.

The remainder of this paper is organized as follows. The next section briefly introduces the public health insurance system in urban China and the institutional setup of the URBMI program. Section 3 describes the data and the identification strategy for the empirical analysis. Section 4 presents the results and robustness checks, and the final section discusses the results and concludes the paper.

2 Institutional Background

2.1 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. The evolution of health insurance in urban China has followed the economic reform and transition of the country. 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). After the market-oriented economic reforms in the 1980s, many workers from state-owned enterprises were laid off and lost eligibility for their original health insurance. Moreover, problems such as overutilization and inefficient resource allocation hampered the old health insurance schemes. In 1998, following health insurance reform for urban formal sector workers, a new public insurance scheme, UEBMI, was established. UEBMI replaced the original LIS and GIS systems and was expanded to the private sector. It was designed to cover all formally employed urban workers and retired employees. 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%). In this system, 70% of employers' contributions enter a social pooled account, and the remaining 30% plus the employees' 2% share are deposited into individual medical savings accounts (Barber and Yao, 2010; Huang and Gan, 2017). 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).[5] The new scheme for formal sector employees no longer covered workers' dependents. Hence, urban residents without formal employment were not covered by any public healthcare program from 1998 to 2006, and in the urban population, the number of individuals left behind was estimated to be 420 million (Lin et al., 2009; Yip and Hsiao, 2009). Even for formal sector employees, the coverage rate of UEBMI was not 100%, especially for fixed-term contract workers. This is likely because providing UEBMI to employees was costly for small employers, and due to a lack of supervision and market irregularities in some areas, not all employers provided UEBMI to their employees. In 2006, approximately 55% of the Chinese population did not have any health care coverage (Süssmuth-Dyckerhoff and Wang, 2010). The blue bars in Figure A.1 present the UEBMI enrollment rates by employment status and type of work unit before the launch of URBMI using the sample data. The figure shows that the majority of long-term employees were covered by UEBMI, but over half of contract workers were not. Most workers in public enterprises were covered by this health insurance, but many who worked in private enterprises or other types were not.

Apart from public health insurance, private health insurance and commercial insurance plans were also available in the market. However, private health insurance was still in an early development stage and usually served as supplementary coverage for medical services not covered by public health insurance. With their high premiums and reimbursement rates, commercial health plans were expensive and mostly targeted high-income individuals. Thus, these plans were not affordable for the majority of people in China (Dong, 2009). In 2008, private health insurance accounted for only 3.8% of total health expenditures, while public health insurance contributed approximately 53% and individual out-of-pocket payments comprised the remainder. People who did not have public or private health insurance were forced to pay out-of-pocket for medical expenditures, and they did not receive reimbursement. Individual out-of-pocket spending reached almost 60% of total health expenditures in 2001, but this percentage decreased after the establishment of public health insurance (Barber and Yao, 2010). Uninsured individuals were more likely to seek informal medical care at local drug stores or community clinics because of their lower costs. However, the primary care system in the country was also underdeveloped, and the medical care it provided was less effective than that of formal hospitals. In response to growing social pressures, the

[5] The exchange rate is approximately 1 CNY = 0.14 USD. According to the National Bureau of Statistics, the average per capita annual disposable income of urban households in 2010 was CNY 19109.4.

Chinese government announced a series of reforms to bring effective and low-cost health services to China's more than 1.3 billion citizens.

2.2 Urban Resident Basic Medical Insurance

To provide health insurance to urban residents who lacked coverage, URBMI was introduced in 2007. According to China's central government, the State Council, the original plan was to "cover over 80% cities in 2009 and all cities in 2010".[6] In 79 pilot cities in 2007 and in an additional 229 cities in 2008, the program was rapidly rolled out across the nation. By the end of 2009, almost all cities in the country had implemented the URBMI program.[7] Figure 1 illustrates the number of URBMI and UEBMI recipients each year from 2007 to 2015. In 2007, only 42.91 million urban residents obtained the new public insurance, whereas in 2015, 376.89 million were insured by URBMI, accounting for almost 49% of all urban residents in China.[8] By the end of 2015, public health insurance covered approximately 96.5% of Chinese citizens (Choi et al., 2018).

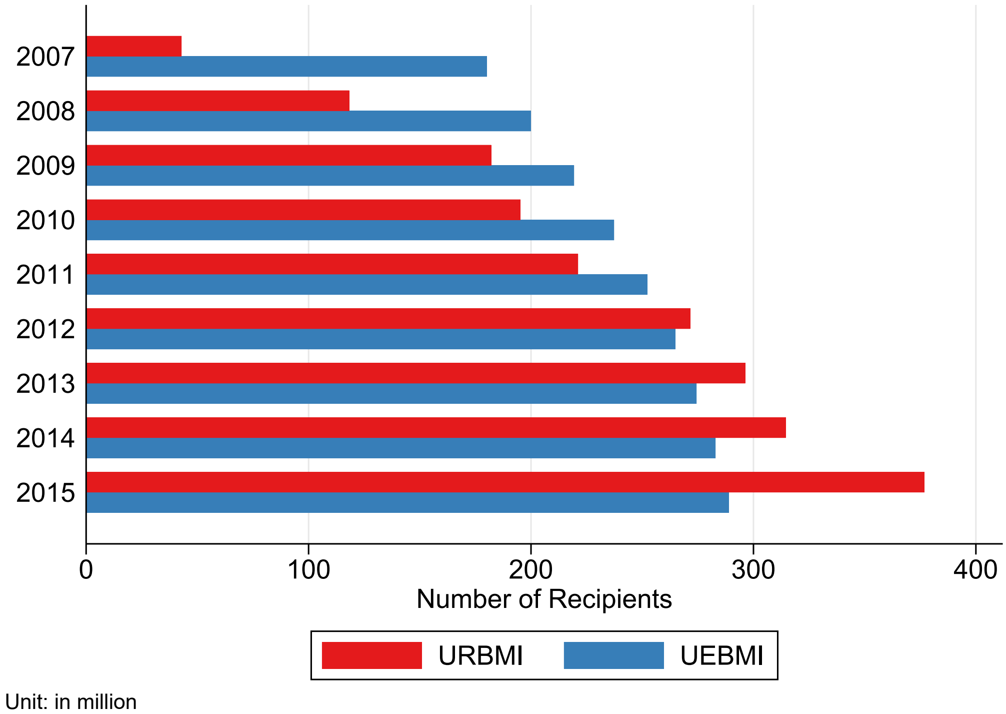

Figure 1: Number of URBMI and UEBMI Recipients, 2007-2015
Source: China Public Health Statistical Yearbook (from 2008 to 2016).

[6]Source: http://www.gov.cn/zwgk/2007-07/24/content_695118.htm.

[7]In August 2009, an official policy announcement from the State Council indicated that all cities in the country would have access to the program in 2009, and for those cities initiating the program in 2009, the program would be effective by the second quarter of 2010. Source: http://www.gov.cn/zwgk/2009-08/05/content_1383950.htm.

[8]The total urban population in China in 2015 was 771.16 million (National Bureau of Statistics, 2016).

URBMI is a large-scale public insurance program operated by the government and managed at the city level. The targeted group is urban residents who do not have UEBMI, including 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. An individual pays less than 50% of the premium, which is no more than 1% of the average disposable income of an urban resident, and the local and central governments together subsidize the remainder (Zhu et al., 2017). The premiums vary slightly across cities and years. In 2010, for instance, the local and central governments' subsidy per person was 180 CNY on average, 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). The disabled and those in poor households are partially 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 whether or not to continue the following year. There are reimbursements for medical expenditures on inpatient services and on outpatient care for chronic and fatal diseases, with some cities offering coverage for a larger range of outpatient services (Liu and Zhao, 2014).

3 Data and Methodology

3.1 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 that have been collected every two to four years since 1989. The longitudinal samples of the survey are from nine provinces in China, which vary in terms of geography, public resources, and socioeconomic development level.[9] A multistage, 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 condition, and health-related behaviors.[10] The CHNS provides data on medical insurance if the individual has it, making it possible to study labor market outcomes on the extensive margin, such as employment status and occupation type.

[9]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.2. 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.

[10]Further information about the CHNS can be found on its website: http://www.cpc.unc.edu/projects/china, and in the review papers by Popkin et al. (2010) and Zhang et al. (2014).

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. Each wave's information on individuals' health insurance, employment status, and basic demographic characteristics can be obtained from the CHNS household and individual surveys. The sample includes a total of 54 cities across nine provinces.[11] After identifying cities' exact locations and cross-referencing this information with the list of URBMI pilot cities (i.e., those that implemented the program during the 2007–2008 period), I find that of the 54 sample cities, 12 cities launched the program in 2007, 36 cities in 2008, and six cities in late 2009 (often December 2009). Considering cities that implemented URBMI during 2007 and 2008 as the pilot cities and the cities that implemented the program in 2009 as the nonpilot cities, my sample for analysis includes 48 pilot cities and six nonpilot 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 China's statutory retirement age is 60 years for males and 55 years for females.[12] Moreover, as URBMI is part of the urban healthcare system and the local urban *hukou* is required when individuals receive insurance in each city, I include only individuals with urban *hukou*. Therefore, the sample used for the analysis consists of an unbalanced panel of 7868 observations, including 2582 in 2004, 2483 in 2006, 1542 in 2009, and 1261 in 2011.[13]

3.2 Variables

I examine the potential effects of URBMI on individuals' labor market decisions and outcomes. The following outcome variables are measured: employment, types of employment, and employment mobility. Employment is defined as whether an individual is currently working. To investigate people's choices regarding employment type, the dependent variables include long-term employees with an open-ended formal employment contract, contract workers with fixed-term (usually short-term) specific labor contracts, self-employed workers, and other informal job workers who lack formal employment contracts, for instance, temporary workers and family workers.[14] The former two types are usually considered formal sector employees, while the latter two types are mostly considered informal sector

[11] The CHNS does not release the exact names of the cities involved 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).

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

[13] I retain individuals who have at least one pretreatment observation in order to analyze their labor market transitions and to assess the direct health effect of the program, given their previous health status. The main results are equivalent if I use all observations from each year in the sample.

[14] In the CNHS questionnaires, a long-term employee is defined as someone who "works for another person or enterprise as a permanent employee". A contract worker is defined as a "contractor with another person or enterprise".

workers. Moreover, I also estimate the overall mobility effect by checking whether an individual changed his or her employment category (from non-working, long-term employee, contract worker, self-employed, and other informal job) since the last wave.

As the key variable of interest is URBMI implementation, the covariates should be exogenous variables that are not affected by the treatment of URBMI to avoid the problem of "bad controls" (Angrist and Pischke, 2009). I control for several individual characteristics, including age, gender, marital status, education level (elementary school, middle school, high school, technical school, and college graduate), whether the individual is currently a student (including part-time study and on-the-job training), household size, and an urbanization index of the community where the individual lives, as reported by the CHNS.[15]

Table 1 presents the summary statistics for the main variables, including URBMI enrollment status, individual characteristics, and labor market outcome variables for the pilot and nonpilot cities. The pilot cities have a higher URBMI enrollment rate (26.0%) than the nonpilot ones (19.7%), whereas the individual characteristics are quite similar in the two groups of cities. Further summary statistics by gender, education level, and previous health status are reported in the Appendix Table A.1 to Table A.3.

3.3 Empirical Strategy

The identification strategy exploits the quasi-exogenous variation in the URBMI implementation timing at the city level. I use a difference-in-differences strategy to compare the labor market outcomes of individuals in cities with staggered adoption of URBMI. Specifically, I use a linear probability model to estimate the following equation:

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

where Y_{ict} denotes a labor market outcome for individual i in city c at time t. The variable $URBMI\_city_{ct}$ 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; these are coded as 1 in 2009. The six nonpilot cities 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; thus, all are coded as 1 in 2011. The effect of interest is captured by β_1, which can be interpreted as the intention-to-treat (ITT) effects of living in a city that had implemented URBMI on an individual's labor market outcome. In other words, the regression model Eq. (1) estimates the reduced-form impacts of implementing URBMI, and the estimated coefficient of β_1 averages the effects of URBMI over all individuals in the cities that introduced the program, although not all are affected by the program. X_{ict} is a vector of

[15] The urbanization index is a comprehensive measure capturing the status of the social, economic, cultural, and physical environment of the community in which an individual resides. See Jones-Smith and Popkin (2010) for a detailed introduction of the index.

Table 1: Summary Statistics

	Full Sample	**Pilot Cities**		**Nonpilot Cities**	
		Pre-URBMI	Post-URBMI	Pre-URBMI	Post-URBMI
Health Insurance:					
URBMI Enrollment	0.0904	0	0.260	0	0.197
	(0.287)	(0)	(0.439)	(0)	(0.399)
UEBMI Enrollment	0.352	0.297	0.487	0.164	0.391
	(0.478)	(0.457)	(0.500)	(0.371)	(0.489)
Any Health Insurance	0.623	0.491	0.878	0.420	0.846
	(0.485)	(0.500)	(0.327)	(0.494)	(0.362)
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)
Urbanization index	84.18	83.29	87.03	81.43	77.84
	(10.32)	(10.32)	(9.584)	(9.366)	(11.56)
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)
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)
Change job category	0.222	0.124	0.411	0.109	0.301
	(0.415)	(0.330)	(0.492)	(0.312)	(0.460)
Observations	7868	4553	2524	512	279

Notes: Standard deviations in parentheses. "URBMI Enrollment" and "UEBMI Enrollment" are indicators for whether the individual has URBMI or UEBMI, respectively. "Any Health Insurance" is a dummy equal to 1 if the individual has any type of health insurance. Individual characteristics include age, gender, marital status, indicators for education levels (elementary school, middle school, high school, technical school, and college graduate), years of schooling, whether the individual is currently a student (including part-time study and on-the-job training), household size, and the urbanization index of the community where the individual lives reported by CHNS. Labor market outcome variables include indicators for whether an individual is currently working, a long-term employee, a worker with a fixed-term contract, self-employed or has another informal job. "Change job category" is a dummy equal to 1 if an individual changed his/her job category (from non-working, long-term employee, contract worker, self-employed, and other informal job) since the last wave.

individual characteristics, including age, gender, marital status, education status, household size, and the log urbanization index. μ_c is a set of city fixed effects, and ν_t controls for year fixed effects, which absorb the effects of time-invariant city characteristics and the influence of aggregate time-series trends, respectively. ϵ_{ict} is an error term. As a robustness check, I also show the results of 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. In all regressions, standard errors are clustered at the city level.

Using this difference-in-differences strategy, the following key identification assumptions need to be satisfied to interpret the results causally. First, only when a city implements the URBMI program can local citizens obtain access to this health insurance. Second, cities with and without the URBMI program should not differ in terms of observable and unobservable characteristics that are correlated with individual labor market outcomes, except for the URBMI program. That is, (1) people in the pilot and nonpilot cities would not trend differentially in the absence of URBMI, and (2) no other shocks occur during the time period that differentially affect people's labor market outcomes in the cities with staggered program adoption.

According to the administration scheme of the URBMI program, residents enroll in the program in the local city where their household is registered, so an individual can only have obtained insurance after his or her city implemented the program. Therefore, an individual's probability of obtaining URBMI should be highly correlated with the introduction of the program at the city level. The timing of URBMI rollout and the selection of pilot cities were determined by the central and provincial governments, so the setup of the program is exogenous to individuals. Moreover, given the country's multilevel government structure, top-down intergovernmental information is often asymmetric and ambiguous in China (Zhan and Qin, 2017). Thus, anticipatory behaviors by ordinary people before actual policy implementation are unlikely in the Chinese context. This is especially true in the case of URBMI because the detailed financing and reimbursement rules are city-specific and difficult to predict before the official URBMI introduction in a given city. Thus, the first identification assumption is valid. The robustness checks in the next section find no evidence of pre-existing trends using preprogram years and no time-varying systematic differences during the period of study between cities with and without the URBMI program affecting people's labor market outcomes, which supports the second identification assumption. Moreover, I conduct a balancing test for individual characteristics on the key variable of interest $URBMI\_city_{ct}$ to check whether there is a selection of individuals, following the procedure proposed by Pei et al. (2019). I find no evidence of selection effects with balancing regressions in Table A.4.

Table 2: Program Implementation and URBMI Enrollment

Sample:	All	Female	Male	Less Edu	More Edu	Unhealthy	Healthy	No Work	Formal	Informal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
URBMI-city	0.125***	0.115***	0.135***	0.162***	0.089***	0.124**	0.126***	0.120**	0.091***	0.113***
	(0.029)	(0.035)	(0.029)	(0.047)	(0.026)	(0.057)	(0.035)	(0.041)	(0.019)	(0.000)
Mean of Dep. Variable	0.090	0.090	0.090	0.124	0.064	0.077	0.098	0.113	0.047	0.142
Exogenous covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7868	3765	4103	3446	4422	2809	5059	2723	3436	1709

Notes: Robust standard errors in parentheses are clustered at the city level. Column (1) presents estimates using the whole sample. Columns (2) and (3) present estimates using the female and male samples, respectively. Columns (4) and (5) present estimates using the samples of less-educated and more-educated individuals, respectively. Columns (6) and (7) present estimates using samples of unhealthy and healthy individuals before the launch of URBMI, respectively. Columns (8), (9), and (10) present estimates using the samples of non-working individuals, formal sector employees, and informal sector workers before the launch of URBMI, respectively. The set of individual characteristics includes gender, age, education dummies, marital status, household size, and the log urbanization index. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

4 Results

4.1 URBMI Enrollment

First, I estimate an individual's probability of taking up URBMI if he or she lives in a city where the program has been implemented. Table 2 presents the results from estimating Eq. (1) on the dependent variable as URBMI enrollment. Column (1) reports the estimate for the whole sample. Living in cities where the program has been implemented increases an individual's probability of taking up URBMI by approximately 12.5 percentage points, which is statistically significant at the 1% level.

Moreover, I also estimate the probability of different subgroups taking up URBMI. Columns (2) and (3) present the results by gender. The enrollment rate is slightly higher among men than among women. Columns (4) and (5) report the results by education level. Based on the nine-year compulsory schooling law in China, the less educated are defined as individuals with nine or fewer years of schooling, i.e., individuals with lower secondary schooling or below. The better educated are those with more than nine years of schooling. The results show that less-educated people are much more likely to take up URBMI than are better-educated people. Columns (6) and (7) report the estimates by previous health status. Based on people's self-reported health status before the program was implemented, I divide the sample into two groups: healthy and unhealthy.[16] Although incentives to take up insurance may differ between those with good vs. poor health status, the URBMI enrollment rates are similar. Finally, Columns (8) to (10) present the results stratified by employment status before the URBMI implementation. Individuals who were not working previously or

[16]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, a loss of one or both arms or legs, or if the self-reported health status is not healthy.

who worked in the informal sector (self-employed or with other informal jobs) have higher enrollment rates than those who were working in the formal sector (long-term employees or contract workers), which is consistent with the URBMI's target population. The results are robust to controlling for city-specific linear time trends, as shown in Table A.5, Panel I.

4.2 Average Effects

As defined in Section 3.2, the main labor market outcome variables in this empirical analysis are an individual's probability of working, employment type, and employment mobility. The dependent variables for type of employment include an individual's probability of being a long-term (open-ended contract) employee, a fixed-term contract worker, self-employed, or working in other informal jobs. Table 3 Column (1) presents the main results for the whole sample. The results show that for the whole sample, on average, having URBMI has no statistically significant causal effect on an individual's probability of working. However, URBMI affects people's choice of employment type. For jobs in the formal sector, having URBMI decreases the probability of working as a long-term employee by 7.3 percentage points, while it increases the probability of working under a fixed-term contract by 4.0 percentage points. For informal sector employment, the probability of being self-employed increases by 5.1 percentage points despite a reduced but insignificant trend of working in other informal jobs. Consistent with the results for employment type, the results regarding the changes in individuals' employment categories since the last wave shows that URBMI introduction is positively associated with an increased trend of employment mobility by 11.7 percentage points. The results are similar to those when controlling for city-specific linear time trends, as shown in Table A.5, Column (1), Panels II to VII.

The results regarding the labor market impacts of implementing URBMI for the whole sample suggest that employment mobility increases from long-term formal jobs to more flexible contract jobs or self-employment. The trend indicates reduced job lock and increased job flexibility. Because URBMI decouples health insurance eligibility from formal employment, transitioning out of formal employment increases. Self-employment becomes more attractive because URBMI reduces the healthcare expenditure risks that were formerly associated with self-employment. Furthermore, from the labor demand side, after the launch of URBMI, small employers can offer this new type of health insurance to their employees as an alternative to UEBMI, which is more costly. Thus, their labor costs decrease, which may increase their labor demand. In Figure A.1, the red bars depict the URBMI enrollment rate by employment characteristics using the sample data. Among the self-employed, who are the targets of the program, approximately 48% have URBMI, while 33% to 35% of nonworkers and informal job workers have it. Although they are not the primary audience for the program, 23% of contract workers and 9% of long-term employees have URBMI. These workers are mainly from private enterprises or other types of work units rather than from

Table 3: Effects of URBMI on Labor Market Outcomes

Sample:	All	Female	Male	Less Edu	More Edu	Unhealthy	Healthy	No Work	Formal	Informal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:										
I.**Probability of Working**	−0.015	−0.004	−0.033	0.013	−0.011	0.029	−0.045	0.020	−0.039	−0.081
	(0.031)	(0.050)	(0.033)	(0.052)	(0.028)	(0.036)	(0.039)	(0.061)	(0.049)	(0.081)
Mean of Dep. Variable	0.651	0.577	0.719	0.531	0.745	0.601	0.679	0.197	0.922	0.830
II.**Long-term Employee**	−0.073**	−0.120***	−0.029	−0.086**	−0.038	−0.060	−0.086**	−0.039	−0.078	−0.036
	(0.033)	(0.038)	(0.043)	(0.033)	(0.046)	(0.045)	(0.032)	(0.028)	(0.054)	(0.060)
Mean of Dep. Variable	0.357	0.300	0.410	0.167	0.505	0.341	0.366	0.060	0.732	0.076
III.**Fixed-term Contractor**	0.040**	0.045**	0.033	0.040	0.043*	0.038**	0.037	0.075***	0.024	0.009
	(0.019)	(0.020)	(0.023)	(0.026)	(0.023)	(0.016)	(0.025)	(0.020)	(0.027)	(0.064)
Mean of Dep. Variable	0.085	0.084	0.087	0.079	0.090	0.074	0.091	0.032	0.143	0.054
IV.**Self-employment**	0.051***	0.040	0.057*	0.104***	0.013	0.053***	0.057**	0.010	0.023**	0.066
	(0.019)	(0.029)	(0.031)	(0.037)	(0.020)	(0.019)	(0.025)	(0.041)	(0.010)	(0.061)
Mean of Dep. Variable	0.124	0.110	0.136	0.172	0.086	0.099	0.138	0.058	0.019	0.441
V.**Other Informal Jobs**	−0.033	0.031*	−0.094**	−0.046	−0.029	−0.001	−0.053*	−0.026	−0.007	−0.120
	(0.024)	(0.016)	(0.044)	(0.044)	(0.024)	(0.037)	(0.029)	(0.040)	(0.016)	(0.093)
Mean of Dep. Variable	0.085	0.084	0.086	0.113	0.063	0.086	0.085	0.048	0.028	0.259
VI.**Change Employment Category**	0.117**	0.169***	0.068	0.129***	0.097	0.162***	0.083	−0.000	0.142**	0.117
	(0.055)	(0.059)	(0.063)	(0.038)	(0.079)	(0.051)	(0.068)	(0.069)	(0.070)	(0.093)
Mean of Dep. Variable	0.222	0.212	0.230	0.245	0.203	0.202	0.232	0.187	0.196	0.328
Exogenous covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7868	3765	4103	3446	4422	2809	5059	2723	3436	1709

Notes: The effect of URBMI implementation is reported in each cell. Robust standard errors in parentheses are clustered at the city level. Column (1) presents estimates using the whole sample. Columns (2) and (3) present estimates using the female and male samples, respectively. Columns (4) and (5) present estimates using the samples of less-educated and more-educated individuals, respectively. Columns (6) and (7) present estimates using the samples of unhealthy and healthy individuals before the launch of URBMI, respectively. Columns (8), (9), and (10) present estimates using the samples of non-working individuals, formal sector employees, and informal sector workers before the launch of URBMI, respectively. The set of individual characteristics includes gender, age, education dummies, marital status, household size, and the log urbanization index. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

public enterprises.

4.3 Heterogeneous Effects

A wide swathe of urban residents can obtain URBMI coverage, and the labor market impacts are likely to vary across different socioeconomic groups. Exploring the potential heterogeneous effects is vital not only in a comprehensive program evaluation but also for policy improvement to ensure the effective delivery of health and social services to different populations. I estimate separate effects for several subgroups by gender, education level, and previous health and employment status. The results are reported in Table 3, Columns (2) to (10). Overall, URBMI implementation does not affect the average level of employment among each subgroup, as presented in Panel I. However, the results in Panel VI show that for women, those who are less educated, those who were previously unhealthy, and those who were formerly formal sector workers, the probability of changing employment categories increases significantly with URBMI implementation. All results are robust to controlling for city-specific linear time trends, as shown in Table A.5, Panels II to VII.

4.3.1 Differences by Gender

Gender discrimination issues and gender earnings gaps exist in the labor markets of many countries, and China is no exception (Gustafsson and Li, 2000; Liu et al., 2014). China is characterized by traditional attitudes toward gender roles and rigid social norms; thus, women are expected to prioritize their families over their careers or to have flexible work schedules to accommodate their familial responsibilities (Du and Dong, 2013; Liu et al., 2010). To assess whether URBMI affects the labor market outcomes of men and women differently, I report the ITT estimates by gender in Table 3, Columns (2) and (3). For women, the program is significantly associated with a decrease in long-term formal sector employment of 12.0 percentage points and with increases in fixed-term contract jobs and other informal jobs of 4.5 and 3.1 percentage points, respectively. The results suggest that reduced job lock exists for women, resulting in an increase in their labor market flexibility. Compared to men, women often assume more responsibility for household duties and childcare, and they face greater dilemmas about how to balance career and family, especially in traditional societies such as China. When URBMI delinks insurance availability and long-term employment, women are able to choose jobs with greater flexibility to achieve a balance between work and family. For men, a transition occurs within the informal sector. With the introduction of URBMI, men are more likely to become self-employed and less likely to perform other informal jobs. Thus, men's transition is not due to reduced job lock but is instead likely from reduced risk aversion. Studies have shown that given the risky nature of self-employment, people who are less risk averse are more willing to pursue self-employment or entrepreneurship (Koudstaal et al., 2015; Skriabikova et al., 2014). Decreased health care risks with URBMI, then, may encourage men in the informal sector to enter self-employment. Consistent with the situation described by Zhang and Pan (2012), women in urban China are less likely to become self-employed due to constraints from family responsibilities.

4.3.2 Differences by Education

Education has long played an important role in individual labor market outcomes. Previous research has documented the effect of education on income distribution and earnings inequality in urban China (e.g., Li et al., 2012; Meng et al., 2013; Wang, 2013). Hence, I examine whether there is any heterogeneous effect on subgroups with different education levels. In Table 3, Columns (4) and (5), the estimates by education level show that for the less educated, the probability of working in a long-term formal job decreases by 8.6 percentage points after URBMI implementation, while the probability of being self-employed increases by 10.4 percentage points. The results suggest that the effect of reducing job lock and promoting self-employment is likely to originate from less-educated people. For better-educated people, URBMI availability is positively associated with working in the formal sector under a fixed-term contract. The reason that job-lock reduction may be more applicable to the less educated is that given the availability of URBMI, their opportunity costs of quitting may be lower than those of better-educated workers, who tend to have better long-term jobs with higher earnings. These job lock results are also consistent with the findings of Hamersma and Kim (2009) and Liu and Zhang (2018).

The results regarding different effects by gender and education are inspiring and of interest to policymakers. In the current labor market in urban China, which is characterized by gender disparities, women and undereducated workers have relatively fewer advantages in the labor market than men and well-educated workers. The URBMI program has a statistically significant impact on vulnerable groups' employment. In particular, by reducing the medical expenditure risks associated with informal sector employment, URBMI availability encourages marginal workers' labor force participation and flexible employment.

4.3.3 Differences by Previous Health Status

As a form of public health insurance, URBMI could have a direct, positive effect on people's health status, thereby enhancing worker productivity or labor supply. Therefore, the labor market impacts of URBMI might differ according to people's health status. The estimates are reported in Table 3, Columns (6) and (7). For healthy people, the availability of URBMI decreases long-term employment in the formal sector by 8.6 percentage points but increases self-employment by 5.7 percentage points. At the same time, healthy people become less likely to work in other informal jobs. These results indicate a reduced job lock effect as well as a transition to self-employment from other informal jobs. For previously unhealthy individuals, the availability of URBMI increases their probability of working under fixed-term contracts by 3.8 percentage points and increases their probability of self-employment by 5.3 percentage points. These results show an increased trend of labor force participation for previously unhealthy individuals, suggesting a health improvement effect. This finding is in line with the results of Pan et al. (2016a), who identified a significant effect of URBMI on health. The job lock reduction is more evident for healthy workers than for unhealthy ones, probably because URBMI is not yet as generous as UEBMI. Therefore, for unhealthy people with potentially high medical costs, keeping UEBMI may be the optimal choice.

4.3.4 Labor Market Transitions

The impact of URBMI may be heterogeneous across subgroups with different employment backgrounds. Moreover, the introduction of the program may influence labor market dynamics by inducing labor flows from one sector to another, as discussed above. To further explore the heterogeneous effects and potential labor market transitions caused by URBMI, Table 3 Columns (8) to (10) separately report the ITT estimates for individuals who were not working, those who were formal sector employees, and those 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 implementation. For formal sector employees, URBMI is significantly associated with increased self-employment by 2.3 percentage points. There are no significant effects for those who were working in the informal sector, probably due to the small sample size.

The results for the previously non-employed are most likely attributable to increased labor demand from reduced labor costs, since small business employers could choose URBMI over the more expensive UEBMI for their employees; this is particularly the case for employers of fixed-term contract workers. The increased probability of self-employment among formal sector employees indicates job lock reduction. With the availability of URBMI, some formal sector employees are more inclined to become self-employed, particularly if they find that self-employment is a better match for them than is formal employment. This finding suggests that URBMI increases job match and job flexibility.

4.4 Robustness Checks

4.4.1 Falsification Tests

As discussed in Section 3.3, one of the key identifying assumptions of the empirical strategy is that cities with and without the URBMI program should not differ in terms of observable and unobservable characteristics correlated with individual labor market outcomes. One concern is that pilot and nonpilot cities could have different preprogram trends and exhibit different trajectories in labor market development. To rule out this potential threat, I conduct a falsification test using only the 2004–2006 panel data under the assumption that the program was already launched in 2006 in the pilot cities, and I check the parallel trends. The test is performed by regressing each labor market outcome on the "placebo" dummy $URBMI\_city_{ct}$. The results in Table 4 Panel A show no significant differences in each labor market outcome in the preprogram period between pilot and nonpilot cities for both the whole sample and each subgroup. This eliminates concerns regarding different time trends of unobservable characteristics between pilot and nonpilot cities.

Moreover, there could be other time-varying differences between cities with and without the URBMI program from 2004 to 2011 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 the residents in each city. To check whether this threat exists, I run the falsification test on the "unaffected" individuals, that is, those who had free medical insurance before URBMI was launched according to their reports in the survey.[17] In principle, these individuals should not have been affected by the URBMI

[17]A few state-owned enterprises or government departments maintained the old government-sponsored health insurance system, which provided free medical insurance to their employees, the so-called Government

Table 4: Falsification Tests

Sample:	**All**	**Female**	**Male**	**Less Edu**	**More Edu**	**Unhealthy**	**Healthy**	**No Work**	**Formal**	**Informal**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Pre-existing trend:										
I.**Probability of Working**	−0.010	−0.055	0.029	−0.044	0.018	−0.046	0.018	−0.050	−0.048	0.087
	(0.041)	(0.038)	(0.056)	(0.056)	(0.035)	(0.044)	(0.058)	(0.062)	(0.031)	(0.109)
Mean of Dep. Variable	0.635	0.565	0.702	0.520	0.724	0.571	0.680	0.114	0.953	0.892
II.**Long-term Employee**	0.001	−0.005	−0.044	−0.009	−0.020	−0.088	0.024	−0.050	−0.018	−0.050
	(0.020)	(0.026)	(0.028)	(0.048)	(0.026)	(0.062)	(0.028)	(0.042)	(0.055)	(0.061)
Mean of Dep. Variable	0.356	0.297	0.414	0.179	0.495	0.321	0.397	0.026	0.777	0.042
III.**Fixed-term Contractor**	−0.021	−0.041	0.006	−0.025	−0.013	−0.007	−0.035	−0.010	−0.064	0.055
	(0.017)	(0.027)	(0.025)	(0.035)	(0.023)	(0.019)	(0.026)	(0.023)	(0.043)	(0.040)
Mean of Dep. Variable	0.072	0.071	0.074	0.063	0.080	0.064	0.078	0.015	0.138	0.025
IV.**Self-employment**	−0.005	−0.002	0.025	−0.011	0.025	0.031	0.003	−0.028	0.003	0.160
	(0.029)	(0.016)	(0.046)	(0.054)	(0.019)	(0.035)	(0.039)	(0.041)	(0.020)	(0.105)
Mean of Dep. Variable	0.120	0.112	0.129	0.166	0.085	0.105	0.120	0.037	0.014	0.504
V.**Other Informal Jobs**	0.013	−0.007	0.042	−0.012	0.018	0.017	0.026	0.039	0.029	−0.079
	(0.029)	(0.034)	(0.046)	(0.072)	(0.028)	(0.057)	(0.022)	(0.056)	(0.019)	(0.163)
Mean of Dep. Variable	0.086	0.086	0.086	0.112	0.065	0.081	0.087	0.036	0.025	0.321
VI.**Change Employment Category**	0.038	0.039	0.027	−0.067	0.048	0.021	0.143*	−0.050	0.185*	−0.034
	(0.035)	(0.038)	(0.040)	(0.093)	(0.035)	(0.036)	(0.063)	(0.062)	(0.067)	(0.131)
Mean of Dep. Variable	0.123	0.119	0.126	0.119	0.125	0.130	0.153	0.114	0.141	0.209
Observations	5065	2485	2580	2220	2845	1647	2668	1559	1947	809
B. Unaffected group:										
I.**Probability of Working**	0.007	−0.212	0.232	0.212	−0.017	−0.070	0.089	0.356	−0.077	0.054
	(0.067)	(0.148)	(0.149)	(0.291)	(0.062)	(0.104)	(0.113)	(0.231)	(0.084)	(0.102)
Mean of Dep. Variable	0.789	0.720	0.838	0.638	0.871	0.694	0.847	0.105	0.963	0.922
II.**Long-term Employee**	0.033	−0.244	0.072	−0.078	−0.119	−0.035	−0.131	−0.011	0.029	0.656
	(0.080)	(0.182)	(0.136)	(0.242)	(0.078)	(0.108)	(0.125)	(0.161)	(0.086)	(0.367)
Mean of Dep. Variable	0.592	0.517	0.646	0.346	0.725	0.536	0.626	0.045	0.831	0.095
III.**Fixed-term Contractor**	0.007	0.047	0.028	0.081	0.044	−0.017	0.019	0.009	0.002	0.033
	(0.039)	(0.059)	(0.031)	(0.080)	(0.036)	(0.064)	(0.052)	(0.027)	(0.027)	(0.063)
Mean of Dep. Variable	0.078	0.076	0.079	0.098	0.067	0.062	0.087	0.015	0.100	0.052
IV.**Self-employment**	0.012	0.018	0.063	0.079	−0.018	−0.054	0.019	0.038	0.024	−0.117
	(0.030)	(0.046)	(0.040)	(0.100)	(0.032)	(0.037)	(0.057)	(0.082)	(0.035)	(0.293)
Mean of Dep. Variable	0.059	0.064	0.056	0.098	0.038	0.028	0.078	0.020	0.014	0.397
V.**Other Informal Jobs**	0.049	−0.022	0.022	0.130	0.013	0.037	0.071	0.209	0.026	−0.518
	(0.034)	(0.079)	(0.037)	(0.103)	(0.041)	(0.069)	(0.043)	(0.192)	(0.021)	(0.376)
Mean of Dep. Variable	0.060	0.064	0.057	0.096	0.041	0.067	0.056	0.025	0.017	0.379
VI.**Change Employment Category**	0.092	−0.103	0.115	0.618	−0.005	0.199	0.146	0.628	0.127	−0.313*
	(0.075)	(0.105)	(0.075)	(0.415)	(0.069)	(0.154)	(0.102)	(0.345)	(0.082)	(0.179)
Mean of Dep. Variable	0.109	0.078	0.132	0.163	0.080	0.117	0.105	0.090	0.097	0.216
Observations	1015	422	593	356	659	386	629	200	699	116
Exogenous covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The effect of URBMI implementation is reported in each cell. 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 unaffected sample (individuals who had free medical insurance before URBMI was implemented) in the 2004–2011 panel data. Column (1) presents estimates using the whole sample. Columns (2) and (3) present estimates using the female and male samples, respectively. Columns (4) and (5) present estimates using the samples of less-educated and more-educated individuals, respectively. Columns (6) and (7) present estimates using the samples of unhealthy and healthy individuals before the launch of URBMI, respectively. Columns (8), (9), and (10) present estimates using the samples of non-working individuals, formal sector employees, and informal sector workers before the launch of URBMI, respectively. The set of individual characteristics includes gender, age, education dummies, marital status, household size, and the log urbanization index. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

program implementation. The results in Table 4 Panel B show no significant differences in each labor market outcome for the unaffected group from 2004 to 2011 in cities with and without the URBMI program for both the whole sample and each subgroup. It is reassuring to see that the falsification tests do not refute the validity of the key identifying assumption.

4.4.2 Specification Checks

Moreover, I conduct several specification checks for the whole sample and for each subgroup. First, to further control for the impact of observable differences between pilot and nonpilot cities, I use propensity score matching to draw a comparable control sample (Rosenbaum and Rubin, 1983). I estimate the propensity score using a probit model with controls for individual characteristics in the preprogram period and construct a propensity score weight using an Epanechnikov kernel weight (Leuven and Sianesi, 2003). The difference-in-differences propensity score matching approach produces estimates that are comparable to the main results, as shown in Table 5, Panel A. Second, 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 robustness check results are similar when IPW is used to correct for panel attrition, as reported in Table 5, Panel B. Third, because logistic models may work better than linear probability models in the case of rare events, I conduct the analysis using a logit model to assess the potential for rare events for some outcomes (Von Hippel, 2015). The average marginal effects for each outcome are presented in Table 5, Panel C, which are similar to the main results using linear probability models. Furthermore, as mentioned above and presented in Table A.5, the results are also robust to controlling for city-specific linear time trends.

5 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 individuals who are unemployed and informally employed and to other urban residents who lack pre-existing employment-based health insurance. To address the self-selection bias resulting from voluntary enrollment in the program, I exploit the time variation in URBMI implementation at the city level. The sample data for analysis are drawn from the CHNS datasets, specifically from the 2004, 2006, 2009, and 2011 waves.

The ITT estimates show that URBMI availability does not have a significant average causal effect on labor force participation. However, it does increase employment mobility by affecting individuals' different types of employment. The probability of long-term formal employment decreases, while fixed-term contract employment and self-employment

Medical Insurance (Yang et al., 2020).

Table 5: Specification Checks

Sample:	**All**	**Female**	**Male**	**Less Edu**	**More Edu**	**Unhealthy**	**Healthy**	**No Work**	**Formal**	**Informal**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Propensity Score Matching:										
I.**Probability of Working**	−0.024	−0.010	−0.039	0.025	−0.028	0.003	−0.047	0.005	−0.009	−0.102
	(0.037)	(0.053)	(0.049)	(0.051)	(0.041)	(0.031)	(0.062)	(0.063)	(0.064)	(0.078)
II.**Long-term Employee**	−0.068**	−0.100**	−0.037	−0.050*	−0.036	−0.079**	−0.063*	−0.043	−0.038	−0.004
	(0.031)	(0.040)	(0.044)	(0.026)	(0.054)	(0.037)	(0.032)	(0.032)	(0.061)	(0.046)
III.**Fixed-term Contractor**	0.032	0.032	0.027	0.030	0.046	0.037**	0.022	0.083***	0.011	−0.007
	(0.022)	(0.029)	(0.025)	(0.031)	(0.032)	(0.018)	(0.032)	(0.023)	(0.032)	(0.067)
IV.**Self-employment**	0.055**	0.023	0.079**	0.095**	0.007	0.054*	0.058*	0.014	0.032**	0.060
	(0.025)	(0.034)	(0.039)	(0.038)	(0.030)	(0.029)	(0.035)	(0.046)	(0.015)	(0.097)
V.**Other Informal Jobs**	−0.044	0.035*	−0.108**	−0.051	−0.045	−0.009	−0.065*	−0.049	−0.013	−0.151
	(0.028)	(0.018)	(0.052)	(0.046)	(0.034)	(0.041)	(0.038)	(0.046)	(0.018)	(0.126)
VI.**Change Employment Category**	0.087	0.143**	0.043	0.129***	0.030	0.095**	0.065	0.001	0.141**	0.117
	(0.057)	(0.071)	(0.059)	(0.038)	(0.102)	(0.045)	(0.089)	(0.079)	(0.070)	(0.094)
Observations	7855	3762	4093	3446	4409	2809	5046	2716	3432	1707
B. Inverse Probability Weighting:										
I.**Probability of Working**	−0.006	0.012	−0.037	0.045	−0.022	0.018	−0.029	0.067	−0.043	−0.036
	(0.035)	(0.056)	(0.030)	(0.061)	(0.027)	(0.042)	(0.045)	(0.054)	(0.049)	(0.087)
II.**Long-term Employee**	−0.078**	−0.113***	−0.045	−0.056*	−0.061	−0.079*	−0.085**	−0.047	−0.075	−0.032
	(0.037)	(0.036)	(0.045)	(0.029)	(0.049)	(0.043)	(0.040)	(0.030)	(0.049)	(0.052)
III.**Fixed-term Contractor**	0.045**	0.046**	0.040	0.039	0.048*	0.038**	0.044	0.097***	0.019	0.026
	(0.021)	(0.021)	(0.026)	(0.026)	(0.026)	(0.017)	(0.029)	(0.033)	(0.029)	(0.050)
IV.**Self-employment**	0.059***	0.048*	0.067**	0.104***	0.021	0.075***	0.056**	0.043	0.023**	0.072
	(0.020)	(0.025)	(0.031)	(0.032)	(0.024)	(0.027)	(0.023)	(0.032)	(0.011)	(0.062)
V.**Other Informal Jobs**	−0.032	0.032	−0.099**	−0.042	−0.030	−0.015	−0.045	−0.026	−0.010	−0.102
	(0.022)	(0.019)	(0.045)	(0.045)	(0.025)	(0.033)	(0.030)	(0.039)	(0.021)	(0.091)
VI.**Change Employment Category**	0.099**	0.136***	0.057	0.120**	0.062	0.155***	0.058	0.066	0.136**	0.080
	(0.042)	(0.042)	(0.061)	(0.052)	(0.064)	(0.049)	(0.069)	(0.075)	(0.066)	(0.119)
Observations	7868	3765	4103	3446	4422	2809	5059	2723	3436	1709
C. Logit:										
I.**Probability of Working**	−0.014	0.006	−0.033	0.011	−0.014	0.026	−0.052	0.061	−0.042	−0.098
	(0.035)	(0.053)	(0.034)	(0.052)	(0.039)	(0.037)	(0.046)	(0.066)	(0.027)	(0.088)
II.**Long-term Employee**	−0.076**	−0.121***	−0.031	−0.086***	−0.037	−0.063	−0.089***	−0.038*	−0.035	−0.033
	(0.035)	(0.036)	(0.044)	(0.031)	(0.053)	(0.046)	(0.033)	(0.023)	(0.056)	(0.065)
III.**Fixed-term Contractor**	0.040	0.044	0.038	0.026	0.098	0.038	0.033	0.069***	0.079	−0.038*
	(0.043)	(0.048)	(0.056)	(0.035)	(0.093)	(0.030)	(0.056)	(0.011)	(0.076)	(0.023)
IV.**Self-employment**	0.056**	0.044	0.067*	0.098**	0.003	0.058*	0.056*	0.034	0.028***	0.055
	(0.023)	(0.039)	(0.040)	(0.040)	(0.033)	(0.031)	(0.033)	(0.031)	(0.008)	(0.065)
V.**Other Informal Jobs**	−0.033	0.101**	−0.091**	−0.038	−0.034	0.007	−0.056**	−0.011	−0.029	−0.129
	(0.024)	(0.047)	(0.038)	(0.039)	(0.028)	(0.051)	(0.026)	(0.046)	(0.024)	(0.096)
VI.**Change Employment Category**	0.095*	0.130**	0.063	0.162***	0.041	0.140***	0.060	0.043	0.102	0.124
	(0.049)	(0.060)	(0.055)	(0.042)	(0.082)	(0.043)	(0.075)	(0.077)	(0.064)	(0.124)
Observations	7866	3764	4102	3430	4411	2808	5043	1800	2280	1118
Exogenous covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The effect of URBMI implementation is reported in each cell. Robust standard errors in parentheses are clustered at the city level. Panel A presents results using the PSM (Kernel matching) method. Panel B presents results using the IPW method. Panel C presents the average marginal effects from the logit model. Column (1) presents estimates using the whole sample. Columns (2) and (3) present estimates using the female and male samples, respectively. Columns (4) and (5) present estimates using the samples of less-educated and more-educated individuals, respectively. Columns (6) and (7) present estimates using the samples of unhealthy and healthy individuals before the launch of URBMI, respectively. Columns (8), (9), and (10) present estimates using the samples of non-working individuals, formal sector employees, and informal sector workers before the launch of URBMI, respectively. The set of individual characteristics includes gender, age, education dummies, marital status, household size, and the log urbanization index. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

increase. URBMI delinks health insurance access and employment, thus encouraging inflows from long-term formal employment into self-employment or other more flexible jobs, indicating reduced job lock. The reduction of job lock is more evident among women, the less educated, and individuals with good health. Unhealthy individuals exhibit increased labor force participation in fixed-term employment and self-employment, possibly due to a direct health improvement effect and reduced medical expenditure risks.

Unlike the findings of many previous studies indicating that public health insurance is negatively associated with the labor supply, in the case of URBMI, there is no generally significant evidence of decreased labor force participation. Notably, more flexible employment appears to increase for some individuals. There are two likely reasons for this. First, the URBMI program is not a free program. Although it is subsidized by the government, individuals must pay a share of the premium; thus, income effects for socioeconomically disadvantaged participants are unlikely. More importantly, China lacks a well-functioning social safety net, and the welfare system is still under development. Therefore, work may be indispensable for some people to maintain self-sufficiency, especially those with low family income or credit constraints. Therefore, the more financially disadvantaged an individual is, the less likely their working incentives are to decrease, even though the availability of URBMI helps reduce medical expenditure risks in daily life.

The evidence of increased informal sector employment for women, the less educated, and less healthy individuals—who belong to vulnerable groups in the labor market, comparatively speaking—could be due to reduced medical expenditure risks associated with informal sector employment and the labor market transitions that occurred after the introduction of URBMI, increasing the number of job opportunities for vulnerable workers. The finding of increased informal employment, especially in vulnerable labor market groups, is in accordance with studies on the labor market impact of public health insurance in developing countries (Aterido et al., 2011; Azuara and Marinescu, 2013; Wagstaff and Manachotphong, 2012). Moreover, women may benefit from the increased labor market flexibility from URBMI when confronting tradeoffs between family and career. Clearly, the URBMI program can supplement the employment-based health insurance system in urban China. Particularly with respect to the relatively disadvantaged and marginalized populations, URBMI provides not only accessible health care but also more labor market opportunities.

The findings of this study should inspire further policy improvements in public health care in China. As a fundamental supplement to previous employment-based health insurance, URBMI does not free people from the labor market; rather, it enables them to pursue more flexible jobs. Moreover, the program covers different population groups, particularly those with a lower socioeconomic status. Hence, compared with other public health insurance programs, URBMI should provide greater equality across heterogeneous populations in terms of both benefits and coverage. Reducing inequalities in public health care across cities and other geographical areas is important for achieving the goal of providing safe, efficient, and low-cost health services to all citizens.

In conclusion, this paper illuminates the impacts of public health insurance on labor market decisions and outcomes in the context of a developing and transitional economy. China is not a singular case, as many countries are on a path to creating well-functioning national health insurance systems. The empirical evidence from China provides insightful policy implications for understanding the labor market effects of public health insurance, especially the effects on job mobility and flexibility. Due to data limitations, many other labor market outcomes have yet to be examined. Provided that more detailed information is available elsewhere—for instance, on working hours and individuals' exact wages—further research could focus on labor supply elasticities at both intensive and extensive margins and provide additional interesting results and implications.

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Appendix A

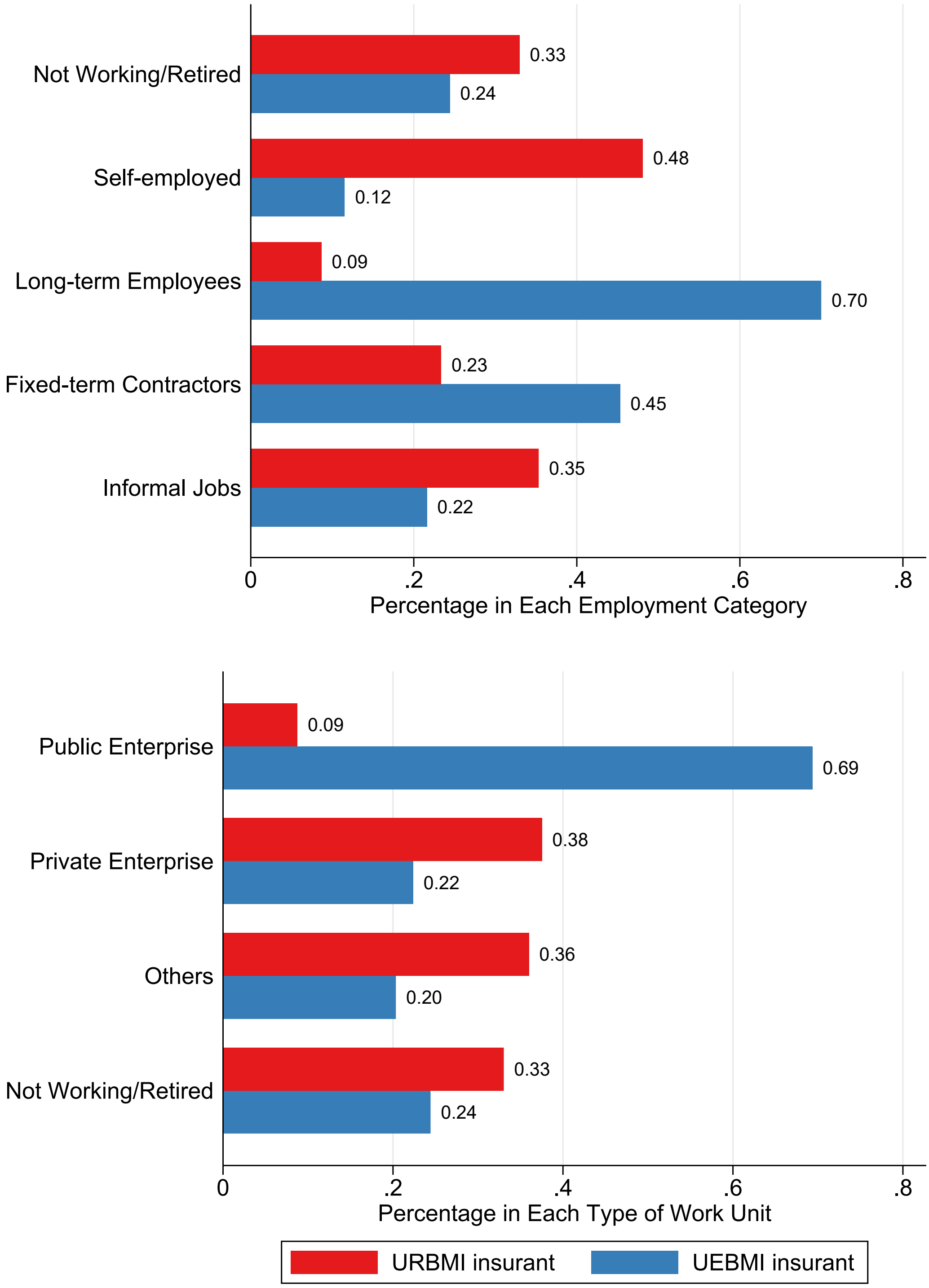

Figure A.1: URBMI/UEBMI Enrollment by Employment Characteristics

Note: Sample data from the *China Health and Nutrition Survey*, waves 2004, 2006, 2009 and 2011. The red bars in the upper panel of the figure depict the URBMI enrollment rate by each employment status *after* URBMI implementation. The blue bars in the upper panel of the figure depict the UEBMI enrollment rate by each employment status *before* URBMI implementation. The employment categories include people who are not working (including retirees), long-term employees (those with open-ended contracts), contract workers (those with fixed-term contracts), the self-employed, and those with other informal jobs. The red bars in the lower panel of the figure depict the URBMI enrollment rate by each type of work unit *after* URBMI implementation. The blue bars in the lower panel of the figure depict the UEBMI enrollment rate by each type of work unit *before* URBMI Implementation. The types of work units are public enterprises (government departments, state services/institutes, state-owned enterprises, small or large collective enterprises), private enterprises (private, individual, foreign-funded enterprises or joint ventures), and other types (family contract farming, etc.).

Map of China

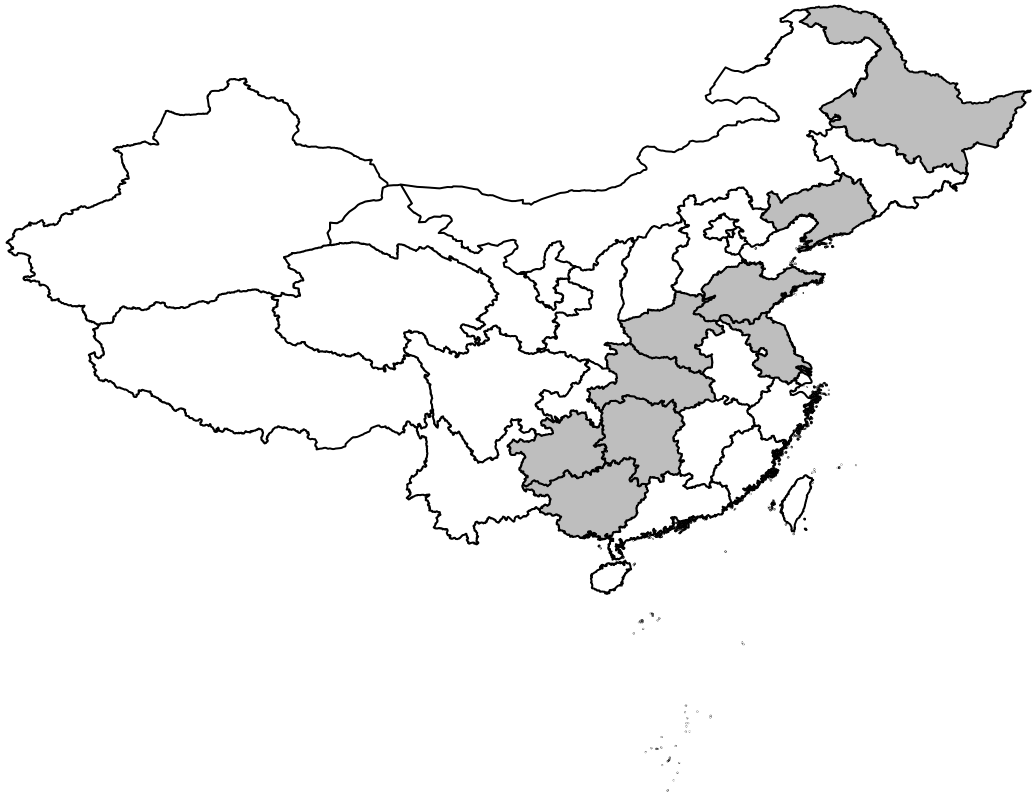

Figure A.2: Map of China with Survey Regions Shaded

Note: The nine survey provinces are shaded gray on the map of China.

Table A.1: Summary Statistics by Gender

Male:	Full Sample	Pilot Cities		Nonpilot Cities		Female: Full Sample	Pilot Cities		Nonpilot Cities	
		Pre	Post	Pre	Post		Pre	Post	Pre	Post
Health Insurance:										
URBMI Enrollment	0.0904	0	0.249	0	0.197	0.0903	0	0.274	0	0.197
	(0.287)	(0)	(0.432)	(0)	(0.399)	(0.287)	(0)	(0.446)	(0)	(0.399)
UEBMI Enrollment	0.367	0.311	0.491	0.167	0.422	0.337	0.281	0.483	0.161	0.356
	(0.482)	(0.463)	(0.500)	(0.374)	(0.496)	(0.473)	(0.450)	(0.500)	(0.368)	(0.481)
Any Health Insurance	0.645	0.519	0.872	0.434	0.871	0.600	0.462	0.886	0.406	0.818
	(0.479)	(0.500)	(0.334)	(0.497)	(0.337)	(0.490)	(0.499)	(0.318)	(0.492)	(0.387)
Individual Characteristics:										
Age	43.49	41.96	46.17	41.18	46.67	41.36	40.10	43.65	40.57	44.13
	(10.68)	(11.05)	(9.699)	(10.01)	(8.567)	(9.331)	(9.820)	(8.008)	(9.180)	(7.395)
Married	0.836	0.814	0.864	0.857	0.898	0.848	0.838	0.872	0.816	0.871
	(0.370)	(0.389)	(0.343)	(0.351)	(0.304)	(0.359)	(0.369)	(0.334)	(0.388)	(0.336)
Years of schooling	10.71	10.64	10.64	11.38	11.44	10.27	10.09	10.45	10.73	10.77
	(3.100)	(3.057)	(3.107)	(3.162)	(3.374)	(3.388)	(3.435)	(3.170)	(3.597)	(3.804)
Current student	0.0266	0.0356	0.0124	0.0319	0.00680	0.0282	0.0391	0.00697	0.0383	0.00758
	(0.161)	(0.185)	(0.111)	(0.176)	(0.0825)	(0.165)	(0.194)	(0.0832)	(0.192)	(0.0870)
Household size	2.635	2.650	2.687	2.390	2.333	2.576	2.594	2.654	2.245	2.242
	(0.932)	(0.901)	(0.981)	(0.885)	(0.924)	(0.944)	(0.922)	(0.983)	(0.891)	(0.866)
Urbanization index	84.02	83.11	86.73	81.47	77.38	84.35	83.48	87.40	81.39	78.36
	(10.47)	(10.46)	(9.782)	(9.656)	(11.62)	(10.15)	(10.16)	(9.333)	(9.098)	(11.52)
Labor Market Outcome:										
Current working	0.719	0.697	0.743	0.745	0.789	0.577	0.555	0.591	0.648	0.697
	(0.450)	(0.460)	(0.437)	(0.437)	(0.409)	(0.494)	(0.497)	(0.492)	(0.479)	(0.461)
Long-term employee	0.410	0.398	0.389	0.562	0.537	0.300	0.278	0.280	0.456	0.523
	(0.492)	(0.490)	(0.488)	(0.497)	(0.500)	(0.458)	(0.448)	(0.449)	(0.499)	(0.501)
Contract worker	0.0868	0.0803	0.114	0.0159	0.0544	0.0837	0.0742	0.118	0.0421	0.0303
	(0.282)	(0.272)	(0.318)	(0.125)	(0.228)	(0.277)	(0.262)	(0.322)	(0.201)	(0.172)
Self-employed	0.136	0.131	0.154	0.104	0.109	0.110	0.115	0.105	0.0881	0.114
	(0.343)	(0.338)	(0.361)	(0.305)	(0.313)	(0.313)	(0.319)	(0.307)	(0.284)	(0.319)
Other informal job	0.0858	0.0880	0.0858	0.0637	0.0884	0.0842	0.0886	0.0871	0.0613	0.0303
	(0.280)	(0.283)	(0.280)	(0.245)	(0.285)	(0.278)	(0.284)	(0.282)	(0.240)	(0.172)
Change job categories	0.230	0.128	0.411	0.116	0.347	0.212	0.121	0.411	0.103	0.250
	(0.421)	(0.334)	(0.492)	(0.320)	(0.478)	(0.409)	(0.326)	(0.492)	(0.305)	(0.435)
Observations	4103	2329	1376	251	147	3765	2224	1148	261	132

Notes: Standard deviations in parentheses. The left panel contains the male subsample, while the right panel contains the female subsample. "URBMI Enrollment" and "UEBMI Enrollment" are indicators for whether the individual has URBMI or UEBMI, respectively. "Any Health Insurance" is a dummy equal to 1 if the individual has any type of health insurance. Individual characteristics include age, gender, marital status, indicators for education level (elementary school, middle school, high school, technical school, and college graduate), years of schooling, whether the individual is currently a student (including part-time study and on-the-job training), household size, and the urbanization index of the community where the individual lives, as reported by CHNS. Labor market outcome variables include indicators for whether the individual is currently working and whether he/she is a long-term employee, a worker with a fixed-term contract, self-employed, or has other informal jobs. "Change job category" is a dummy equal to 1 if the individual changed his/her job category (from non-working, long-term employee, contract worker, self-employed, and other informal job) since the last wave.

Table A.2: Summary Statistics by Education Level

	Lower: Full Sample	Pilot Cities		Nonpilot Cities		Higher: Full Sample	Pilot Cities		Nonpilot Cities	
		Pre	Post	Pre	Post		Pre	Post	Pre	Post
Health Insurance:										
URBMI Enrollment	0.124	0	0.342	0	0.400	0.0645	0	0.195	0	0.0651
	(0.329)	(0)	(0.475)	(0)	(0.492)	(0.246)	(0)	(0.396)	(0)	(0.247)
UEBMI Enrollment	0.240	0.197	0.356	0.0558	0.182	0.440	0.376	0.591	0.232	0.527
	(0.427)	(0.398)	(0.479)	(0.230)	(0.387)	(0.496)	(0.485)	(0.492)	(0.423)	(0.501)
Any Health Insurance	0.522	0.377	0.832	0.152	0.709	0.702	0.582	0.915	0.587	0.935
	(0.500)	(0.485)	(0.374)	(0.360)	(0.456)	(0.457)	(0.493)	(0.279)	(0.493)	(0.247)
Individual Characteristics:										
Age	44.64	43.34	47.04	43.30	46.43	40.78	39.22	43.43	39.35	44.85
	(9.248)	(9.580)	(8.138)	(9.434)	(8.143)	(10.43)	(10.85)	(9.421)	(9.383)	(8.068)
Male	0.508	0.488	0.556	0.442	0.500	0.532	0.530	0.536	0.521	0.544
	(0.500)	(0.500)	(0.497)	(0.498)	(0.502)	(0.499)	(0.499)	(0.499)	(0.500)	(0.500)
Married	0.888	0.886	0.898	0.858	0.873	0.806	0.777	0.844	0.822	0.893
	(0.315)	(0.318)	(0.303)	(0.350)	(0.335)	(0.396)	(0.417)	(0.363)	(0.383)	(0.309)
Years of schooling	7.634	7.551	7.793	7.640	7.536	12.74	12.63	12.75	13.18	13.46
	(2.391)	(2.465)	(2.232)	(2.438)	(2.429)	(1.703)	(1.663)	(1.686)	(1.815)	(1.899)
Current student	0.0125	0.0124	0.0125	0.0102	0.0182	0.0389	0.0573	0.00781	0.0508	0
	(0.111)	(0.111)	(0.111)	(0.101)	(0.134)	(0.193)	(0.232)	(0.0881)	(0.220)	(0)
Household size	2.630	2.636	2.687	2.396	2.373	2.588	2.612	2.660	2.267	2.237
	(0.933)	(0.919)	(0.950)	(0.961)	(0.887)	(0.942)	(0.906)	(1.006)	(0.840)	(0.901)
Urbanization index	82.66	81.79	85.39	79.16	77.32	85.36	84.49	88.34	82.85	78.18
	(10.78)	(10.44)	(10.01)	(11.51)	(15.64)	(9.785)	(10.06)	(9.028)	(7.398)	(7.884)
Labor Market Outcome:										
Current working	0.531	0.522	0.547	0.503	0.591	0.745	0.713	0.773	0.816	0.846
	(0.499)	(0.500)	(0.498)	(0.501)	(0.494)	(0.436)	(0.452)	(0.419)	(0.388)	(0.362)
Long-term employee	0.167	0.178	0.138	0.183	0.227	0.505	0.468	0.499	0.711	0.728
	(0.373)	(0.383)	(0.345)	(0.387)	(0.421)	(0.500)	(0.499)	(0.500)	(0.454)	(0.446)
Contract worker	0.0789	0.0652	0.113	0.0406	0.0545	0.0902	0.0870	0.118	0.0222	0.0355
	(0.270)	(0.247)	(0.317)	(0.198)	(0.228)	(0.287)	(0.282)	(0.323)	(0.148)	(0.186)
Self-employed	0.172	0.164	0.180	0.183	0.209	0.0864	0.0905	0.0938	0.0413	0.0473
	(0.377)	(0.370)	(0.384)	(0.387)	(0.409)	(0.281)	(0.287)	(0.292)	(0.199)	(0.213)
Other informal job	0.113	0.114	0.116	0.0964	0.100	0.0631	0.0680	0.0625	0.0413	0.0355
	(0.317)	(0.318)	(0.321)	(0.296)	(0.301)	(0.243)	(0.252)	(0.242)	(0.199)	(0.186)
Change job categories	0.245	0.116	0.474	0.152	0.464	0.203	0.131	0.362	0.0825	0.195
	(0.430)	(0.320)	(0.500)	(0.360)	(0.501)	(0.403)	(0.337)	(0.481)	(0.276)	(0.398)
Observations	3446	2023	1116	197	110	4422	2530	1408	315	169

Notes: Standard deviations in parentheses. The left panel contains the lower-educated subsample, the right panel contains the higher-educated subsample. "URBMI Enrollment" and "UEBMI Enrollment" are indicators of whether the individual has URBMI or UEBMI, respectively. "Any Health Insurance" is a dummy equal to 1 if the individual has any type of health insurance. Individual characteristics include age, gender, marital status, indicators for education level (elementary school, middle school, high school, technical school, and college graduate), years of schooling, whether the individual is currently a student (including part-time study and on-the-job training), household size, and the urbanization index of the community where the individual lives, as reported by CHNS. Labor market outcome variables include indicators of whether the individual is currently working and whether he/she is a long-term employee, a worker with a fixed-term contract, self-employed, or has other informal jobs. "Change job category" is a dummy equal to 1 if the individual changed his/her job category (from non-working, long-term employee, contract worker, self-employed, and other informal job) since the last wave.

Table A.3: Summary Statistics by Previous Health Status

Unhealthy:	Full Sample	Pilot Cities		Nonpilot Cities		Healthy: Full Sample	Pilot Cities		Nonpilot Cities	
		Pre	Post	Pre	Post		Pre	Post	Pre	Post
Health Insurance:										
URBMI Enrollment	0.0765	0	0.231	0	0.170	0.0980	0	0.275	0	0.211
	(0.266)	(0)	(0.422)	(0)	(0.378)	(0.297)	(0)	(0.447)	(0)	(0.409)
UEBMI Enrollment	0.385	0.331	0.532	0.171	0.415	0.334	0.277	0.464	0.160	0.378
	(0.487)	(0.471)	(0.499)	(0.378)	(0.495)	(0.472)	(0.448)	(0.499)	(0.367)	(0.486)
Any Health Insurance	0.644	0.536	0.887	0.398	0.819	0.611	0.465	0.874	0.432	0.859
	(0.479)	(0.499)	(0.316)	(0.491)	(0.387)	(0.487)	(0.499)	(0.332)	(0.496)	(0.348)
Individual Characteristics:										
Age	45.26	44.12	47.59	43.44	47.87	40.92	39.27	43.70	39.46	44.25
	(9.484)	(9.811)	(8.407)	(9.636)	(8.071)	(10.12)	(10.49)	(9.095)	(9.281)	(7.889)
Male	0.533	0.521	0.581	0.436	0.489	0.515	0.506	0.527	0.520	0.546
	(0.499)	(0.500)	(0.494)	(0.497)	(0.503)	(0.500)	(0.500)	(0.499)	(0.500)	(0.499)
Married	0.859	0.857	0.875	0.807	0.872	0.832	0.807	0.864	0.852	0.892
	(0.348)	(0.351)	(0.331)	(0.396)	(0.335)	(0.374)	(0.394)	(0.343)	(0.356)	(0.311)
Years of schooling	10.09	10.00	10.26	9.994	10.15	10.73	10.59	10.70	11.62	11.62
	(3.487)	(3.544)	(3.321)	(3.643)	(3.634)	(3.085)	(3.061)	(3.027)	(3.123)	(3.478)
Current student	0.0210	0.0257	0.00697	0.0497	0.0106	0.0308	0.0441	0.0114	0.0272	0.00541
	(0.143)	(0.158)	(0.0832)	(0.218)	(0.103)	(0.173)	(0.205)	(0.106)	(0.163)	(0.0735)
Household size	2.501	2.518	2.537	2.271	2.309	2.665	2.683	2.742	2.341	2.281
	(0.878)	(0.848)	(0.914)	(0.887)	(0.962)	(0.965)	(0.941)	(1.008)	(0.892)	(0.864)
Urbanization index	84.40	83.79	87.11	80.83	77.14	84.05	82.99	86.99	81.76	78.20
	(10.28)	(10.25)	(9.339)	(9.938)	(12.42)	(10.33)	(10.34)	(9.711)	(9.038)	(11.11)
Labor Market Outcome:										
Current working	0.601	0.585	0.617	0.646	0.649	0.679	0.653	0.703	0.722	0.795
	(0.490)	(0.493)	(0.486)	(0.479)	(0.480)	(0.467)	(0.476)	(0.457)	(0.449)	(0.405)
Long-term employee	0.341	0.328	0.340	0.431	0.426	0.366	0.346	0.339	0.550	0.584
	(0.474)	(0.469)	(0.474)	(0.497)	(0.497)	(0.482)	(0.476)	(0.474)	(0.498)	(0.494)
Contract worker	0.0744	0.0669	0.107	0.0110	0.0319	0.0913	0.0833	0.120	0.0393	0.0486
	(0.262)	(0.250)	(0.309)	(0.105)	(0.177)	(0.288)	(0.276)	(0.325)	(0.195)	(0.216)
Self-employed	0.0990	0.0986	0.0848	0.144	0.149	0.138	0.138	0.156	0.0695	0.0919
	(0.299)	(0.298)	(0.279)	(0.352)	(0.358)	(0.344)	(0.344)	(0.363)	(0.255)	(0.290)
Other informal job	0.0858	0.0915	0.0848	0.0608	0.0426	0.0846	0.0865	0.0872	0.0634	0.0703
	(0.280)	(0.288)	(0.279)	(0.240)	(0.203)	(0.278)	(0.281)	(0.282)	(0.244)	(0.256)
Change job categories	0.202	0.113	0.389	0.110	0.245	0.232	0.131	0.423	0.109	0.330
	(0.401)	(0.317)	(0.488)	(0.314)	(0.432)	(0.422)	(0.337)	(0.494)	(0.312)	(0.471)
Observations	2809	1673	861	181	94	5059	2880	1663	331	185

Notes: Standard deviations in parentheses. The left panel contains the subsample of those who were previously unhealthy, the right panel contains the subsample of those who were previously healthy. "URBMI Enrollment" and "UEBMI Enrollment" are indicators of whether the individual has URBMI or UEBMI, respectively. "Any Health Insurance" is a dummy equal to 1 if the individual has any type of health insurance. Individual characteristics include age, gender, marital status, indicators for education level (elementary school, middle school, high school, technical school, and college graduate), years of schooling, whether the individual is currently a student (including part-time study and on-the-job training), household size, and the urbanization index of the community where the individual lives, as reported by CHNS. Labor market outcome variables include indicators of whether the individual is currently working and whether he/she is a long-term employee, a worker with a fixed-term contract, self-employed, or has other informal jobs. "Change job category" is a dummy equal to 1 if the individual changed his/her job category (among non-working, long-term employee, contract worker, self-employment, and other informal job) since the last wave.

Table A.4: Balancing Regressions

Dependent Variable:	Age	Student	Married	Household Size	Primary Schl	Middle Schl	High Schl	Tech Schl	College	Urbanization Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
URBMI-city	−0.363	0.008	−0.010	−0.015	−0.019	0.035	−0.008	0.001	−0.003	0.038
	(0.464)	(0.008)	(0.014)	(0.066)	(0.017)	(0.026)	(0.024)	(0.019)	(0.029)	(0.025)
Ind. char. (excl. dep. var.)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City linear trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7868	7868	7868	7868	7868	7858	7868	7868	7868	7868

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

Table A.5: Robustness Check: City-specific Linear Trends

Sample:	**All**	**Female**	**Male**	**Less Edu**	**More Edu**	**Unhealthy**	**Healthy**	**No Work**	**Formal**	**Informal**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:										
I.**URBMI Enrollment**	0.126***	0.103**	0.144***	0.255**	0.099***	0.142*	0.121**	0.170***	0.077*	0.198***
	(0.038)	(0.045)	(0.038)	(0.117)	(0.033)	(0.072)	(0.060)	(0.060)	(0.039)	(0.041)
Mean of Dep. Variable	0.090	0.090	0.090	0.124	0.064	0.077	0.098	0.113	0.047	0.142
II.**Probability of Working**	−0.013	0.016	−0.053*	0.044	−0.030	0.024	−0.041	0.087	−0.048	−0.070
	(0.024)	(0.046)	(0.030)	(0.056)	(0.019)	(0.055)	(0.025)	(0.056)	(0.030)	(0.069)
Mean of Dep. Variable	0.651	0.577	0.719	0.531	0.745	0.601	0.679	0.197	0.922	0.830
III.**Long-term Employee**	−0.061**	−0.097***	−0.036	−0.043***	−0.042	−0.085***	−0.057**	−0.048**	−0.055	−0.030
	(0.023)	(0.027)	(0.031)	(0.000)	(0.033)	(0.031)	(0.023)	(0.023)	(0.034)	(0.068)
Mean of Dep. Variable	0.357	0.300	0.410	0.167	0.505	0.341	0.366	0.060	0.732	0.076
IV.**Fixed-term Contractor**	0.044**	0.035***	0.051*	0.034	0.057**	0.042*	0.043	0.122***	0.018	0.030
	(0.022)	(0.000)	(0.027)	(0.032)	(0.028)	(0.024)	(0.030)	(0.046)	(0.025)	(0.039)
Mean of Dep. Variable	0.085	0.084	0.087	0.079	0.090	0.074	0.091	0.032	0.143	0.054
V.**Self-employment**	0.048**	0.053*	0.043**	0.103***	0.006	0.077**	0.043***	0.014	0.010*	0.110
	(0.022)	(0.029)	(0.002)	(0.038)	(0.021)	(0.035)	(0.001)	(0.030)	(0.004)	(0.093)
Mean of Dep. Variable	0.124	0.110	0.136	0.172	0.086	0.099	0.138	0.058	0.019	0.441
VI.**Other Informal Jobs**	−0.045*	0.025**	−0.112**	−0.050	−0.052**	−0.010	−0.069*	−0.001	−0.020	−0.180
	(0.026)	(0.001)	(0.046)	(0.058)	(0.023)	(0.022)	(0.038)	(0.038)	(0.018)	(0.109)
Mean of Dep. Variable	0.085	0.084	0.086	0.113	0.063	0.086	0.085	0.048	0.028	0.259
VII.**Change Employment Category**	0.090*	0.127**	0.056	0.153***	0.038	0.130***	0.058	0.037	0.087**	0.135
	(0.047)	(0.049)	(0.057)	(0.048)	(0.073)	(0.041)	(0.073)	(0.089)	(0.002)	(0.134)
Mean of Dep. Variable	0.222	0.212	0.230	0.245	0.203	0.202	0.232	0.187	0.196	0.328
Exogenous covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-specific linear trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7868	3765	4103	3446	4422	2809	5059	2723	3436	1709

Notes: The effect of URBMI implementation is reported in each cell. Robust standard errors in parentheses are clustered at the city level. Column (1) presents estimates using the whole sample. Columns (2) and (3) present estimates using the female and male sample, respectively. Columns (4) and (5) present estimates using the samples of less-educated and more-educated individuals, respectively. Columns (6) and (7) present estimates using the samples of unhealthy and healthy individuals before the launch of URBMI, respectively. Columns (8), (9), and (10) present estimates using the samples of non-working individuals, formal sector employees, and informal sector workers before the launch of URBMI, respectively. The set of individual characteristics includes gender, age, education dummies, marital status, household size, and the log urbanization index. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.