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ABSTRACT

Can Information Influence the Social Insurance Participation Decision of China's Rural Migrants?*

This paper uses a randomized information intervention to shed light on whether poor understanding of social insurance, both the process of enrolling and costs and benefits, drives the relatively low rates of participation in urban health insurance and pension programs among China's rural-urban migrants. Among workers without a contract, the information intervention has a strong positive effect on participation in health insurance and, among younger age groups, in pension programs. Migrants are responsive to price: in cities where the premia are low relative to earnings, information induces health insurance participation, while declines are observed in cities with high relative premia.

JEL Classification: H53, H55, J46, J61, O15, O17, O53, P35

Keywords: migration, social insurance, information, randomised controlled trial

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1 Introduction

One well-documented and common feature of economic development involves a structural change in which labor moves from agriculture to non-agricultural sectors, and from rural to urban areas. With higher productivity, incomes and standards of living rise, but individuals and families are often exposed to new sources of risk. Declines in fertility and increased population mobility, which frequently accompany structural change, make traditional means of risk-coping through support of family members less reliable. Lack of insurance against risk in urban areas may make migration plans temporary and limit the extent to which rural migrants make permanent decisions (and investments) related to their future in the city. Rising average incomes and improvements in administrative capacity, however, enable governments to introduce social insurance systems capable of helping their citizens face a range of uncertainties, including potential adverse health and employment shocks and the risk of poverty in old age.

Even as governments recognize the importance of providing social insurance to their populations, implementation may be fraught with both poor understanding of social insurance programs among intended beneficiaries and institutional features that create disincentives to participate. Mandating participation by firms and employees, and even by the informal sector, is fraught with the problem that enrolling in social insurance may reflect a choice. Research on Latin American economies, for example, contains numerous examples in which the high "labor tax wedge" associated with employer-based social insurance creates incentives for both firms and workers to "exit" from the formal sector (Levy, 2008; Perry et al., 2007).[1]

Globally, China's rural-urban migrants are one of the largest populations of informal sector workers not covered by social insurance. As of 2015, there were 160 million rural migrants working in China's cities, of whom 130 million had moved within the past 15 years (Frijters et al., 2015). While the sheer number of migrants is unprecedented, it is not sufficient to offset current labor shortages in urban areas. The supply of labor is limited by policies that treat migrants as 'guest workers' in cities, which leads to shorter migration spells than if migrants viewed their moves to be permanent (Meng, 2012). Recognizing that continued increases in the supply of labor to urban areas requires facilitating longer-term migration, China's government has initiated reforms aiming to increase migrant participation in urban employee health insurance and pension programs. Recently introduced laws, the Labor Contract Law (2008) and Social Insurance Law (2011), require employers to make contributions to health, unemployment and work injury insurance and pensions for migrant

[1]Outside of a few studies in Latin America, existing research on program participation focuses mainly on developed countries (see, for example, Ashenfelter, 1983; Chetty and Saez, 2013; Chetty et al., 2013; Grogger, 2003).

workers. Although considerable time has passed since these laws were implemented, migrant participation remains low. The 2015 wave of the Rural-Urban Migration in China survey (RUMiC), for example, indicates that only 30 percent of migrant workers were enrolled in urban health insurance or pension programs.

What explains the slow progress in expanding migrant participation in urban social insurance programs? Earlier research has highlighted the following contributing factors: poor incentives for local governments to enforce laws, the possibility that employers try to avoid making contributions to employee social insurance accounts, and the lack of enthusiasm among migrants for participation, which may be due to the fragmented nature of the system and consequent lack of geographic portability of enterprise contributions (Meng and Manning, 2010; Meng, 2012; Giles et al., 2013; Gallagher et al., 2014). Posessing little or no prior experience with urban employee social insurance schemes, China's migrants may lack full understanding of the potential benefits from enrollment and participation in these programs.[2] More importantly, given the complexity of the social insurance schemes (the costs, benefits, as well as enrollment procedures), which vary across regions and by type of job, migrants may find it difficult to make decisions and act on them, and simply decide against participation.[3] Lack of knowledge about the benefits and costs of insurance or inability to figure out how to enroll may then interact with strong employer preferences for avoiding contributions, and lead to the current low levels of participation.

This paper exploits a field experiment to assess the extent to which lack of information about urban employee health insurance and pension programs contributes to low participation among rural migrants. It also estimates how treatment effects vary with relative premia, which allows us to estimate the effect of the intervention on demand at different relative prices.[4] From the estimated change in demand we calculate the welfare gain from the information intervention.

After reviewing the institutional background, the paper introduces a simple model to conceptualize individuals' decisions to participate in social insurance programs without accurate information and to understand their potential responses to an information campaign. Following Handel et al. (2019) the model includes information frictions over the cost and benefits of participating in an insurance program. The model highlights the possibility of a heterogeneous response to the information intervention depending on whether individu-

[2]While many migrants had prior experience with China's New Rural Cooperative Medical System (NRCMS), evaluations have found that NRCMS increased insurance participation but afforded only modest protection against financial risk (Wagstaff and Lindelow, 2008; Wagstaff et al., 2009).

[3]Gallagher et al. (2014) find that a high share of migrants understand that they are eligible to participate in social insurance, but it is unlikely that migrants understand program details or benefits.

[4]'Relative premia' is defined as the city level minimum premium for a self-employed worker divided by the city level average migrant earnings. Explanation of this formulation for relative premium is explained in Section 6.1.

als' perceived costs and benefits of participating in social insurance were accurate prior to the intervention. In the case of misinformation, the heterogeneous response also depends on the degree and direction of the discrepancy between the perceived and actual costs and benefits of participation. The effect of the information campaign is driven by the groups who were misinformed prior to the information campaign. The magnitude depends on the degree of misinformation and the number of individuals who were positively and negatively misinformed. The model then provides a welfare analysis to allow us to gauge the cost of information frictions.

Empirically, the study utilizes the existing Rural-Urban Migration in China (RUMiC) longitudinal survey, which was conducted annually from 2008 to 2016. The survey comprises approximately 5000 rural-to-urban migrant households each year with around 7,000-8,400 individual workers from 15 Chinese cities. The information intervention randomly selected approximately 34% of households from 13 of the 15 survey cities in the 2015 survey round (2,200 out of 6,500 total observations in 2015 wave) and provided them with detailed information regarding the costs and benefits of participating in the health insurance and pension programs available in their respective cities.[5] Respondents were also informed as to whether social insurance programs were portable or not in the event that they were to move home or to another city, and how to contact the representatives in local social-protection bureaus responsible for enforcing laws and regulations governing employer participation. In the following wave of the RUMiC survey, implemented later in 2016, respondents were then asked about their actual and planned participation in these insurance programs. The final analytical sample consists of 4,587 individuals with 1,582 treated subjects.

Over the full RUMiC sample, the average information intervention effect does not differ statistically from zero. Consistent with a pre-specified plan to examine heterogeneity across workers with and without a contract, however, this "zero average effect" masks considerable heterogeneity across cities and workers in formal and informal sectors. For individuals with an employment contract (formal sector employment), program participation rates were already quite high at 76% for health insurance and 74% for pension programs in 2015. For this subgroup the intervention had a limited effect. By contrast, for the 68% of workers in the informal sector, the information intervention led to a 3.2 percentage point increase in health insurance participation, which is a 23% increase from the baseline 13.8% enrollment rate. The effect of the intervention on pension program participation is also positive and significant for those informal sector workers young enough to reap full benefits from the program.[6] We find a 4 percentage point increase for young informal employees, which is an economically

[5]The randomization was conducted at the household level.

[6]Without fifteen years of participation at retirement age, older workers effectively lose employer contributions and, at mandatory retirement age, may only withdraw deposits from their employee account or convert their employee contribution to the individual account of the (rural) resident pension scheme.

significant 27% increase from their baseline 15% enrollment rate.[7]

As suggested by the model, we find that the treatment effect on health insurance varies across different levels of relative premia: in cities where the cost of participating in insurance is low (relative to earnings), the information intervention has a strong positive effect on participation, but where the insurance premia are relatively high, the information intervention has a limited or even negative effect on participation. Based on the estimated price elasticity from the intervention, the welfare effect of the information intervention is calculated, and the welfare change for migrant workers without a written contract and lacking health insurance in the baseline (accounting for 68% of our sample) is substantial. The estimated welfare gain from the information campaign is, on average, 2.8 to 5.1 times the cost of a well-organised information campaign, if costs are calculated based on the actual cost of our information intervention. As a large-scale information campaign should be able to exploit economies of scale, this is likely an underestimate of the welfare gain. Put in perspective of the current government advertising budget for the urban social insurance program, the welfare gain from eliminating information frictions could be as high as 34 to 62 times the current budget.

The paper adds to a growing body of research investigating how information frictions influence individual behavior in different settings (e.g., Chetty et al., 2009; Liebman and Luttmer, 2015; Bergman, 2015). The canonic approach exploits relatively inexpensive interventions that enable individuals to make more informed decisions, and thus 'nudge' them into optimal choices that they might not otherwise make (Chetty, 2015). Among these studies those which are closest to this one examine the role of information on participation in health insurance programs by informal sector workers and the poor in both developing and developed countries (see, for example, Thornton et al., 2010; Das and Leino, 2011; Guthmuller et al., 2014; Wagstaff et al., 2016). Most of these studies, however, fail to find a positive impact of information alone on health insurance participation, and even when subsidies are included with information, the impact on health insurance participation is not judged to be economically significant (Wagstaff et al., 2016).

This study makes several contributions to the literature on social insurance participation. First, it provides strong evidence from a large developing country on a population, rural migrants, whose social insurance participation will likely shape the country's urbanization process in fundamental ways. The positive and economically meaningful impacts of the information intervention on the decisions of workers lacking contracts suggest that participation can be increased by as much as 23-26% by simply raising awareness among China's rural

[7]Interestingly, for those older workers who could not work long enough to reap full pension benefits, the information intervention led to increased earnings equal to roughly half the minimum required employer contribution to individual pension accounts, which suggests that perhaps older workers share the value of forgone pension contributions with their employers. Unfortunately, we are unable to provide rigorous supporting evidence that this outcome reflects a bargaining process between employers and employees.

migrants of both the benefits of social insurance programs, and how to participate in them.

Second, this study reveals that the impact of improving understanding of social insurance among China's rural migrants may be stronger when paired with incentives: the interaction of a price effect and provisions of information on health insurance participation suggests that premium subsidies might be a means of expanding coverage.[8]

Finally, while previous studies tend to examine either decisions related to pensions or health insurance, this paper examines the impact on participation in both programs. By doing so, the paper examines how information and prices differentially affect participation in programs with different design features, rules, and insuring against risks with different time horizons.

The paper is structured as follows. Section 2 presents background on migration and the migrant social insurance participation decision. Section 3 presents a simple theoretical model of the social insurance participation decision. Section 4 introduces the main data source, the randomized information intervention, and summary statistics. Empirical strategies and results are presented in sections 5 and 6: section 5 introduces the estimation of the average treatment effect and the heterogeneity of the treatment effect by contract type, while section 6 examines the heterogeneity of the treatment effect at different levels of relative premium, and then calculates the welfare effect of the information campaign. The final section discusses policy implications and directions for future research.

2 Migrant Social Insurance Participation

Rural-urban migration has played a significant and well-appreciated role in China's economic growth miracle (Bosworth and Collins, 2008; Tombe and Zhu, 2015). During the 1990s and 2000s, rural China was an abundant source of young workers (16-25 years of age), who supported the growth of labor-intensive industries. Despite their significant contributions, migrants are treated as "guest workers" in cities under China's household registration (*hukou*) system: the social insurance programs and services benefitting urban locals are either not available to migrants, or are unsubsidized and much more expensive. Lack of access to social insurance in cities leads migrants to return to rural areas when sick or unemployed, to raise their families or to care for elderly family members (see, for example, Giles and Mu, 2007; Meng, 2012). Consequently, *hukou* restrictions shorten the duration of migrant stays in cities (which currently average to 8-9 years), limits the potential stock of migrant labor supply in cities as older migrants return home, and thus exacerbates a labor shortage that contributes

[8] Instead of using randomized subsidies to identify the interaction of price and information, as in Guthmuller et al. (2014); Thornton et al. (2010); Wagstaff et al. (2016), this paper first controls for potentially endogeneous city fixed-effects and then identifies the heterogeneous effect of the information by interacting the treatment with the city-wide relative prices of health insurance and pensions.

to rising labor costs.

Recognizing that permanent migration may help to solve labor shortage problems, the central government has introduced laws and regulations requiring employers to contribute to the social insurance accounts of migrant employees. The 2008 Labor Contract Law stipulates that all workers are entitled to participate in urban social insurance programs, that details of the schemes should be explicitly written into labor contracts and that all migrant workers should have a written contract (Gallagher et al., 2014; Meng, 2017). In 2010, the central government provided new guidelines on pension portability, which allows migrants to transfer 12% of employer contributions, in addition to their own contributions, to accounts either in new migrant destinations or in their home counties (State Council, 2009). In mid-2011 a new Social Insurance Law explicitly stipulated that employees should participate in social insurance programs, and that the self-employed may participate voluntarily. Further, fines may be imposed on employers who fail to make contributions to their employees' accounts in a timely manner (National People's Congress, 2011).

Despite efforts of the central government, the urban social insurance participation rates of migrant workers remain low. Evidence from the RUMiC survey suggests only a modest increase in pension and health insurance participation rates over the period from 2008 to 2016 (see Panels A and B of Figure 1). By 2016 the health insurance and pension participation rates for the full sample were both just over 34%, with higher rates for employees than the self-employed. Among employees (Panels C and D of Figure 1), it is evident that higher participation rates are strongly associated with having a written contract. Participation rates among individuals without written contracts are similar to those of the self-employed. While participation among employees increased between 2011 and 2012, when fines were imposed on employers who failed to contribute their share to social insurance payments (see Panel B of Appendix Table A.1), the rate of increase was slow afterwards and through 2015. Between 2015 and 2016 there was another significant increase within the RUMiC sample, which is likely driven by the information intervention that is the focus of this paper. There are several potential reasons for slow progress in increasing participation among migrants.

First, although the central government passed laws and developed policies aimed at increasing the health insurance and pension participation rates of migrants, implementation details and the enforcement of laws and regulations are left to local governments. As local leaders are generally evaluated based on how well they meet growth targets (Li and Zhou, 2005), the prospect of rising labor costs is a frequent concern and reduces incentives to enforce laws requiring employers to make payroll contributions. Unless they are particularly law-abiding, employers have no incentive to make voluntary contributions when enforcement is not effective. Previous studies have found that formal sector firms, which are more likely to face inspections (particularly state-owned enterprises, foreign invested and joint venture firms), generally provide written contracts to their workers and make social insurance contributions to their employees (Giles et al., 2013; Li and Freeman, 2015). The majority of migrant workers, however, are not working in large, formal sector firms.

Second, the financing of social insurance schemes is also left to local governments, but decentralized administration continues to limit portability of social insurance accounts, and thus limits migrant willingness to participate. While payments made by firms and young, healthy migrants are positive contributions to local health insurance and pension funds, most local governments are reluctant to transfer funds to other regions when migrants relocate as this would have immediate budgetary consequences. The main sticking point centers on how the employer portion of accounts is handled. Although they comprise two-thirds to 75% of total health insurance and pension fund accounts, a migrant is only able to transfer less than half of employer contributions. Further, even transferring one's own contributions when moving faces hurdles as the fund manager accepting the transfer is required to match the employer contribution if it is not transferred, and this is a stipulation that destination governments almost never accept. These obstacles to portability mean that migrants, with relatively short time-horizons in the city, have weaker incentives to participate in social insurance than local residents (Giles et al., 2013).

Third, as program details are formulated by local governments, rules vary along multiple dimensions: by type of insurance, by type of employment, and, more importantly, across regions – the program specifics that a migrant finds in a new city are very likely to be different from those learned through prior experience. Program specifics, including premium and benefit levels, are both complicated and vary considerably across cities, and are frequently neither available nor understandable to migrant workers.[9] As an example of program complexities, Appendix A.2 summarizes information on the costs and benefits of health insurance and pensions for two of the 13 cities in which the information intervention was implemented.[10] These ***simplified*** policy details were summarized after a careful reading of the city-level websites and confirmed with follow-up phone conversations with city-level bureaucrats charged with managing the programs. In the face of such complexity and incomplete information, migrants are left to make uninformed decisions. Combined with short time horizons in the city, they may find it easier to opt out, especially when employers offer employees some increase in compensation to opt out of participating. Further, nearly a third of migrants are self-employed and the costs of participating for this group are even higher as

[9]When designing this intervention, one of the co-authors put in considerable effort to find details on policies and procedures for each of the 15 RUMiC cities. Apart from Guangzhou, Dongguan and Shenzhen, website information for other cities was either not up-to-date or difficult to understand. When local social welfare bureaus were contacted by phone, there was typically either no answer or a long queue (more than 20-30 minutes wait-time to speak with a representative).

[10]The information for the remaining cities is available upon request from the authors.

they must make both the employer and employee contributions.

Finally, even as bringing rural residents into urban social insurance schemes is an explicit policy objective, existing rural programs may be viewed as substitutes for "expensive" urban insurance schemes. With respect to health insurance, 81 percent of rural migrants in the baseline (2015) survey were enrolled in the New Rural Collective Medical System (NRCMS) program. Even as it is a highly imperfect substitute for coverage through the urban employee health insurance program, the existence of this alternative may contribute to delays in enrolling in the urban program.

This paper examines migrant participation in urban health insurance and pension schemes. The two programs have been available to employed registered residents of the city since the 1990s, but have only encouraged participation of rural-urban migrants since the Labor Contract Law in 2008. Although the programs vary significantly in terms of premia and benefits across cities, all cities required joint employer-employee contributions to these programs at the time of the information intervention. With respect to the urban employee health insurance program, nominal employee and employer contributions average 2% and 6%, respectively. The urban employee pension scheme has a greater burden, with individuals contributing at least 8% of their monthly earnings while employers contribute 14-21% of the average wage in the firm. At retirement, only those workers who have contributed for at least 15 years may receive a full pension that includes employer contributions. Those workers who have contributed for less than 15 years may still receive a lump sum payment from their own accumulated contributions, but they will not receive a pension payment, nor the employers' contribution, which will remain with the city pension authorities.[11]

3 A Theoretical Model

Local cadres' promotion incentives, the lack of portability, the lack of certainty in policies relating to the future for migrants and their families, and the complexity of social insurance schemes may all contribute to low participation rates among China's migrant workers. This paper focuses on the extent to which information about schemes and enrollment processes affects migrants' participation in urban pension and health insurance programs. Below, we first employ a stylized model, incorporating information frictions over the cost and benefits of an insurance program, to characterize an individual's decision to participate and her/his responses to an information campaign. The model, which draws inspiration from Einav et al. (2010) and Handel et al. (2019), starts from the individual participation decision, to charac-

[11] Alternatively, migrant participants may convert their city employee contribution to the individual account of their rural hometown resident pension scheme. Doing this, however, requires the willingness of city pension authorities to approve the transfer.

terize how providing information on the costs (premium) and benefits (coverage) introduces heterogeneity in the response to the information intervention. Next, assumptions are added to the model to characterize a heterogeneous treatment effect, in which the treatment effect varies with price, and the welfare impact of reducing information frictions.

3.1 Individual Participation Decision

Let the willingness to pay for, and the cost (premium) to an individual of participating in a social insurance scheme be w_i and c, respectively, when there is full information. In the case of an information friction, the individuals perceived willingness to pay and cost can be denoted as $\tilde{w}_i$ and $\tilde{c}_i$. The information frictions associated with willingness to pay and cost can then be represented as $f_{wi} \equiv \tilde{w}_i - w_i$ and $f_{ci} \equiv \tilde{c}_i - c$, respectively, where f_{wi} and f_{ci} may be greater than, smaller than or equal to zero.

Based on this simple setting, a utility maximizing individual, i, will choose to participate in the insurance scheme if and only if $w_i - c \geq 0$ under full information and $\tilde{w}_i - \tilde{c}_i \geq 0$ under information frictions. There are potentially four groups of individuals:

Group One (*Always Participate*): Those who happen to have $w_i - c \geq 0$ under full information, and $\tilde{w}_i - \tilde{c}_i \geq 0$ under information frictions and thus will always choose to participate (or equivalently, $w_i - c \geq 0$ and $w_i - c + f_{wi} - f_{ci} \geq 0$).

Group Two (*Never Participate*): Individuals for whom $w_i - c < 0$ under full information, and $\tilde{w}_i - \tilde{c}_i < 0$ under information frictions, and hence will never choose to participate (or equivalently, $w_i - c < 0$ and $w_i - c + f_{wi} - f_{ci} < 0$).

Group Three (*Switches to Participation*): Individuals for whom $\tilde{w}_i - \tilde{c}_i < 0$ under information frictions, but $w_i - c \geq 0$ under full information (or equivalently, $w_i - c \geq 0$ and $w_i - c + f_{wi} - f_{ci} < 0$). Thus, this group will switch from not participating under information frictions to participating under full information.

Group Four (*Exit from Participation*): Individuals for whom $\tilde{w}_i - \tilde{c}_i \geq 0$ under information friction and $w_i - c < 0$ under full information (or equivalently, $w_i - c < 0$ and $w_i - c + f_{wi} - f_{ci} \geq 0$). This group will switch from participating under information friction to not participating under full information.

In the familiar LATE framework, those groups always participating and never participating are the "always-takers," and "never-takers," while those switching to participation are "compliers" and those exiting participation are "defiers", respectively.

3.2 Effect of Information Intervention on the Aggregate Participation Rate

Under information frictions, the aggregate participation rate can be calculated as $P(\tilde{w}_i - \tilde{c}_i > 0)$, and with the information friction eliminated, as $P(w_i - c > 0)$. The effect of the information intervention on the participation rate will be:

$$\Delta \equiv P(w_i - c > 0) - P(\tilde{w}_i - \tilde{c}_i > 0). \tag{1}$$

Since

$$P(w_i - c > 0) = P(w_i - c > 0, \tilde{w}_i - \tilde{c}_i > 0) + P(w_i - c > 0, \tilde{w}_i - \tilde{c}_i \leq 0)$$

and

$$P(\tilde{w}_i - \tilde{c}_i > 0) = P(w_i - c > 0, \tilde{w}_i - \tilde{c}_i > 0) + P(w_i - c \leq 0, \tilde{w}_i - \tilde{c}_i > 0),$$

Equation (1) can be rewritten as:

$$\Delta = P(w_i - c > 0, \tilde{w}_i - \tilde{c}_i \leq 0) - P(w_i - c \leq 0, \tilde{w}_i - \tilde{c}_i > 0). \tag{2}$$

The above equation shows that the total effect of the information intervention is driven by two groups of individuals: those who switch from being uninsured to being insured, and those who drop insurance after learning its benefits do not outweigh its actual premium. The estimated effect of the information intervention depends on the size of the two mis-informed groups.

3.3 Misperception, Information Friction, and Heterogeneous Treatment Effects

The model considers the decision of rural-urban migrants, who are drawn to cities primarily by employment opportunities and have little knowledge of the potential social insurance programs that they may enroll in upon arriving in the city.[12] To the extent that they know of options to enroll in urban health insurance and pensions, we assume that they have a common prior belief in the premium, p, before migration. After migrating to a particular city, migrants may update their priors, but due to information frictions, the update is incomplete. To incorporate these into the model, we impose two assumptions on the structure of information frictions f_{wi} and f_{ci}.

Assumption 1: Allow the information friction associated with the premium to be $f_{ci} = \alpha(p - c)$, where $0 < \alpha \leq 1$ and p is migrants' prior belief on the premium and c is the true

[12]In this paper we do not consider a welfare magnet motive.

premium.

Remark: Assumption 1 implies that the (mis)perceived premium is partially affected by the prior with weight α and partially affected by the true premium c: $\tilde{c}_i = c + f_{ci} = \alpha p + (1-\alpha)c$. Under this assumption, one systematically overestimates the price when $p > c$ and underestimates the price when $p < c$.

To simplify the analysis, we assume that the friction on cost (premium), f_{ci}, is the same across individuals. One can extend f_{ci} as: $f_{ci} = \alpha(p-c) + \epsilon_{ci}$ to allow individuals to differ in their misperceived premium, where ϵ_{ci} is a random variable which is independent of w_i and with a distribution that is not affected by, c. In this case, model predictions are unchanged.[13]

Because of limited knowledge, migrants may also infer the benefit of city insurance based on their (mis)perceived premium. They may overestimate or underestimate the benefit of social insurance when they compare their (mis)perceived premium and their prior on the premium. Given this we make the following assumption.

Assumption 2: The information friction on willingness to pay is $f_{wi} = \gamma(p - \tilde{c}_i)$.

Remark: In order to incorporate all possible cases, this assumption does not impose any restriction on the size and sign of γ.

Because our empirical analysis is based on the true city premium c, rather than individual (mis)perception $\tilde{c}_i$, we further express f_{wi} in terms of c to be in line with our empirical analysis. Specifically, as $\tilde{c}_i = c + f_{ci}$, under Assumption 1, $f_{wi} = \gamma(p - c - f_{ci}) = \gamma(1-\alpha)(p-c)$. Letting $\beta = \gamma(1-\alpha)$, Assumption 2 can be rewritten as follows.

Assumption 2': The information friction on willingness to pay is $f_{wi} = \beta(p - c)$.

Remark: This formulation suggests three cases. First, when $\beta = 0$ the information friction associated with an individual's value of insurance (willingness to pay) is not systematically related to the premium, c. Second, when $\beta < 0$ then migrants in cities with a high (low) premium systematically overestimate (underestimate) the benefits from insurance. Finally, when $\beta > 0$ this assumption implies that migrants in cities with a high (low) premium systematically underestimate (overestimate) the benefit.

The characterization of frictions on willingness to pay may also be extended as: $f_{wi} = \beta(p-c) + \epsilon_{wi}$ to allow individuals to have different information frictions, where ϵ_{wi} is a random variable which is independent of w_i and its distribution function is not affected by c. In this case, model predictions are unchanged.

To further simplify our analysis, we make an additional assumption:

Assumption 3: Assume the probability density function of w_i, $n(x)$, is a positive constant and not affected by c. In other words, w_i is drawn from a uniform distribution $U[l, u]$.

[13] We have also derived a model with individual heterogeneous frictions, which is available upon request from the authors.

Remark: Assumption 3 is equivalent to assuming a linear, downward-sloping demand curve for insurance.

Under the above assumptions, we reach the following theorems.

Theorem 1: (Heterogeneous Treatment Effect with Respect to Price): Under Assumptions 1 to 3, $\partial\Delta/\partial c = (\beta - \alpha)n(c)$. Thus, the signs of the heterogenous treatment effects with respect to price depend on the signs of $(\beta - \alpha)$.

Theorem 2 (Demand for Insurance under Information Frictions): Under Assumptions 1 to 3, $\partial P(\tilde{w}_i - \tilde{c}_i)/\partial c < 0$ if and only if $1 + \beta - \alpha > 0$.

Remark: Given that the sign of β is not determined and combining the two sources of information friction together, the signs for $\beta - \alpha$ and $1 + \beta - \alpha$ are not determined either. Thus, the directions of the heterogeneous treatment effects with respect to price and the demand response under information friction are empirical questions.

3.4 Welfare Implications

Based on the model presented above, this subsection considers the welfare implications of the information intervention. As discussed above, the information friction drives differences between the perceived and the true willingness to pay and cost. Although participation in the insurance program depends on the perceived (and possibly false) willingness to pay and cost, consideration of the true willingness to pay and premium costs are more relevant to a welfare evaluation (see, for example, Bronnenberg et al., 2015; Spinnewijn, 2017; Handel et al., 2019). This is because they are the true utility an individual receives from the insurance when they face risks. In other words, we assume that information frictions per se does not affect the true utility an individual receives from the insurance. Therefore, in the following analysis examines the welfare impact based on the true willingness to pay and cost.

Denote the number of individuals in the market N. With the complete information, the total $CS^1 = N\int_c^U (w_i - c)n(w_i)dw_i$; and with information frictions, the total $CS^2 = N\int_{c+f_{ci}-f_{wi}}^U (w_i - c)n(w_i)dw_i = N\int_{c+(\alpha-\beta)(p-c)}^U (w_i - c)n(w_i)dw_i$.[14] The second equality follows from Assumptions 2 and 3.

Let the change of the consumer surplus caused by the information intervention be ΔW. Then,

$$\Delta W = CS^1 - CS^2 = N \cdot \int_c^U (w_i - c)n(w_i)dw_i - N \cdot \int_{c+(\alpha-\beta)(p-c)}^U (w_i - c)n(w_i)dw_i. \quad (3)$$

[14] Notice that inside the integral sign we used w_i is used instead of $\tilde{w}_i$ from the "information frictions" case. This is because w_i is the true utility one receives when facing risks even if information is not accurate.

ΔW is a function of the premium, c. When $(\alpha - \beta)(p - c) > 0$, $\Delta W = N \int_c^{c+(\alpha-\beta)(p-c)} (w_i - c)n(w_i)dw_i > 0$ as $w_i - c > 0$ in the integral range; when $(\alpha - \beta)(p - c) < 0$, $\Delta W = -N \cdot \int_{c+(\alpha-\beta)(p-c)}^{c} (w_i - c)n(w_i)dw_i > 0$ as $w_i - c < 0$ in the integral range; and when $(\alpha - \beta)(p - c) = 0$, $\Delta W = 0$. Given this, providing correct information does not reduce true welfare for consumers and in most cases increases their welfare. In Section 6.3 we will estimate the welfare gain associated with the information intervention quantitatively.

4 Research Design and the Data

The data used in this study come from the 2015 and 2016 waves of a panel survey from the Rural-Urban Migration in China (RUMiC) project. An information intervention was implemented in a randomly selected subset of the households from December 2015 to January 2016.

4.1 The RUMiC Survey

The Rural-Urban Migration in China (RUMiC) survey is a longitudinal study with nine rounds: the initial wave was carried out in 2008, with additional rounds conducted annually during the subsequent 8 years. Migrants are surveyed in 15 cities, including such coastal migrant destinations as Guangzhou, Shenzhen, Dongguan, Shanghai, Wuxi, Nanjiang, Hangzhou, and Ningbo, as well as major cities in interior regions, including Chengdu, Chongqing, Wuhan, Hefei, Bengbu, Zhengzhou and Luoyang. The RUMiC surveys are unique among surveys of migrants in China. Unlike other surveys of migrant workers in China, in which migrants are sampled primarily by urban residential address, the RUMiC uses a workplace sampling strategy. In contrast with urban local residents, rural migrants frequently move to cities alone and often live in factory dormitories or other workplaces. Even in cases in which migrants bring their families to the city, high urban rents deter them from living in the type of urban residences that comprise standard sample frames (such as those maintained by the National Bureau of Statistics). More conventional urban household sampling frames tend to yield a biased sample of migrants, over-representing those who are more affluent, have longer tenure and more secure positions in the city than the "representative" migrant. By using a sampling frame based on a census of work-places, RUMiC avoids this bias.[15]

Although RUMiC is designed as a longitudinal survey, the young and mobile nature of the migrant population leads to some attrition between annual survey waves. To maintain sample size, the RUMiC team randomly draws a refreshment sample for each wave, designated as a "New Household Sample." Thus, the RUMiC survey has two sub-samples in each year:

[15] For detailed discussion of RUMiC sampling procedure, see Gong et al. (2008).

the non-attrited households from the previous year's sample ("old-households"), and a new representative refresher sample ("new households") (Meng, 2013). The implementation of the RUMiC surveys normally begins in late March to early April each year, after migrants return from visiting their homes during the Chinese New Year. Because tracking takes time and there is also a need to draw and enumerate refresher samples, the survey typically runs for 6-8 months and is completed by November. This paper uses RUMiC survey data from the 2015 and 2016 waves. In the 2016 survey round, which serves as the end-line for the information intervention evaluated in this paper, 28.3 percent of respondents from the 2015 baseline had attrited from the sample.

4.2 Information Intervention

To provide relevant information to migrants randomly selected for treatment, pamphlets were developed through extensive consultations with relevant program managers and staff responsible for administering health insurance and pension programs in each city. This pamphlet discusses city-specific features of health insurance and pension programs, and summarizes program rules, which vary significantly across cities and for different categories of employment (e.g., wage employment and self-employment). In discussions with local bureaucrats, the rules, premia, and the benefits for each type of worker (as shown in Appendix A.2) were verified. Appendix A.3 provides an example of the easy-to-understand pamphlet provided as a guide to workers in Dongguan. In addition, the pamphlets use lay terms to highlight the risk-management benefits of participating in pension and health insurance programs.

The information intervention was implemented between early December 2015 and the end of January 2016. The city-specific information pamphlets were distributed to a randomly selected sample of 35% of the 2015 RUMiC sample households in 12 of 15 survey cities (and the randomization was done within cities). As the Shanghai RUMiC sample size is significantly larger than the rest of the cities, we randomly selected 25% rather than 35% of the households in the 2015 sample for treatment. This decision was driven by cost and time considerations.[16]

The information intervention was implemented by 33 enumerators, of which 64% were university students (either undergraduate or graduate) and the rest were RUMiC survey

[16]The 2015 survey was completed later than previous rounds, and the Guangzhou and Zhengzhou surveys ran through the end of 2015 with data available even later. These cities were not included in the intervention because there was not sufficient time to both distribute the pamphlets and allow respondents time to react before the 2016 RUMiC survey. In addition, within the 13 included cities, households lacking a working migrant worker, defined as someone with a rural *hukou* and currently working and not retired (aged 16-55 for women and 16-60 for men), are excluded from the random selection for the intervention sample. Further, 8 households (from both treatment and control groups), were not included because their homes were too far from the city center. In total we excluded 304 households, which accounted for 6.9% of households in the 13-city sample.

firm enumerators.[17] In each city, enumerators received classroom and field training from one of the coauthors over a two day period. In the intervention, enumerators first presented a small gift and an information pamphlet to each of the randomly selected sample respondents. After a short introduction, the enumerator read a brief summary of the benefits and costs of participating in pension and health insurance programs from the first page of the pamphlet. The enumerator next identified key characteristics of the respondent to determine which of the more detailed program information and enrollment procedures to highlight, including whether he/she is a wage employee or self-employed, and whether or not he/she holds local *hukou*.[18] Using these characteristics, the enumerator located the programs and policies that applied to the respondent and provided him/her with detailed and relevant information. After doing this, the enumerator then pointed out the contact details (address and phone number) for social insurance related consultations at the local Bureau of Labor and Social Security. Finally, the respondent was asked whether he/she had any further questions. If so, the enumerator answered the question(s) and if not, the respondent was informed that there would be a confirmation phone-call made from survey headquarters to confirm the receipt of the gift and pamphlet. The total information delivery process was designed to take less than 25 minutes.

When respondents were not found on a first effort, enumerators followed a protocol that required repeated efforts at contact by phone or SMS every two to three days over a two-week period. To increase the probability of contact, calls were made at different times of the day. An individual was only classified as attrited if no contact was made after two weeks of successive efforts. Conditional on participating in the 2015 survey round, only 6-7% of the respondents who were randomly assigned for the information treatment did not receive the pamphlet.

The 2016 RUMiC survey (the 9th wave) began in late March 2016, two months after the information intervention, and was completed eight months later in November 2016. In addition to the normal survey questions, those respondents to whom the pamphlet was delivered were also asked to confirm whether they received the pamphlet, and whether they understood the information provided in the pamphlet. All respondents (in both the treatment and control groups) were asked whether they intended to participate in health insurance and pension programs in 2016 if they were not already covered. Participation, both intended and actual, are the main outcome variables in the analysis below. Social insurance participation

[17] Of the 13 cities, 8 used enumerators from the survey firm responsible for the 2015 and 2016 RUMiC survey, and 5 used students. When students were used as enumerators, a person from the survey firm was hired to accompany students to the enumeration site to insure that the target respondent was interviewed.

[18] 'Local *hukou*' (local residential registration) could be either rural or urban, as long as it is located within the metropolitan region. Thus, although RUMiC targets rural-urban migrants, it does include some "local" rural migrants.

intentions are included for two reasons. First, as the information treatment (pamphlet delivery) occurred not long before the 2016 survey round began in some cities, it is possible that respondents interviewed at that time simply did not have sufficient time to enroll in a pension or health insurance. Indeed, when one estimates actual participation against survey month and city fixed effects, survey month has a strong positive effect on participation: the later the follow-up survey was implemented in 2016, the more likely that the respondent had enrolled. Intention to participate, on the other hand, shows a negative correlation with survey month. Second, use of intended behavior is not uncommon in the literature on information interventions and decisions related to social insurance, particularly when not enough time has passed to observe actual decisions. Liebman and Luttmer (2015), for example, similarly examine how an information intervention affects future intentions over when to draw social security benefits in the US.[19]

Concerns related to attrition are also relevant when considering use of an information experiment jointly with the RUMiC survey. Due to the young and mobile nature of the migrant population, attrition across RUMiC waves is not low. From 2015 to 2016, the attrition rate was 28.3%, which is similar to the 28% reported in (Chetty and Saez, 2013). As the information intervention was implemented in the 2015 sample while the outcome of interest (insurance participation) was recorded in the 2016 wave, one might worry that attrition is associated with treatment status. To check this concern, a balance test is conducted in the next subsection and robustness checks employing sample selection models are conducted to examine whether the results could be driven by attrition bias.

4.3 Summary Statistics and Balance Test

Balance tests and summary statistics are presented in Table 1.[20] In panel A, a balance test is shown for all the control variables in the full sample of the base year (2015), and the test for 2015 respondents remaining in the 2016 wave is shown in Panel B.

The first two columns of Panel A present mean values of key variables for control and treatment groups, separately, in the base year and column 3 shows the difference between the two groups. From these summary statistics it is evident that all individual characteristics are similar across the treatment and control groups in the base year. However, some imbalances are observed for firm level characteristics: workers in the treatment group are more likely to be in small firms than their counterparts in the control group and the treatment group has a slightly higher share of workers in foreign/joint venture firms. Further, the size of the treatment group is smaller in Shanghai. Given these imbalances, we favour models that

[19] In a robustness check, we examine results using actual participation as the dependent variable to estimate the model.

[20] The number of observations included here are those without missing values for all the covariates.

control for these characteristics to avoid any bias. Panel B presents the same balance test for the panel respondents in the 2016 sample, where we observe results similar to those for the 2015 full sample.

Panel C presents the summary statistics for the total 2016 sample as well as for those with and without a written contract, separately. Column 7 shows that the average age of respondents is 37. As 15 years of contributions are necessary to receive full pension benefits at retirement, we note that 18% of women and 15% of men are already too old to receive full pension benefits at mandatory retirement ages. Men comprise 57% of the respondents, and the average years of schooling of respondents is nearly 9 years and 75% of the sample are married, and have 1.16 children. Nearly all respondents, 99.6%, were working in the previous year, with 36% self-employed, and *hukou* policy permitting, 64% would prefer to stay in the city permanently. When comparing those with a contract (Column 8) to those without (Column 9), it is clear that migrants in the formal sector (with a written contract) are younger, more educated, more likely to be men, less likely to be married and have fewer children. Employees with a contract are more likely to work in large firms (with more than 100 workers) than those without a contract. In addition more than 60% of workers with a contract work in firms that are state/collectively owned, domestic private, or foreign/joint venture firms. The corresponding share for those without contracts is only 19%.

5 The Average Treatment Effect and Heterogeneity by Contract Type

5.1 Estimation Strategy and the Model

Assuming implementation protocols were followed and that a balance test is passed, random assignment of the information intervention allows us to identify whether poor understanding of the urban health insurance and the pension programs and enrollment procedures reduces the likelihood that respondents participate in them. This base model involves regressing participation in insurance in 2016 on lagged participation, the information treatment and city fixed effects. In addition to the base model, a full model of the decision to participate in social insurance is estimated, which is specified as:

$$Y_{1ij} = \alpha + \beta T_{ij} + \theta Y_{0ij} + \mathbf{X}'_{0ij}\gamma + \mathbf{W}'_{0ij}\kappa + \delta_j + \varepsilon_{ij}, \tag{4}$$

where the subscripts 0 and 1 indicate variables measured in the pre-treatment (2015) and post-treatment (2016) survey rounds, respectively. Y_{0ij} is a lagged (pre-treatment) participation indicator; T_{ij} indicates that individual i in city j was assigned to receive the information treatment between the 2015 and 2016 survey rounds; $\mathbf{X}_{0ij}$ is a set of pre-treatment (2015) individual-level controls, which include age,[21] gender, education, marital status, number of children, whether an individual is self-employed, an interaction between the self-employed indicator and lagged participation, and indicators for whether he/she would remain in the city permanently if policy permitted and whether he/she is working or not. $\mathbf{W}_{0ij}$ is a set of pre-treatment firm size and ownership indicator variables for the employer of individual i; and δ_j are city fixed effects, which control for both time invariant city-level factors and within city changes between years 0 (2015) and 1 (2016), including systematic changes in the costs and benefits of the health insurance and pension schemes.[22] The coefficient of interest in equation (4) is β, the average treatment effect of exposure to the information intervention. Here the estimate of β should reflect the Δ in Equation 1 of our model, which depends on the size of the effect on those who switch from being uninsured to insured and those who drop insurance after learning its benefits do not outweigh the premium. Of course, the model is just a simplification. In reality, an information intervention should also have a priming effect, which is not included in the model.

Existence, or lack, of a written employment contract introduces one potential source of heterogeneous impacts. In design of the intervention and at the pre-analysis stage, the team anticipated that the effect of providing information about social insurance will differ considerably depending on whether a respondent has an employment contract.[23] As shown in Figure 1, health insurance and pension participation rates for those with employment contracts in 2015 were around 75%, while participation was only 13% for those without a written contract. As it is likely that those without a written contract will be most affected by the information intervention, we estimate equation (4) including an indicator for "no written contract" in 2015, NC_{0ij}, and the interaction of NC_{0ij} and the treatment indicator, T_{ij}:

$$Y_{1ij} = \alpha + \beta T_{ij} + \pi NC_{0ij} + \varphi T_{ij} * NC_{0ij} + \theta Y_{0ij} + \mathbf{X}'_{0ij}\gamma + \mathbf{W}'_{0ij}\kappa + \delta_j + \varepsilon_{ij}, \qquad (5)$$

[21] In addition to age in years, we also include two indicator variables: whether the respondent is a woman and over 40, and a man and over 45, respectively. These threshold indicators are included because pension rules mandate that participants cannot receive full benefits without paying the premium for 15 years, and the retirement age for migrant women and men in China is 55 and 60 years, respectively. As they cannot expect to receive full benefits, individuals already within 15 years of the retirement age threshold may have less incentive to participate in a pension program.

[22] As the randomization was implemented separately in each of the 13 cities in the sample and city level costs and benefits vary significantly, the baseline model includes the set of city fixed effects, δ_j, along with the treatment indicator and lagged participation. Further, as randomization into treatment was implemented at the household level, we equally weight each household in the following analysis to provide efficient estimates (Athey and Imbens, 2017). Household members may also share cost and benefits of social insurance in China, and social insurance participation is a joint decision of household members, especially for poor migrant households.

[23] The heterogeneities studied in this paper are in the pre-analysis plan unless otherwise indicated.

In this specification, the coefficients of interest are β, which indicates the treatment effect for individuals with a written contract in 2015, and $\beta + \varphi$, treatment effect for individuals without a written contract in 2015. φ indicates whether or not the treatment effects for the two groups differ.

5.2 Results

As the information intervention was randomly assigned, we use an 'assignment to treatment' indicator to estimate the intention-to-treat (ITT) effect. Panel A of Table 2 presents the OLS estimation of equation (4), and it is evident that, after controlling for base year health insurance and pension participation, the average effect of assignment to the information intervention is zero (model 1), and the effect does not change as base period individual controls and firm-level controls are added in models (2) and (3), respectively. As the RUMiC survey is sampled through workplaces, standard errors in all models are clustered at the workplace of the household head.

This average zero impact, however, masks considerable heterogeneity in the effect of the information intervention on individuals with and without written employment contracts. To examine this difference, Panel B of Table 2 presents the selected estimates of the OLS regression for equation (5).[24] The bottom line of the panel shows the treatment effect on individuals without contracts by adding the coefficient on treatment (β) to that on the interaction between treatment and the indicator for not having a contract in the base year (2015) (φ in equation (5)). The brackets under the treatment effects are p-values from F-tests for significance of $\beta + \varphi$. Coefficients on the indicator variable for "no contract" suggest that individuals without a written contract in 2015 were less likely to participate in both health insurance and pensions. From the coefficient on the no-contract and the treatment indicator interaction term it is evident that for health insurance participation, the impact of the information intervention is significantly different for respondents with and without contracts in 2015. For those with contracts in the base year, there is no information intervention effect. Given that before the intervention 75% of our sample with written contracts already had health insurance, this should not be a surprise. The effect on those without contracts, though, is positive and statistically significant. On average, the intervention increased health insurance participation for those previously without a contract by 3.2 percentage points, or a 23.2 percent increase over the 2015 participation rate of this group (which was 13.8%). To put the size of the effect in perspective, between 2010 and 2015 the total participation rate for this group increased from 9% to 14%, a 5 percentage point increase in five years. Most of these increases occurred between 2012 and 2013 when the central government introduced

[24]The full results of these estimates are reported in the Online Appendix A.4

fines on employers who failed to contribute their share on behalf of employees, which led to a 2 percentage point increase between 10% to 12%. The estimated information intervention effect of a 3.2 percentage point increase is 60% larger than the government policy change effect.

Participation in pensions, however, was not affected by the information intervention, regardless of whether the individual had a contract or not. This result was puzzling at first, and led us to explore heterogeneity in treatment effects with age of the recipient in a post hoc analyses. Such heterogeneity may be related to the fact that to be eligible for full benefits from the urban pension scheme, the participants had to have contributed for at least 15 years at the time of the retirement. If, at the time of pension program participation some individuals were unable to reach the 15 year limit to contribute to the scheme before retirement age, their employers' contribution would remain in the city general social pool, while their own contribution would be paid in a lump-sum or converted to their rural pension when they retire. Knowing this, it is unlikely that the information intervention will have an effect on the decisions of individuals who were not already participating in the pension scheme and were too old to reach the 15 years participation requirement (men over age 45 and women over 40).[25] In the analysis sample, a fairly large share is within 15 years of retirement age (18% of men and 15% of women). To examine the possibility of heterogeneous response to the information intervention due to the years of participation requirement, those individuals within fifteen years of the retirement age are excluded. The remaining sample is labelled the "young" sample. For this restricted "young" sample, the estimated results for the average treatment effects and heterogeneous effects are reported in Panel C of Table 2. Although the information intervention had a zero average effect for this group, the impact for those without a written contract is positive and statistically significant. Specifically, for "young" individuals without a contract, the intervention increased pension participation by 3.9 percentage points, or a 25% increase in the participation rate of the group.[26]

As discussed previously, workers in the formal sector are more likely to have already had social insurance at baseline, while individuals without a formal contract (both employees and self-employed) had substantially lower rates of social insurance participation. The question

[25]This potential heterogeneity was not considered by the research team at the planning stage. However we believe that the different response due to this policy variation is reasonable and hence added this part of the analysis.

[26]Interestingly, for those individuals who have less than 15 years to contribute to the pension scheme, there is a wage responses to the information intervention. Among 'older' employees (within 15 years of retirement), the treated group experiences a 7.2 percent wage increase with the information intervention even as their pension program participation remains unchanged. Whereas among the 'young' sample, whose participation into the urban pension program was increased, there is no similar increase in the wage earned. Thus, while older workers expect to gain less from pension enrollment, the information intervention may have facilitated a bargaining outcome in which workers split the surplus from not participating with their employers (see the Online Appendix A.5 for the detailed discussion of the estimation and the results).

naturally arises as to whether the positive treatment effect we observed is due to more people switching from the informal sector to the formal sector (the extensive margin) or the effect is mainly generated by changes in participation within a particular employment category (the intensive margin). To examine this question, we estimated the treatment effect on transition across different employment sectors (employees with formal contract, employees without a formal contract, and self-employment). A multinomial logit method is estimated taking employees with a formal contract as the base outcome. We find that there is no treatment effect on switches between formal sector employee and self-employment from 2015 to 2016. However, for employees with and without a formal contract we found a small but statistically significant treatment effect, suggesting information intervention generated a small movement from the formal sector (with a contract) to employment without a contract. In other words, we observe a negative treatment effect at the extensive margin. Thus, the overall positive treatment effects are driven by the intensive margin. These results are presented in Online Appendix A.6.[27]

6 Demand Response to Information Intervention: Heterogeneity with Price

Across China's cities, the considerable heterogeneity in insurance premia not only contributes to the likelihood that migrants may have imperfect information about the cost (and benefits) of the insurance, but also raises the likelihood that treatment effects will vary with city-level premia. Using this source of variation we next examine the demand response to the information intervention for health insurance and the pension scheme separately. This will also allow us to gauge the welfare effects of the information intervention.

6.1 The Estimation Model

To this end, we estimate models in which the treatment indicator, T_{ij}, is interacted with a city relative price (premium) variable:

$$Y_{1ij} = \alpha + \beta T_{ij} + \phi T_{ij} * P_j + \theta Y_{0ij} + \mathbf{X}'_{0ij}\gamma + \mathbf{W}'_{0ij}\kappa + \delta_j + \varepsilon_{ij}, \tag{6a}$$

where P_j is the minimum premium required for self-employed individuals in city j divided by the city average monthly earnings of migrants in the RUMiC sample. The reason we use the 'relative premium' is to ensure that conditional on the city fixed effect, the variable $T_{ij} * P_j$ is

[27]The small observed job-switching effect likely reflects a secondary effect of the information intervention. Once gaining knowledge of their eligibility for health insurance, migrants may find riskier types of jobs more attractive. Unfortunately, our data do not allow us to investigate further along this line.

picking up heterogeneity in the treatment effect with respect to price as opposed to simply an income effect. The plausibility that the 'relative premium' (P_j) and city level average income are unrelated is evident in the figure presented in Online Appendix A.7. Panels A and C of the figure show the strong correlation between the health insurance and pension premia and their respective relative premia, respectively (with correlation coefficient for health being 0.95 and for pension, 0.84), and Panels B and D demonstrates that there is no systematic relationship between the relative premia and the average monthly earnings of migrants in the city (correlation coefficients are 0.17 for health and 0.47 for pension).[28]

The premium paid by the self-employed is used for three reasons. First, an employee may participate in the health insurance or pension programs at the self-employed premium if employers are not participating. Second, labor markets are competitive, and when employers participate, costs associated with employer contributions are passed on to employees through a lower monthly salary net of social insurance contributions. Thus, the self-employed premium is a base price that provides a reasonable proxy for the cost of participation faced by both employees and self-employed migrants. Finally, even as the self-employed and employee contributions differ, these premia vary similarly across cities.

The coefficients of interest from Equation (6a) are β and ϕ. As the city fixed effect controls for city premium levels, the coefficient on the treatment*premium interaction, ϕ, identifies how the treatment effect varies with the city level relative premium. β is the average treatment effect when the premium is zero.

Finally, we estimate a model including a full set of interactions: the contract indicator and its interaction with the treatment, as in Equation (5), the city premium (captured by city fixed effects) and the city premium interacted with the treatment, as in Equation (6a), as well as interactions between city premium, contract, and treatment, or:

$$\begin{aligned} Y_{1ij} =& \alpha + \beta T_{ij} + \phi T_{ij} * P_j + \varphi T_{ij} * NC_{0ij} + \lambda NC_{0ij} * P_j + \mu T_{ij} * NC_{0ij} * P_j \\ &+ \pi NC_{0ij} + \theta Y_{0ij} + \mathbf{X}'_{0ij}\gamma + \mathbf{W}'_{0ij}\kappa + \delta_j + \varepsilon_{ij}, \end{aligned} \tag{7a}$$

6.2 Results

The results from estimation of equation (6a) are presented in Panel A of Table 3. As the city fixed effects are included to control for differences in all city level unobserved characteristics, including the average earnings of migrants and the city level premia for social insurance, the inclusion of the interaction between the relative premia and the treatment allows us to identify variation in treatment effects across different levels of premia. The coefficient on this

[28] There is a larger negative correlation between the pension relative premium and average city-level earnings. Although this correlation is not statistically significant, we further ensure that results are not driven by city-level income in a robustness test (below), in which the treatment interacted with the city-level average earnings, $T_{ij} * INC_j$, is included as a regressor, in addition to city fixed-effects.

interaction term for health insurance is negative in all three specifications. The baseline model suggests that after controlling for the relative price level (through the city fixed effect), the price effect on the treated group is a negative 1.02, indicating that 1% increase in the relative health insurance premium reduces participation by 1.02 percentage points. Controlling for individual observables increases the price effect to 1.18, and in the third model, when firm size and ownership characteristics are also included, the price effect of treatment increases again to 1.24.

Next, in Panel B of Table 3, additional interactions of the information treatment, city-level relative premium and contract status are included. Based on these estimates, the price effect of treatment for the non-contract group and predicted treatment effect at different relative premium level are shown in the bottom of the panel. Note that the price elasticity of treatment on health insurance among employees without a contract is of greater magnitude at negative 1.77. Based on this elasticity, the calculated treatment effect increases from 2.6 percentage points at the median relative price (0.075) to 7.7 and 12.4 percentage points at the 25th and 10th percentiles of the city-relative premium distribution, respectively.[29]

Figure 2 plots these heterogeneous treatment effects by relative premium for health insurance. We first use the linear functional form estimates from Panels A and B of Table 3 to predict for each relative price point (each city) the treatment effect for the sample as a whole (panel (a) of Figure 2) and for those without a formal contract (panel (b) of Figure 2). These predictions, indicated by diamonds in the figure, shows that individuals receiving information in cities with lower relative premia experienced a larger treatment effect. This is true for both the full sample and for the subsample of individuals without contracts, but the effect is larger for the latter group.

One may worry, however, that the linear functional form used in equations 6a and 7a. To gauge whether the shape of the effect indicated in Figure 2 is generated by the linear functional form, we next estimated a more flexible form of equations 6a and 7a. More specifically, the following equations are estimated:

$$Y_{1ij} = \alpha + \sum_{j=1}^{13} \beta_j T_{ij} * \mathbf{1}(city = j) + \theta Y_{0ij} + \mathbf{X}'_{0ij}\gamma + \mathbf{W}'_{0ij}\kappa + \delta_j + \varepsilon_{ij}, \tag{6b}$$

where $\mathbf{1}(city = j)$ is the dummy variable for city j, and

[29] As of the base year (2015), the participation rate in urban health insurance was 13.8% for employees without written contract, this reflects 19, 56 and 90 percent increases in participation rates as relative health insurance premia decline from the median to the 25th and 10th percentiles.

$$
\begin{aligned}
Y_{1ij} =& \alpha + \sum_{j=1}^{13} \beta_j T_{ij} * \mathbf{1}(city = j) * NC_{0ij} + \sum_{j=1}^{13} \phi_j T_{ij} * \mathbf{1}(city = j) * Cont_{0ij} \\
&+ \lambda NC_{0ij} * P_j + \pi NC_{0ij} + \theta Y_{0ij} + \mathbf{X}'_{0ij}\gamma + \mathbf{W}'_{0ij}\kappa + \delta_j + \varepsilon_{ij},
\end{aligned} \tag{7b}
$$

where $Cont_{0ij}$ is the indicator for having contract at baseline, i.e. $Cont_{0ij} = 1 - NC_{0ij}$. The resulting coefficients for β_j from equations 6b and 7b are plotted as crosses, (+), in panels (a) and (b) of Figure 2, for the total and the no-contract samples, respectively. As can be seen, the flexible form provides consistent predictions of the relationship between the treatment effect and the relative premia for both the total and the non-contract samples.

One might be concerned, also, that job-switching drives movement toward non-participation in cities where health insurance premia are high. Of individuals who exited from health insurance programs between 2015 and 2016, only 15% had started a new job since the information intervention, and these were evenly distributed across all cities. Thus, it is unlikely that changes in employment in high premium cities can explain the effect of higher relative premia on participation in health insurance.

The above results suggest that when premia are relatively low, information frictions may inhibit health insurance participation. At the same time when the premia are high and participants are misinformed, some may make an uninformed decision to participate. Upon receiving more accurate information, some migrants may withdraw from the urban health insurance program. In our model we assumed that prior to migration to a particular city migrants' perception of the cost (and benefit) of the social insurance in cities are uniform across all cities. Upon arriving in a particular city migrants may partially update their perceptions based on information available in the city. Because of their uniform prior, some of the individuals who move to cities where actual insurance premium is higher than their prior ($p < c$) may systematically underestimate the cost (and/or overestimate the benefit), while those who moved to cities with insurance premium lower than their prior ($p > c$) would likely to systematically overestimate the cost (and/or underestimate the benefit). Thus, by correcting such misperceptions, the information intervention increased participation rates in low cost cities and reduced participation rates in high cost cities.[30]

In contrast to the role of the relative premium in the impact of information on the health insurance participation decision, there is no evidence that the relative pension premium

[30] It is unlikely that migrants are responding to a "welfare magnet motive" when choosing destination cities, that is, it is unlikely that they make a migration destination decision based on the relative value of health or pension benefits in the city. In other settings, in which such information is far easier to obtain, researchers have not found evidence that a welfare magnet motive drives migrant destination choices (e.g., Frey, 1997; Giulietti, 2014; Kaushal, 2005). In any case, even if migrants priors vary across cities, the city-fixed effects in the estimated models can control for the city-level variation in priors.

interacts with information to influence participation in the pension program. Coefficients on the interaction term are small and not statistically significant for pensions (Panel A of Table 3). Even among respondents without a contract the treatment effect does not vary with the relative pension premium, as evident in Panel B of Table 3.

Why does the treatment effect on participation vary with the relative premium for health insurance but not for pension? One likely explanation turns on the difference in the time horizon for health insurance and pension schemes. As pension payoffs will not occur until one's retirement and risks in distant future are hard to account for, it may be difficult for individuals to gauge the 'right' price and to respond to price information. Further, migrants may deeply discount risks in the future. Digging deeper into the data, we find that more patient individuals are more likely to participate in the urban pension scheme while the effect on health insurance participation is much smaller and not statistically significant.[31] Health insurance, on the other hand, covers near term risk associated with illness or injury and the costs and benefits are more salient for migrants.

6.3 Welfare Estimation

The theoretical model shows that the information intervention should not reduce consumer surplus and in most cases it should increase it. The estimation provided above permits estimating the size of the change in consumer surplus associated with the change in health insurance participation as a result of the information intervention.[32]

The results in Table 3 show that the effect of the information intervention is negative in price. In other words, where premia are high, the information intervention reduced participation and in places where premia are low, it increased health insurance participation. The information intervention induced welfare changes are illustrated graphically in Figure 3, where $D1$ and $D2$ denote the demand curves with and without information frictions, respectively. Panel (a) of Figure 3 highlights the case when the information intervention increases the quantity of demand (or participation rate for the insurance), and instances in which the information intervention reduces the quantity of demand are depicted in Panel (b). The horizontal line p^* in both panels indicates the supply curve, and the intercept between 'p^*' and D1 on the x-axis, N1, represents the quantity demanded under the information frictions, and between p^* and D2, N2, the quantity demanded after the information intervention. As can be seen in the figure, the welfare gain due to the information intervention is the triangle

[31] In the experiment, a patience game with cash payoffs is also conducted. Results when including a patience variable are presented in the Online Appendix A.8. It should be noted that exploiting the patience information for this analytical exercise were not part of our pre-analysis plan.

[32] The results presented in Table 3 indicate that the heterogeneous treatment effects in price are negligible and not statistically significant for pensions, so it is difficult to provide reliable estimates of the change in consumer surplus for pensions.

'def' in Panel (a), and the welfare loss is the triangle 'cde' in Panel (b). Note that because we are evaluating the consumer surplus based on the true willingness to pay (in other words, based on the demand curve D2), the areas 'abc' in Panel (a) and '$abcd$' in Panel (b) are not part of the true consumer surplus, and therefore are excluded in the calculation of the welfare changes.

To calculate the size of these triangles, we need to first estimate the willingness to pay under mis-perception ($D1$) and that under the information intervention ($D2$). The coefficients on the interaction term between 'treated' and the 'relative premium' ($T_{ij} * P_j$) and the dummy variable 'treated' (T_{ij}) presented in Table 3 capture the change in the demand curve due to the information intervention. After obtaining the slopes and the intercepts of D1 and D2 , N1 and N2 can be determined. As the consumer surplus should be based on the true willingness to pay, the triangles 'def' in Panel (a) and 'cde' in Panel (b) are then calculated based on $\frac{1}{2}|N2 - N1|de$, where de refers to the distance between the points d and e.

In the estimating the specifications of Equations (6a) and (7a) we do not directly observe the demand curve under information frictions. This is because the estimations control for city fixed-effects, which are collinear with the city level premia. In order to estimate both $D1$ and $D2$ curves, we changed the model specifications of Equations (6a) and (7a) by replacing city fixed-effects with the relative premium variable and a vector of city characteristics, including city public finance expenditure, GDP level and the GDP growth rate. The results of these estimations are reported in the Online Appendix A.9 and coefficients on treatment and interaction terms with relative premia are not statistically different from those reported in Table 3.

Based on the estimated coefficients in the Online Appendix A.9, together with the information on annual earnings and the size of the migrant population in each of the 13 surveyed cities, the change in consumer surplus is calculated. The information on the number of migrants in each city is collected from an annual publication titled 'National Economy and Social Development Reports' (NESDR) published by the National Bureau of Statistics and its branches for each province and from the 2015 1% population survey.[33]

The calculated consumer surplus results are presented in Table 4 for the full sample and the sample of migrant workers with and without a written contract, separately. Our results based on Equation (6a) suggests that the annual average consumer surplus for an average migrant is 28.2 yuan. If we use results from Equation (7a), the annual consumer surplus is calculated to be 50.87 yuan for an average migrant. If we consider the 13 cities as a whole, the consumer surplus gain will range from 521 to 940 million yuan. These changes in consumer surplus due to the information intervention can be interpreted as the cost of the information

[33]In particular, information on the 'number of permanent residents' is collected from the city NESDR. The 9.5% random sample from the 2015 1% population survey is used to calculate the ratio of migrant workers to 'permanent residents', which then facilitates backing out the migrant worker population.

friction.

How big is the welfare gain of the information intervention? If we compare the welfare gain (28.2 to 50.9 yuan per person) with the actual implementation cost of our field experiment (around 10 yuan per person) the gain from providing accurate information to migrant workers is 2.8 to 5.1 times of the costs. Due to the small scale implementation and the experimental nature of the campaign, the implementation cost suggested by the information intervention will be at the high end of a reasonable range, and the gain calculated using unit costs from the information intervention will lead to lower bound estimate of the welfare gain. If using the 13 city governments' 2016 advertising expenses for social insurance, which is around 0.8 yuan per person, one might envision a much larger gain. Using per capita expenses based on current government advertising budget, which has not succeeded in reaching migrants, an estimated welfare gain would be the 34 to 63 times.[34] Of course, this government advertising cost will be a lower bound of what a properly run information campaign might cost. It does not reflect the marginal costs of reaching migrant workers who do not currently have the knowledge of social insurance costs and benefits.

While trying to gauge the benefits from the information campaign, it is also important to keep in mind that the consumer surplus calculated above is an annual figure, while the benefits of participating in social insurance will accrue to migrants for many years in the future. Further the calculation of the consumer surplus does not take into account the potential social benefits from individual migrants' social insurance participation. Thus, the calculation above is likely to be an under-estimate.

7 Robustness Checks

In this section we conduct a series of sensitivity checks to ascertain whether the results are robust.

First, we examine whether the treatment effect on the treated differs significantly from the intention to treat effects presented in Sections 5 and 6. As discussed in Section 4, roughly 7% of respondents who were assigned to the treatment group did not receive a pamphlet and explanation of the benefits and costs of participating in health insurance and pension programs. While a rather small proportion, estimates of the effect of treatment on the treated tend to be larger in magnitude than "reduced form" intent-to-treat estimates. To estimate the effect of treatment-on-treated, we employ an instrumental variables approach in which

[34] Information on each city's social insurance management cost can be found in their respective annual reports for 2016 (the detailed calculation of the total social insurance management cost is presented in the Online Appendix A.10). However, the share of advertising cost is only available for Dongguan city (3.7%). Thus, the above calculation is based on the assumption that the share of advertising cost in the social insurance management cost is the same for Dongguan as for other cities.

the variable T_{ij} in equations (4), (5), (6a), and (7a) is an indicator of actual receipt of a pamphlet and information, and assignment to the treatment is used as an instrument. The results for model 3 of equations (5) and (6a) are reported in Panel A of Table 5.[35] The results confirm that all the conclusions based on estimates presented in Tables 2 and 3 remain, except that the estimated magnitudes increase and they are more precisely estimated.[36]

One should also be concerned that there might be bias introduced due to the level of attrition in the survey. Because of the mobile nature of the migrant population, one observes considerable attrition between RUMiC waves. Between 2015 and 2016 the sample attrition rate was 28.3%, thus it is reasonable to consider whether attrition might affect randomization and influence the interpretation of the results. To examine this question, we first examine the balance tests presented in Table 1. The table shows that most individual characteristics are balanced for the 2015 sample upon which the randomization was implemented, as well as for the 2016 respondents (excluding attritors). Hence, they should also be balanced for those who attrit after the 2015 wave as well. The imbalances in firm-level control variables and in city dummy variables across control and treatment groups are quite similar for both the 2015 sample and the 2015 stayers, suggesting no significant variation in imbalances between stayers and attritors. Although one does not observe a difference in the balance test between the attritors and the stayers, attrition bias may still arise due to correlation with unobservables. To examine the extent to which this is the case, a Heckman sample selection correction model is employed for all the estimated regression models. The results for equations (5) and (6a) are presented in Panel B of Table 5. These results suggest that the attrition is not driving the main conclusions.[37]

Another concern is related to the estimated premium effect for the information intervention. As discussed in Section 6, the 'relative premium' variable (absolute premium divided by city level average earnings) is used instead of the 'absolute premium' in the estimation to make sure that the variable captures only the premium effect after controlling for the underlying income variation across cities through the city fixed-effect. In this section, we perform further tests of whether using the 'relative premium' captures the pure premium effect. In particular, an interaction term between city-level average earnings and the indicator

[35] As one would expect, with a strong correlation between intended and actual treatment, the instrument is quite strong and there is no reason to be concerned with weak instrument bias. As the F-statistics are over 800, we do not report these values in Panel A of Table 5. The first stage estimation results are available upon request.

[36] The results are consistent across all specifications and are available upon request from the authors.

[37] The Online Appendix A.11 discusses the estimation details, the validity of the IVs, and presents the Heckman selection correction results from estimating all other models in the paper and provides the first step estimation results. An alternative inverse probability weighting method (IPW), suggested by Fitzgerald et al. (1998), is also employed and the results are largely consistent with the conclusions drawn from Panel B of Table 5. The IPW results are not presented in the paper but are available upon request from the authors.

for treatment is added to Equation (6a) to control for any potential remaining income effect. A version of Equation (6a) is also estimated with direct controls for individual log earnings. Both results are reported in Panel C of Table 5, which confirms that directly controlling for city level or individual level income does not alter the estimated premium effect.

Next, we examine whether there is a differential effect between employed without a contract and self-employment. Recognizing that workers without a contract also include the self-employed, one might be concerned that the stronger result among workers without a contract is driven by the self-employed and not changes in participation of workers without a contract. To assess this, we split the sample into those who are wage-employed and self-employed at baseline in 2015, and separately estimate the impact of providing information. In Panel D of Table 5, we show that the magnitude of the "no contract effect" is larger among the wage earners and still significant at the 10% level for health insurance. The direction of the treatment effect is similar for the self-employed group, and the magnitude is still economically, if not statistically, significant. For pension participation, the effect for both groups is of similar size.

As the dependent variable in the main estimation models includes both actual and stated intentions to participate in 2016, we next test whether excluding 'intention to participate' changes the estimation results. The main reason for including 'intention to participate' is that, in some cities, the survey was conducted only a short time after the information intervention, and some respondents who received the information treatment may not have had enough time to act on an intention to change behavior. This is evident in Figure 4, where the survey month is plotted first against the proportion of respondents who increased actual participation in health insurance and pension programs between 2015 and 2016, and second, against the proportion of those who indicated that they intended to participate in 2016. The figure shows that the actual additional participation increases over the survey months while the intention to participate decreases over the same period.

To examine whether the treatment effect has the same trend when using actual participation, we estimate equations (5) and (6a) as ordered-probit models, in which the dependent variable is replaced by a variable with 3 categories: those who did not participate and have no reported intention to participate in 2016 are coded as zero, those with intention to participate at the time of the 2016 survey are coded as 1, and those who actually participated at the time of survey are set to 2. Selected marginal effects for health insurance and pension are reported in Panels E and F of Table 5, respectively. The results confirm that the groups which were assigned to the information intervention treatment have a higher proportion of respondents both intending to participate and actually participating. Taking the results from the estimation of equation (5) (columns 3 and 4), for example, the increase in actual participation for those without contract is 2.1 percentage points, while the increase in intention to participate is 0.2 percentage points. Both effects are precisely estimated at the 10% significance levels.

Finally, it is also important to examine potential spillover effects. Although the information experiment is based on random assignment, it is possible that some individuals are working in large workplaces where members of both the treatment and control groups are present, and information may be spread from treated individuals to those who are in the control group. Similarly, migrants who move from the same sending county to the same destination city are often part of the same social network, and within such a network, information may flow between members of the treatment and control groups. To test for these types of spillover effects, two dummy variables are generated: one indicating individuals from a workplace where both treated and control respondents coexist (mixed-firm);[38] the other indicating that a home-county network has members of both control and treatment groups (mixed-home-county). These two dummy variables are then interacted with the treatment assignment dummy variable. Three different specifications are estimated for equation (6a): 1. including the mixed firm dummy and its interaction term with the assignment to treatment; 2. including the mixed home-county dummy and its interaction term; 3. including both mixed-firm and mixed-home county dummies together with their interaction terms with assignment to the treatment. The results for health and pension are presented in Panel G of Table 5. As can be seen from these results, spillover effects are not affecting the main results.

8 Conclusions

In the economic development and urbanization process, social insurance can play an important role in reducing risks faced by all members of society, and this may be particularly important for preventing those at the lower end of income distribution from falling into destitution as a result of random shocks affecting their economic well-being. Because of the positive externalities associated with social insurance and the potential high discount rates of large shares of working-age individuals, increasing participation in social insurance requires government effort to inform, convince, and make enrollment attractive to individuals. Through the design and implementation of a field experiment, this study found that lack of information contributes to low rates of social insurance participation among informal sector workers. The study finds that the information intervention was particularly effective for informal sector workers who did not have a written contract in the base year (both wage employees and the self-employed). For this group, the base year participation rate in the urban employee health insurance program was relatively low at 13.8%. With assignment to

[38]We also generated a continuous variable which measures the proportion of coworkers who are in the treated group. The results are very similar to the results presented in Table 5. These results are available upon request from the authors.

the information treatment, the participation of this group increased by 3.2 percentage points. The treatment effect also varied considerably with the city-level relative health insurance premium, with the treatment effect increasing from 2.6 percentage points at the median relative premium to 7.7 and 12.4 percentage points, respectively, as the relative premium declines to the 25th and then 10th percentiles of the city relative premium distribution. In the context of the findings of Wagstaff et al. (2016) and Thornton et al. (2010), this constitutes a dramatic increase within one year, and offers the promise of boosting participation through relatively low cost education drives aimed at informing informal sector workers about the benefits of health insurance and other forms of social insurance. Our welfare estimation further indicated that the cost of information frictions among rural migrants in China is very high, and suggests a high rate of return to the government from implementing an education campaign targeted to rural migrants.

Information interventions alone, however, are unlikely to bring full urban health insurance coverage to the rural migrant population. A one-year boost in coverage by 3.2 percentage points still leaves more than 80 percent of migrants without employment contracts lacking health insurance coverage in the cities where they work. While there may be potential for information interventions to have a cumulative effect over time and to be reinforced by steps to reduce the transaction costs associated with enrolling (Capuno et al., 2016), we view it likely that institutional reforms unifying health insurance programs across urban and rural areas and providing premium subsidies for lower income workers may be necessary to approach full coverage.

With respect to pension program participation, the effect of providing information was also positive and significant for informal sector workers young enough to contribute for sufficient time to receive a full benefit at retirement. Unlike health insurance, pension program participation does not vary with relative premia, but this likely reflects the fact that the benefits of health insurance can be received in a short time-frame, while pension benefits would not be received until one's retirement. As calculating the present value of future benefits relative to current costs is complicated when benefits are so far in the future, migrants may lack the capacity to respond to information intervention regarding the current relative price of participating.

In both China and the international policy communities there is broad recognition that social insurance has an important role to play in the process of economic development and urbanization. Indeed, the 2019 World Development Report (World Bank, 2019) emphasizes the importance of extending social insurance coverage to informal sector workers, which in China are primarily rural-urban migrants lacking formal contracts. There is a tendency for those providing policy advice, however, to simply assume that "mandating participation" in a social insurance scheme will be sufficient to cover informal sector workers. The China experience, however, should offer caution to the belief that mandates alone will suffice to raise participation. Informal sector workers, including new migrants from the countryside, are often not participating in urban employee social insurance schemes for a number of reasons. Finding a way to bring such informal sector workers into social insurance systems, even with mandates and a government with relatively high administrative capacity, may pose a challenge for policy makers in many settings. Results from this paper suggest that lack of information may contribute to reducing participation among those workers who lack contracts, and that providing information may be a relatively low cost means of raising coverage.[39]

The China example also raises the prospect that fiscally decentralized systems targeting different populations may lead to only nominal "universal coverage."[40] While most migrants have access to insurance in their home counties, through the New Rural Collective Medical System (NRCMS), accessing subsidized care requires returning home when ill or suffering an injury. Thus, in practice, it is often not feasible for rural migrants to access care through NRCMS insurance.

[39] In spite of mandates, some employers may simply decide not to make contributions on behalf of their employees. This may be particularly likely for smaller firms facing little likelihood of an audit from the labor bureau.

[40] Yu (2015) among others have declared China's success in providing universal health insurance to 1.3 billion people, yet as survey-based research has confirmed, rural migrants tend to remain without coverage or are covered by rural policies that are difficult to exercise when working and living in distant cities.

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Table 1: Balance Tests and Summary Statistics

	2015 Sample			2016 Sample					
	Panel A: 2015 Balance Test			Panel B: 2016 Balance Test			Panel C: 2016 Summary Stats		
	Control	Treated	Diff	Control	Treated	Diff	Total	W/t Contract	With Contract
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Main Outcomes									
Health Insurance with Intention				0.418	0.435	0.016	0.424	0.225	0.768
Pension with Intention				0.429	0.442	0.013	0.434	0.237	0.773
Health Insurance excl. Intention				0.371	0.376	0.005	0.372	0.159	0.742
Pension excl. Intention				0.381	0.375	-0.006	0.379	0.171	0.737
Baseline Indiv. Charact.									
2015 Health Insurance	0.339	0.337	-0.002	0.361	0.370	0.009	0.364	0.141	0.751
2015 Pension	0.338	0.349	0.011	0.359	0.384	0.024	0.368	0.156	0.734
Age	34.98	35.41	0.430	37.07	37.26	0.185	37.14	38.21	35.30
	(10.39)	(10.50)		(10.12)	(10.16)		(10.13)	(10.27)	(9.62)
Woman aged >40	0.149	0.164	0.015	0.179	0.185	0.006	0.181	0.219	0.114
Men aged >45	0.114	0.115	0.002	0.144	0.149	0.004	0.146	0.155	0.130
Years of Schooling	8.967	9.000	0.033	8.898	8.996	0.099	8.932	8.413	9.831
	(3.12)	(3.11)		(3.16)	(3.14)		(3.15)	(3.06)	(3.11)
Dummy for Males	0.567	0.570	0.003	0.565	0.586	0.021	0.572	0.559	0.595
Dummy for Being Working	0.996	0.997	0.001	0.995	0.997	0.002	0.996	0.994	1.000
Written Contract	0.370	0.361	-0.009	0.368	0.363	-0.005	0.366	0.000	1.000
Self-Employed	0.305	0.318	0.013	0.354	0.367	0.014	0.358	0.564	0.001
Willing to Stay Permanently	0.615	0.615	0.000	0.646	0.640	-0.006	0.644	0.656	0.622
Married	0.696	0.706	0.010	0.749	0.742	-0.007	0.746	0.787	0.677
Number of Children	1.068	1.095	0.027	1.159	1.165	0.006	1.161	1.256	0.997
	(0.90)	(0.89)		(0.88)	(0.88)		(0.88)	(0.87)	(0.87)
Firm Level Controls									
Firm Size	4.530	4.342	-0.188***	4.323	4.204	-0.119	4.281	3.186	6.178
	(2.61)	(2.50)		(2.57)	(2.50)		(2.55)	(2.19)	(1.94)
Firm Ownership									
State and collective	0.070	0.063	-0.007	0.072	0.068	-0.004	0.071	0.028	0.145
Domestic private	0.272	0.254	-0.018	0.246	0.231	-0.015	0.241	0.150	0.398
Foreign and joint venture	0.088	0.106	0.018**	0.090	0.110	0.020*	0.097	0.015	0.238
Self-employed	0.560	0.568	0.008	0.584	0.583	0.000	0.583	0.802	0.204
Other	0.009	0.009	0.000	0.008	0.008	0.000	0.008	0.004	0.015
City Indicators									
Dongguan	0.065	0.069	0.004	0.059	0.064	0.005	0.061	0.025	0.122
Shenzhen	0.064	0.066	0.001	0.071	0.072	0.001	0.071	0.051	0.107
Luoyang	0.065	0.067	0.002	0.076	0.078	0.002	0.077	0.084	0.064
Hefei	0.089	0.093	0.004	0.085	0.096	0.011	0.088	0.114	0.044
Bengbu	0.044	0.046	0.002	0.043	0.040	-0.003	0.042	0.061	0.009
Chongqing	0.086	0.093	0.007	0.089	0.106	0.017*	0.095	0.100	0.087
Shanghai	0.131	0.087	-0.044***	0.125	0.084	-0.041***	0.111	0.113	0.108
Nanjing	0.088	0.088	0.001	0.091	0.071	-0.020**	0.084	0.077	0.096
Wuxi	0.044	0.047	0.004	0.042	0.048	0.005	0.044	0.021	0.085
Hangzhou	0.091	0.095	0.004	0.080	0.088	0.009	0.083	0.080	0.088
Ningbo	0.047	0.051	0.004	0.041	0.048	0.007	0.043	0.029	0.068
Wuhan	0.095	0.100	0.005	0.096	0.097	0.000	0.096	0.120	0.055
Chengdu	0.092	0.097	0.005	0.102	0.108	0.007	0.104	0.125	0.067
No. of Observations	4244	2152		3005	1582		4587	3112	1475
P-value of F-test for Joint Sig.			0.079			0.158			

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Note: Standard deviation in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

Table 2: OLS Estimation of Average Treatment Effect and Contract Heterogeneity

	Panel A: Average Treatment Effects					
	Health Insurance			Pension		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Treated	0.008	0.011	0.011	-0.004	0.000	-0.000
	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
Lagged Dependent Variable	0.656***	0.546***	0.534***	0.627***	0.519***	0.504***
	(0.016)	(0.025)	(0.026)	(0.017)	(0.025)	(0.026)
R-squared	0.488	0.519	0.523	0.453	0.501	0.505
No. of Observations	4,587	4,587	4,587	4,560	4,560	4,560
	Panel B: Heterogeneous Treatment Effects					
	Health Insurance			Pension		
Treated	-0.030	-0.024	-0.028	-0.028	-0.020	-0.023
	(0.020)	(0.019)	(0.019)	(0.020)	(0.019)	(0.019)
Treated*No-Contract	0.062**	0.056**	0.060**	0.042	0.032	0.035
	(0.026)	(0.025)	(0.025)	(0.027)	(0.025)	(0.025)
No-Contract	-0.187***	-0.161***	-0.140***	-0.219***	-0.171***	-0.144***
	(0.023)	(0.026)	(0.026)	(0.024)	(0.027)	(0.026)
Lagged Dependent Variable	0.562***	0.545***	0.533***	0.519***	0.519***	0.504***
	(0.021)	(0.025)	(0.025)	(0.022)	(0.025)	(0.026)
R-squared	0.505	0.519	0.524	0.479	0.501	0.506
No. of Observations	4,587	4,587	4,587	4,560	4,560	4,560
No-Contract Treatment Effect	0.033**	0.031**	0.032**	0.015	0.012	0.013
Treated+[Treated*No-Contract]	[0.044]	[0.049]	[0.042]	[0.405]	[0.476]	[0.452]
	Panel C: Pension with Young Sample					
	Average Effects			Heterogeneous Effects		
Treated	0.002	0.011	0.012	-0.035	-0.028	-0.030
	(0.016)	(0.015)	(0.015)	(0.022)	(0.021)	(0.021)
Treated*No-Contract				0.072**	0.066**	0.071**
				(0.032)	(0.031)	(0.031)
No-Contract				-0.195***	-0.157***	-0.124***
				(0.029)	(0.032)	(0.032)
Lagged Dependent Variable	0.641***	0.496***	0.480***	0.544***	0.496***	0.480***
	(0.018)	(0.031)	(0.032)	(0.027)	(0.031)	(0.032)
R-squared	0.489	0.530	0.536	0.507	0.531	0.537
No. of Observations	2,925	2,925	2,925	2,925	2,925	2,925
No-Contract Treatment Effect				0.037*	0.038*	0.040*
Treated+[Treated*No-Contract]				[0.097]	[0.078]	[0.059]

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Notes: The dependent variable includes both actual and intended participation. The additional variables included in Model 1 are a vector of city fixed effects; in Model 2 we also add individual level controls (age, gender, education, marital status, number of children, dummies for self-employment, dummy for working and an interaction between self-employment and lagged (2015) dependent variable and dummy for "willingness to remain in the city permanently if policy permits."), while Model 3 adds firm level controls (pre-treatment firm size and ownership indicator variables) as well. Robust standard errors clustered at the workplace level are in parentheses. P-values from the F-tests for joint significance are in brackets. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: OLS Estimation of Treatment Effects with Relative Premium Interactions

	Health Insurance			Pension		
Panel A: Average Treatment Effects						
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Treated	0.078**	0.091***	0.095***	-0.005	0.002	-0.005
	(0.032)	(0.031)	(0.031)	(0.053)	(0.052)	(0.052)
Treated*Price	-1.020**	-1.175***	-1.240***	0.044	0.063	0.109
	(0.434)	(0.421)	(0.422)	(0.327)	(0.316)	(0.319)
Lagged Dependent Variable	0.655***	0.544***	0.532***	0.641***	0.496***	0.480***
	(0.016)	(0.025)	(0.026)	(0.018)	(0.031)	(0.032)
R-squared	0.489	0.520	0.524	0.489	0.530	0.536
No. of Observations	4,587	4,587	4,587	2,925	2,925	2,925
Panel B: Heterogeneous Treatment Effects						
	Health Insurance			Pension		
Treated	0.027	0.030	0.032	0.028	0.037	0.029
	(0.041)	(0.041)	(0.041)	(0.071)	(0.070)	(0.070)
Treated*No-Contract	0.128**	0.123*	0.126**	-0.040	-0.053	-0.051
	(0.064)	(0.063)	(0.063)	(0.105)	(0.102)	(0.102)
Treated*Price	-0.917	-0.879	-0.979*	-0.404	-0.421	-0.381
	(0.597)	(0.591)	(0.589)	(0.465)	(0.454)	(0.451)
No-contract dummy	-0.146***	-0.128***	-0.095**	-0.031	0.015	0.045
	(0.046)	(0.047)	(0.046)	(0.068)	(0.070)	(0.071)
No-contract*Price	-0.725	-0.621	-0.783	-1.012**	-1.052***	-1.041**
	(0.635)	(0.617)	(0.611)	(0.409)	(0.398)	(0.406)
No-contract*Price*Treated	-0.798	-0.823	-0.789	0.696	0.742	0.760
	(0.859)	(0.848)	(0.851)	(0.658)	(0.633)	(0.632)
Lagged Dependent Variable	0.557***	0.542***	0.528***	0.546***	0.502***	0.486***
	(0.021)	(0.025)	(0.026)	(0.026)	(0.031)	(0.032)
R-squared	0.507	0.521	0.526	0.509	0.532	0.539
No. of Observations	4,587	4,587	4,587	2,925	2,925	2,925
No contract treated price effect	-1.715***	-1.702***	-1.768***	0.292	0.321	0.379
	[0.001]	[0.005]	[0.004]	[0.519]	[0.457]	[0.384]
No contract treatment effect						
At median premium	0.026	0.025	0.026*	0.031	0.032	0.033
	[0.104]	[0.113]	[0.100]	[0.177]	[0.160]	[0.139]
At 25th percentile premium	0.076***	0.074***	0.077***	0.021	0.020	0.019
	[0.001]	[0.001]	[0.001]	[0.511]	[0.513]	[0.526]
At 10th percentile premium	0.121***	0.119***	0.124***	0.015	0.014	0.012
	[0.001]	[0.001]	[0.001]	[0.691]	[0.707]	[0.743]

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Notes: The additional variables included in Model 1 are a vector of city fixed effects; in Model 2 we also add individual level controls (age, gender, education, marital status, number of children, dummies for selfemployment, dummy for working and an interaction between self-employment and lagged (2015) dependent variable and dummy for "willingness to remain in the city permanently if policy permits."), while Model 3 adds firm level controls (pre-treatment firm size and ownership indicator variables) as well. Robust standard errors clustered at workplace of household head are in parentheses. P-values are in brackets. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Welfare Impact of the Information Intervention

	Eq (6): Price Interaction		Eq (7): Price and Contract Interactions					
			With Contract		No contract		full sample	
	Total Annual Increase (in 10,000 Yuan)	Average Annual Effect (in Yuan)	Total Annual Increase (in 10,000 Yuan)	Average Annual Effect (in Yuan)	Total Annual Increase (in 10,000 Yuan)	Average Annual Effect (in Yuan)	Total Annual Increase (in 10,000 Yuan)	Average Annual Effect (in Yuan)
Dongguan	11965.25	39.05	687.25	3.04	9762.53	121.41	10449.78	34.11
Shenzhen	33721.77	80.16	4312.85	18.62	43496.86	230.06	47809.71	113.65
Luoyang	105.19	12.24	4.13	1.56	285.79	47.96	289.92	33.72
Hefei	0.53	0.01	413.61	38.76	251.06	5.27	664.67	11.40
Bengbu	16.77	2.86	6.16	13.62	104.70	19.34	110.86	18.90
Chongqing	439.25	5.77	209.90	8.26	1502.23	29.61	1712.14	22.49
Shanghai	3750.51	8.32	19466.71	120.73	759.26	2.62	20225.98	44.84
Nanjing	33.38	0.74	1122.61	59.39	27.43	1.05	1150.04	25.51
Wuxi	0.54	0.01	2154.82	43.20	121.96	5.76	2276.78	32.03
Hangzhou	70.29	0.53	3285.35	64.26	150.82	1.88	3436.17	26.13
Ningbo	889.42	11.69	218.23	5.01	1646.21	50.63	1864.44	24.51
Wuhan	294.96	3.40	1236.09	68.45	25.65	0.37	1261.75	14.55
Chengdu	838.90	7.54	2536.90	97.10	260.40	3.06	2797.30	25.15
Total	52126.76	28.20	35654.62	41.19	58394.90	59.40	94049.52	50.87

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Notes: The estimates are based on demand curves estimated in Appendix A.9.

Table 5: Robustness Checks

	Health Insurance		Pension	
Panel A: Treatment on the Treated				
	Eq (5): Contract Int.	Eq (6): Price Int	Eq (5): Contract Int.	Eq (6): Price Int
Received a Pamphlet	-0.029	0.102***	-0.033	-0.005
	(0.020)	(0.033)	(0.023)	(0.054)
Received a Pamphlet*No-Contract	0.064**		0.075**	
	(0.026)		(0.032)	
Received a Pamphlet*Price		-1.328***		0.111
		(0.447)		(0.327)
No-Contract Treatment Effect	0.035**		0.042**	
RP+[RP*No-Contract]	[0.040]		[0.057]	
No. of Observations	4,587	4,587	2,925	2,925
Panel B: Correcting for Potential Attrition Bias				
	Health Insurance		Pension	
	Eq (5): Contract Int.	Eq (6): Price Int	Eq (5): Contract Int.	Eq (6): Price Int
Treated	-0.018	0.105	-0.033	0.005
	[-0.060, 0.026]	[0.037, 0.173]	[-0.081, 0.019]	[-0.101, 0.118]
Treated*No-Contract	.055		0.071	
	[0.001, 0.105]		[0.010, 0.137]	
Treated*Price		-1.287		0.029
		[-2.249, -0.393]		[-0.646, 0.722]
F-statistics	14.56	14.48	9.09	9.05
No. of Observations	4,587	4,587	2,925	2,925
Panel C: Correcting for Potential Income Effect				
	Health Insurance		Pension	
	City Income	Individual Income	City Income	Individual Income
Treated	0.232**	0.094***	-0.026	0.006
	(0.090)	(0.032)	(0.144)	(0.052)
Treated*Price	-1.294***	-1.260***	0.080	0.028
	(0.439)	(0.424)	(0.357)	(0.318)
Treated*(City Ave. Mig. Mon. Earnings/1000)	-0.038*		0.006	
	(0.022)		(0.031)	
Ln(Individual Monthly Earnings)		-0.006		-0.001
		(0.011)		(0.014)
No. of Observations	4,587	4,471	2,925	2,834
Panel D: Excluding the Self-employed				
	Health Insurance		Pension	
	Eq (5): Contract Int.	Eq (6): Price Int	Eq (5): Contract Int.	Eq (6): Price Int
Employed				
Treated	-0.026	0.101***	-0.031	-0.021
	(0.019)	(0.035)	(0.021)	(0.060)
Treated*No-Contract	0.067**		0.070*	
	(0.032)		(0.040)	
Treated*Price		-1.525***		0.122
		(0.472)		(0.372)
No. of Observations	2,638	2,638	1,848	1,848
No-Contract Treatment Effect	0.041*		.039	
Treated+[Treated*No-Contract]	[0.098]		[0.224]	
Self-employed				
Treated	0.024	0.071	0.039	0.014
	(0.021)	(0.071)	(0.028)	(0.092)
Treated*Price		-0.630		0.152
		(0.926)		(0.555)
No. of Observations	1,949	1,949	1,077	1,077

To be continued on the next page

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Notes: All regressions are using the Model 3 specification (see note to Table 2). Panel A conducts IV estimation where "received a pamphlet" is the endogenous variable, and the treatment status is the IV. Panel B conducts Heckman Two-step estimation to correct potential attrition bias where the trustworthiness and reliableness of respondents are taken as the exclusion restrictions. Panel C conducts OLS estimation to control for potential income effect, and Panel D conduct OLS estimation on the employed and self-employed samples, respectively. Except Panel B, robust standard errors clustered at workplace of household head are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1. In Panel B, the 95% bootsraping percentile confidence intervals are in the square brackets, which are calculated by pair cluster bootstrap with 1000 replications.

Table 5: Robustness Checks (continued)

Panel E: Actual vs Intended Participation – Health Insurance

	Eq (5): Contract Int.				Eq (6): Price Int	
	One Interaction		Two Interactions			
	Intension	Actual	Intension	Actual	Intension	Actual
Treated	-0.001	-0.017			0.005**	0.064**
	(0.002)	(0.018)			(0.002)	(0.026)
Treated*Price					-0.070**	-0.827**
					(0.030)	(0.346)
Treated*No-contract	0.003*	0.038*	0.002*	0.021*		
	(0.002)	(0.022)	(0.001)	(0.012)		
Treated*Contract			-0.001	-0.017		
			(0.002)	(0.018)		
No. of Observations	4,587		4,587		4,587	

Panel F: Actual vs Intended Participation – Pension

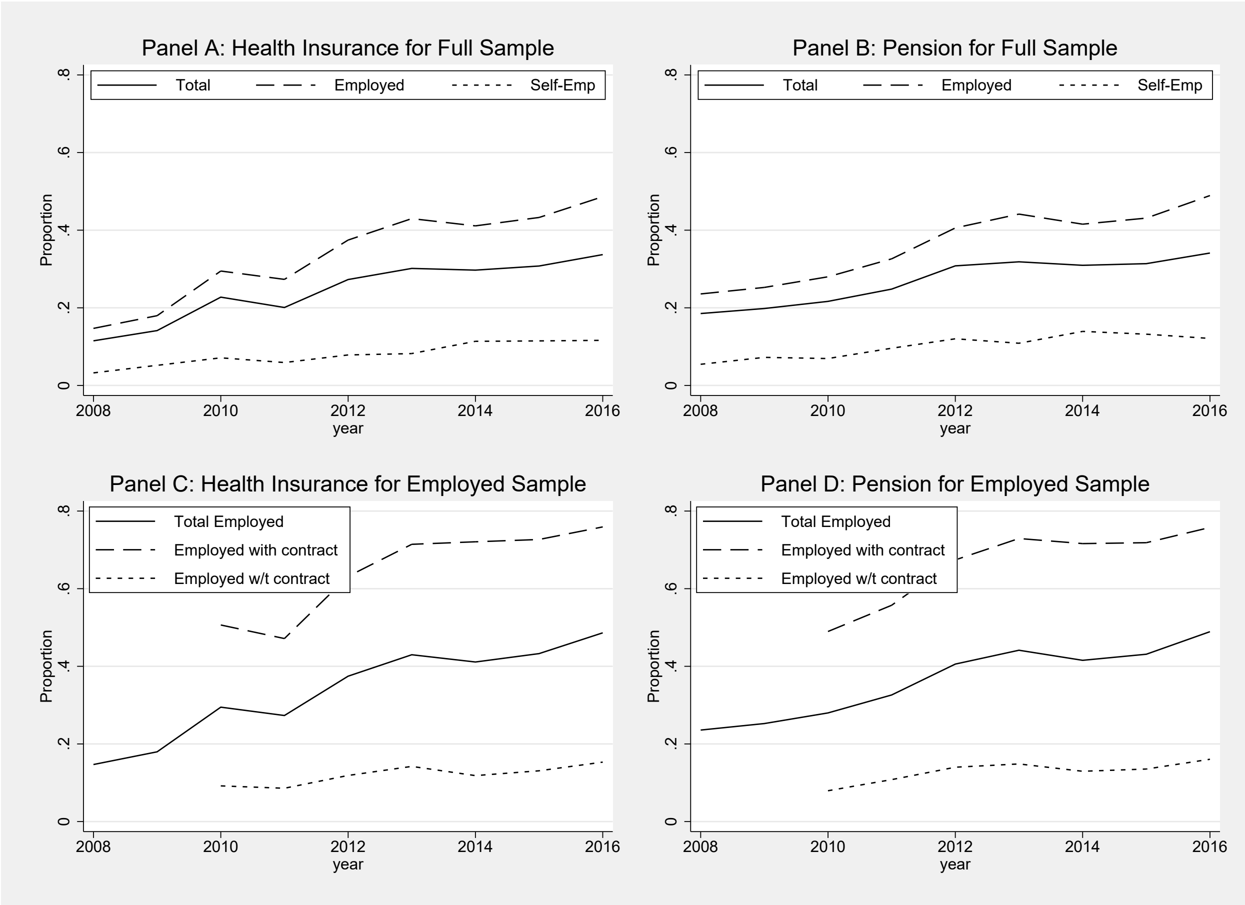
	Eq (5): Contract Int.				Eq (6): Price Int	
	One Interaction		Two Interactions			
	Intension	Actual	Intension	Actual	Intension	Actual
Treated	-0.003*	-0.038*			-0.002	-0.036
	(0.001)	(0.022)			(0.003)	(0.045)
Treated*Price					0.016	0.241
					(0.017)	(0.275)
Treated*No-contract	0.004***	0.062**	0.002	0.024		
	(0.001)	(0.027)	(0.001)	(0.015)		
Treated*Contract			-0.003	-0.038*		
			(0.002)	(0.022)		
No. of Observations	2,925		2,925		2,925	

Panel G: Test for spillover effect

	Health Insurance			Pension		
	Firm spill.	HC spill.	Both	Firm spill.	HC spill.	Both
Treated	0.090***	0.121***	0.116***	-0.005	0.014	0.015
	(0.033)	(0.034)	(0.037)	(0.053)	(0.053)	(0.054)
Treated*Price	-1.231***	-1.101***	-1.092***	0.127	0.196	0.216
	(0.423)	(0.421)	(0.423)	(0.319)	(0.324)	(0.324)
Mixed-Firm	-0.016		-0.016	-0.018		-0.017
(both treated & control)	(0.019)		(0.019)	(0.023)		(0.023)
Treated*Mixed-Firm	0.018		0.019	-0.006		-0.008
	(0.027)		(0.027)	(0.035)		(0.035)
Mixed-Home Cnty		-0.015	-0.016		0.002	0.002
(both treated & control)		(0.015)	(0.015)		(0.018)	(0.018)
Treated*Mixed-Home Cnty		-0.050*	-0.049*		-0.051	-0.052
		(0.027)	(0.027)		(0.032)	(0.032)
No. of Observations	4,587	4,587	4,587	2,925	2,925	2,925
R-squared	0.524	0.525	0.526	0.536	0.537	0.537

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Notes: All regressions are using the Model 3 specification (see note to Table 2); Panels E and F present the marginal effects from ordered Probit models. Robust standard errors clustered at workplace of household head are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

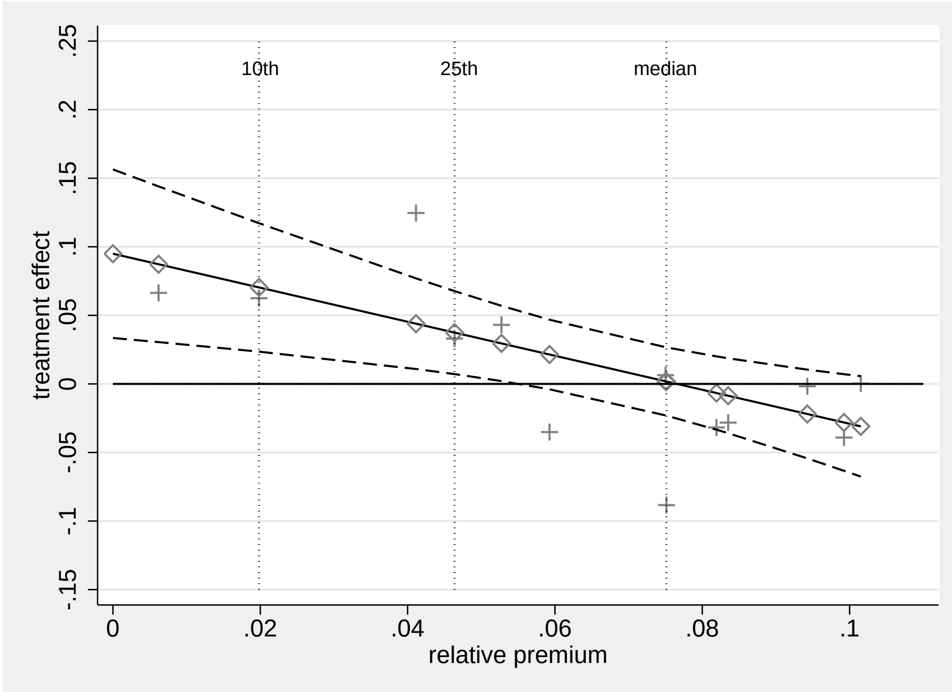
Figure 1: Rates of Participation in Urban Employee Health Insurance and Pension Programs among China's Rural Migrants



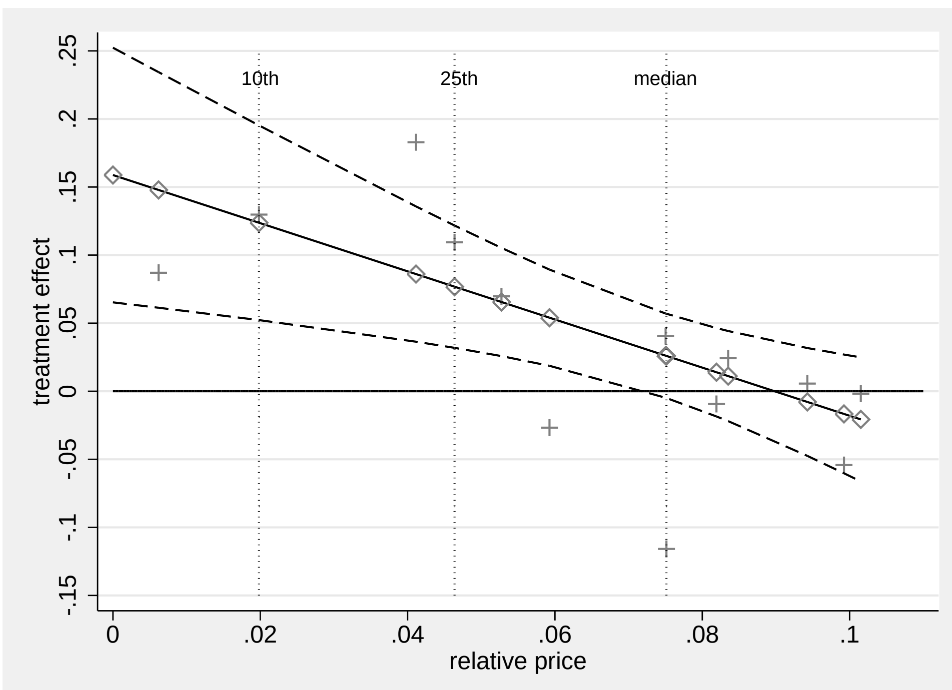
Source: 2008-2016 waves of the Rural-Urban Migration in China (RUMiC) Survey.

Notes:The employed sample of migrants excludes self-employed workers. Of the total 2015 RUMiC sample 32 percent, 30 percent and 38 percent were employed with a contract, employed without a contract and self-employed, respectively.

Figure 2: The Treatment Effect for Migrants Declines with the City Relative Health Insurance Premium



(a) The effect on all migrants, predicted from Model 3 of Eqs. (6a and 6b)

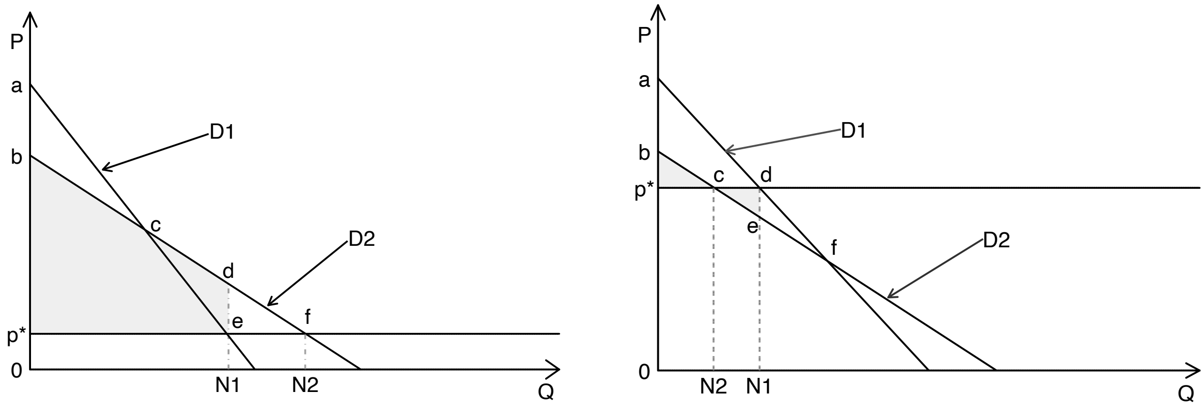


(b) The effect on migrants without a contract, predicted from Model 3 of Eqs. (7a and 7b)

Source: 2015 and 2016 waves of the Rural-Urban Migration in China (RUMiC) Survey, and RUMiC Information Intervention Survey, 2016.

Notes: The vertical dotted lines indicate the 10th percentile, 25th percentile and median relative premiums. The diamonds are predicted values using equations 6a and 7a while the crosses are estimated coefficient of β_j for each city from equations 6b and 7b.

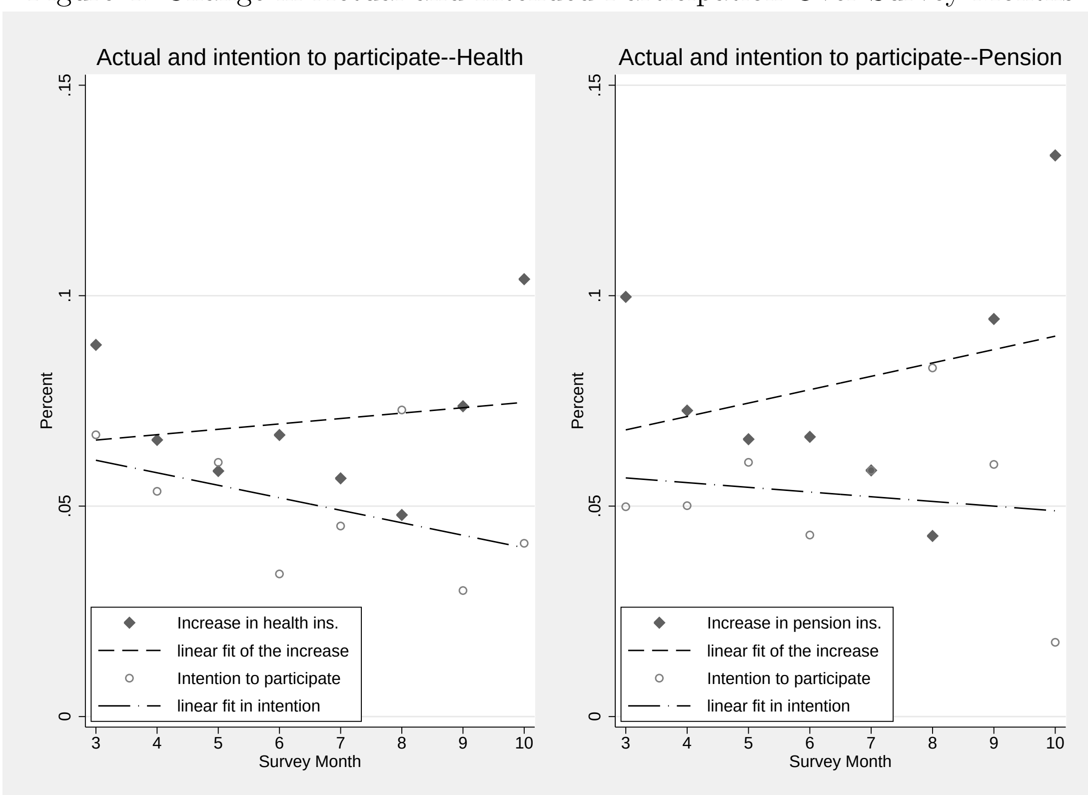
Figure 3: Consumer Surplus with and without Information Frictions



(a) $\alpha - \beta > 0$, $N1 < N2$

(b) $\alpha - \beta > 0$, $N1 > N2$

Figure 4: Change in Actual and Intended Participation Over Survey Months



Source: 2015 and 2016 waves of the Rural-Urban Migration in China (RUMiC) Survey, and RUMiC Information Intervention Survey, 2016.

Notes:The figures above show the change in actual and intended participation in health insurance and pension programs, respectively.

Online Appendix

The following tables and figures are intended for a supplementary appendix to be made available on-line.

A.1 Summary Statistics

Table A.1: Annual Participation Rates in Pension Programs and Health Insurance

	Panel 1: Full Sample			Panel 2: 2008 and New Sample			Panel 3: 2008 and Old Sample		
Panel A: Overall participation									
	Total	Employee	Self-emp	Total	Employee	Self-emp	Total	Employee	Self-emp
Panel A1: Health insurance									
2008	11.50	14.71	3.24	11.50	14.71	3.24	11.50	14.71	3.24
2009	14.14	17.97	5.19	14.04	16.83	5.25	14.30	20.39	5.13
2010	22.75	29.48	7.12	20.52	24.90	6.47	25.00	35.05	7.55
2011	20.09	27.33	5.91	18.23	22.26	7.30	21.34	31.40	5.25
2012	27.28	37.46	7.86	31.35	39.02	7.98	25.23	36.48	7.82
2013	30.16	42.99	8.22	27.26	35.93	6.16	31.50	46.89	8.91
2014	29.71	41.12	11.38	28.32	35.31	12.06	30.40	44.62	11.14
2015	30.78	43.28	11.48	29.36	36.10	11.87	31.48	48.00	11.36
2016	33.72	48.62	11.63	31.19	40.34	8.93	34.85	53.45	12.40
Panel A2: Pension									
2008	18.53	23.58	5.46	18.53	23.58	5.46	18.53	23.58	5.46
2009	19.82	25.26	7.24	20.24	24.53	6.85	19.12	26.79	7.64
2010	21.66	27.99	6.94	18.53	22.11	7.05	24.83	35.13	6.86
2011	24.83	32.62	9.59	24.48	28.98	12.28	25.06	35.54	8.31
2012	30.82	40.57	12.02	33.19	40.06	12.13	29.61	40.90	11.99
2013	31.85	44.14	10.87	28.44	36.17	9.64	33.44	48.56	11.29
2014	30.95	41.54	13.93	29.27	35.43	14.87	31.79	45.25	13.60
2015	31.38	43.11	13.21	30.45	37.30	12.55	31.84	46.94	13.41
2016	34.11	48.92	12.12	31.66	40.71	9.59	35.22	53.70	12.85
Panel B: Participation Rate among Employees									
	overall	with contr.	without contr.	overall	with contr.	without contr.	overall	with contr.	without contr
Panel B1: Health insurance									
2010	29.48	50.65	9.20	24.90	42.79	8.09	35.05	59.76	10.63
2011	27.33	47.16	8.59	22.26	39.11	6.62	31.40	53.49	10.22
2012	37.46	63.18	11.88	39.02	63.03	13.36	36.48	63.27	11.00
2013	42.99	71.44	14.21	35.93	64.20	9.51	46.89	75.17	17.17
2014	41.12	72.08	11.85	35.31	64.97	9.10	44.62	76.08	13.66
2015	43.28	72.68	13.08	36.10	61.84	10.77	48.00	79.57	14.69
2016	48.62	75.92	15.32	40.34	67.61	10.15	53.45	80.43	18.62
Panel B2: Pension									
2010	27.99	48.98	7.94	22.11	39.22	6.23	35.13	60.22	10.16
2011	32.62	55.73	10.81	28.98	49.04	10.29	35.54	61.03	11.24
2012	40.57	67.41	14.01	40.06	64.33	14.10	40.90	69.48	13.95
2013	44.14	72.93	14.85	36.17	64.10	9.54	48.56	77.49	18.18
2014	41.54	71.61	12.96	35.43	63.33	10.73	45.25	76.30	14.44
2015	43.11	71.85	13.54	37.30	63.60	11.38	46.94	77.11	15.05
2016	48.92	75.77	16.06	40.71	67.93	10.21	53.70	80.03	19.77

Source: RUMiC Migrant Survey 2008 and 2016.

A.2 Examples of City-Level Health Insurance and Pension Details

Table A.2: Basic features of health insurance and pension schemes in Shenzhen.

Shenzhen		Health Insurance	Pension
Cost	Employees	*First Class:* Employer Contribution: 6.2 % of wage or minimum wage base. Employee Contribution: 2 % of wage or minimum wage base. Minimum Wage Base: 60 % of city-average employee wage in previous year. *Second Class:* Employer Contribution: 0.6% of city average employee wage in previous year. Employee Contribution: 0.2% of city average employee wage in previous year. *Third Class:* Employer Contribution: 0.45% of city average employee wage in previous year. Employee Contribution: 0.10% of city average employee wage in previous year.	Employer Contribution: 13% of payroll. Employee Contribution: 8% of wage. Minimum Wage Base: Minimum wage.
	Self-Employed	Minimum cost to participate *First Class:* 4.92% of city average employee wage in previous year. *Second Class:* 0.8% of city average employee wage in previous year. *Third Class:* 0.55% of city average employee wage in previous year.	Minimum Cost to Participate: 21% of minimum wage.
Benefit	Inpatient	Deductibles: (Same for all three classes) Tier 3 Hospital: 300 Yuan RMB. Tier 2 Hospital: 200 Yuan RMB. Tier 1 Hospital or below: 100 Yuan RMB. Reimbursement Share: First and Second Class: 90% for all hospitals Third Class: Tier 3 Hospital: 75% Tier 2 Hospital: 80% Tier 1 Hospital or below: 85%	After retirement, individuals eligible for pension if they have made 15 years of contributions. Pension = Base pension + Pension from individual account. Base pension is a function of number of years participating in the pension scheme, the total of annual premiums paid into the scheme, and the city-average wage when the pension is paid out. For example, if a participant made payments into the system for X years ($x \geq 15$), and the pay base is the city average wage, then the base pension benefit is X%*city average wage.
	Outpatient	First Class: Individual account covers some medical expense when the out-of-pocket expenses are more than 5% of the average city wage in the previous year, in which case 70% over this threshold may be reimbursed. 30% of expenses at community clinics can be reimbursed. Treatment for some special diseases may be reimbursed. Second and Third Class: No treatments or drugs may be expensed from the individual account, with the exception of some special diseases and drugs which may be partially reimbursed.	The pension paid from the individual account = (accumulation in the account)/139. All of the employee contributions are paid into individual accounts, and 8/21 of payments made by the self-employed are paid into individual accounts.

Table A.2: Basic features of health insurance and pension schemes in Ningbo.

Ningbo		Health Insurance	Pension
Cost	Employees	*Urban Employee Basic Medical Insurance:* Employer Contribution: 11% of previous years payroll + 5 yuan/month Employee Contribution: 2% of average monthly wage in previous year. Minimum Wage Base: 60% of city-average employee wage in previous year. *Migrant Medical Insurance:* Employer Contribution: 3.3% of city-average employee wage in previous year. Employee Contribution: 0.6% of city-average employee wage in previous year.	*Urban Employee Basic Pension:* Employer Contribution: 14% of previous year payroll. Employee Contribution: 8% of average monthly wage in previous year. Minimum Contribution Base: 60% of city-average employee wage in previous year. *Migrant Pension:* Employer Contribution: 14% of previous year payroll. Employee Contribution: 8% of average monthly wage in previous year. Minimum Contribution Base: Minimum wage.
	Self-Employed	*Urban Employee Basic Medical Insurance (min cost to participate):* 7.8% of city-average employee wage in previous year + 5 yuan/month *Migrant Medical Insurance (min cost to participate):* 3.9% of city-average wage in previous year.	*Urban Employee Basic Pension (min cost to participate):* 14.4% of city-average employee wage in previous year. *Migrant Pension (min cost to participate):* 18% of minimum wage.
Benefit	Inpatient	Deductibles: (Same for both schemes) Tier 3 Hospital: 1200 Yuan RMB. Tier 2 Hospital: 600 Yuan RMB. Tier 1 Hospital: 600 Yuan RMB. Community Clinic: 300 Yuan RMB. Reimbursement Share (same for both schemes): Under 35K: 80% (85% for community clinics). 35K-70K: 85% (90% for community clinics). Over 70K: 95%	*Urban Employee Basic Pension:* After retirement, individuals are eligible for a pension if they have made 15 years of contributions. Pension=Base Pension + Pension from individual account. Base pension is a function of number of years participating in the pension scheme, the total of annual premiums paid into the scheme, and the city-average wage when the pension is paid out. For example, if a participant made payments into the system for X years($X \geq 15$), and the pay base is the city average wage, then the base pension benefit is X%*city average wage. The pension paid from the individual account = (accumulation in the account)/139. All of the employee contributions are paid into individual accounts, and 8/21 of payments made by the self-employed are paid into individual accounts. *Migrant Pension:* The pension scheme can be discounted as the low standard pension scheme in Ningbo.
	Outpatient	Both schemes establish individual account which can cover out-patient expenses. The individual account accumulation is more in *UEBMI* scheme than *MMI* scheme. When individual account is used up, *UEBMI* scheme provide additional reimbursement on out-patient expenses as follows. Deductible: those under 45: 900 Yuan those aged 45 or above: 600 Yuan Reimbursement share: Tier 3 hospital: 75% Tiers 2 and 1 hospital: 86% Community clinic: 80% Expense on some special diseases and drugs, and treatment can be partially reimbursed for both schemes.	

A.3 Pamphlet Example

东莞社保部门地址

东莞市人力资源和社会保障局
地址：东莞市万江区107国道石美路段渔涌湾综合大楼

莞城社保局
地址：东莞市莞城区旗峰路309号浩宇大厦二楼

东城社保局
地址：东城大道综合服务楼（新世界花园对面，东城区府旁边）

南城社保局
地址：东莞市南城区袁屋边宏北路2号（东莞市南城汽车客运站斜对面）

万江社保局
地址：东莞市万江区107国道石美段渔涌湾综合大楼（在名泰家居广场旁边）

长安社保局
地址：东莞市长安镇体育路育才街社保大楼

虎门社保局
地址：东莞市虎门镇行政区金龙路63号劳动保障大楼（明苑大酒店对面）

厚街社保局
地址：东莞市厚街镇厚街大道西13号（劳务市场侧）

中堂社保局
地址：东莞市中堂镇北潢西路7号（中堂镇斗朗工业大道江南农批市场旁）

黄江社保局
地址：黄江镇江海城富海大道68号（环保分局对面，中移动黄江分公司旁边）

大朗社保局
地址：东莞市大朗镇升平路71号

常平社保局
地址：东莞市常平镇南城路常平社保分局大楼

石龙社保局
地址：东莞市石龙镇黄洲京瓷北路14-3小区社保大楼

石碣社保局
地址：东莞市石碣镇崇焕中路（镇消防队西侧）

茶山社保局
地址：东莞市茶山镇下朗村马安岭（茶山镇人民政府大院右边）

横沥社保局
地址：东莞市横沥镇财贸路（横沥交通分局侧面）

东坑社保局
地址：东莞市东坑镇东坑大道70号社保大楼三楼（东坑镇政府斜对面）

寮步社保局
地址：东莞市寮步香市大道行政小区

道滘社保局
地址：东莞市道滘镇西部干道道滘路段旁（即道滘绿福大酒楼斜对面）

麻涌社保局
地址：东莞市麻涌镇中麻公路新基路段（邻近新基村路口）

谢岗社保局
地址：东莞市谢岗镇公园街一号

桥头社保局
地址：东莞市桥头镇桥光大道社保大楼

企石社保局
地址：东莞市企石镇振兴路86号（企石购物酒楼对面）

清溪社保局
地址：东莞市清溪镇清风路行政新区社保大楼（电信大楼斜对面）

塘厦社保局
地址：塘厦镇塘龙东路61号社会保险大厦（云海酒店旁边、东浦市场对面）

沙田社保局
地址：东莞市沙田镇港口大道沙田段（海关大楼对面）

洪梅社保局
地址：东莞市洪梅镇桥东路42号（东莞银行洪梅支行对面）

凤岗社保局
地址：东莞市凤岗镇政通路6号社保大楼（位于凤岗国税与工商分局之间）

樟木头社保局
地址：樟木头镇东城区政通路1号社保大楼（国税分局后面、供电公司旁）

大岭山社保局
地址：东莞市大岭山镇大岭山大道368号

望牛墩社保局
地址：东莞市望牛墩镇镇中路花园街1号（南方电网后面、国土分局旁）

松山湖社保局
地址：东莞市松山湖高新技术产业开发区礼宾路1号行政办事中心附楼

注：由于社保政策每年都会调整，具体情况请参见东莞当地人力资源和社会保障局。电话：0769-12333。

免责声明：由于社保政策每年都会调整，请您参保前咨询当地社保部门。如本宣传册与当前政策有所不同，中国外来务工项目不承担任何责任。

东莞市外来务工人员

社会医疗养老保险指南

社会保障，让生活更美好

中国外来务工人员项目组

亲爱的外来务工朋友，您知道如果您参加了东莞市的社会医疗和养老保险，您可以获得什么福利吗？

医疗保险：
住院费用：超过起付标准以上的费用报销35%-95%；
门诊费用：报销35%-70%的费用。（详情请见第2页）

养老保险：从您退休开始，您可以按月领取养老金，直至去世。（详情请见3页）

如果您离开东莞呢？**如果转入地同意接收**，您可以将您的医疗和养老保险带走，在新的定居地继续享受医疗，养老保险。

要想得到这些福利您需要花多少钱来参加这些保险呢？

东莞社会基本医疗和养老保险

单位雇工：医疗保险每月只需交纳15元，养老保险需缴纳您月工资的8%。

个体户：医疗保险每月缴纳69元，养老保险每月至少缴纳506元。

以上只是东莞社保的大致情况，具体缴费标准和福利待遇需要根据您的具体情况确定。如您想了解详细的保险缴费和福利信息，请翻阅本手册。您也可以前往东莞市各区人力资源和社会保障局（地址见最后一页）或拨打0769-12333来了解相关情况。

一、医疗和养老保险的适合人群

无论您是雇工还是个体户，您都可以参加东莞社会基本医疗和养老保险。

当您离开东莞时，**如果转入地同意接受**，您可将医疗和养老保险转走。

二、参加东莞社会基本医疗保险

1. 费用缴纳：

若您是用人单位的雇工，2015年您每月只需缴纳15.02元，保费由用人单位按月代扣代缴。

若您是个体户，2015年您每月只需缴纳69.12元。

2. 保险待遇：

市内医院住院报销比例：

医院机构等级	起付标准（元）	5万元以下	5万至10万	10万至15万	15万以上
三级	1300	85%	65%	45%	35%
二级	800	90%	70%	50%	40%
一级及以下	500	95%	75%	55%	45%

3. 门诊报销：在参保社区指定的社区卫生服务机构就医，门诊费用可报销70%。如需转诊，在转诊医院的门诊费用可报销35%至70%。对于特殊疾病，门诊费用可报销75%。详情请询问当地社保部门.

4. 大病医疗：在参保年度内，如您个人需要支付的住院或特定门诊费用超过3.5万元，您还有机会获得额外的补助。详情请咨询当地社保部门。

三、参加东莞社会基本养老保险

1. 费用缴纳：

如您是单位的雇工，您需按月工资的8%缴纳保费，保费由用人单位按月代扣。您的保费全部进入个人账户。此外，用人单位和政府会对个人账户进行额外补贴。

如果您是个体户，您有多档保费可供选择，2015年的最低参保费用是每月505.68元。您的部分保费将进入您的个人账户，具体个人账户累计情况请咨询当地社保部门。

2. 保险待遇：

社会基本养老保险享受的方式是参保人员到达法定退休年龄后，从办理退休起，按月领取养老金，直至死亡。退休金额将由缴费数量、缴费年限和退休时平均工资决定。缴费越多、缴费年限越长，退休时社会平均工资越高，则养老金越高。

Dear migrant workers, are you aware of the benefits of purchasing social medical insurance and age pension insurance in Dongguan?

Medical insurance

- Hospital and medical cover: 35% -90% of your expenditure above the minimum standard to receive benefits
- Outpatient treatment cover: 35-%70% of your expenditure (please refer to Page 2 for more details)

Age pension insurance:

- you are entitled to get pension every month from your retirement until death. (please refer to Page 3 for more details)
- If you no longer lives in Dongguan , your previously purchased social medical and age pension insurance can be transferred to the new city you are moving to as long as it is acceptable there.

How much you need to pay to enjoy the benefit of these insurances?

Basic social medical insurance and age pension insurance

- As an employee: the cost is RMB 15 per month for medical insurance and 8% of you monthly salary for an age pension insurance
- If self-employed: the cost is RMB 69 per month for medical insurance and a minimum of RMB 506 per month for an age pension insurance

The above is the standard social insurance information for Dongguan, conditions may change and the premium and entitlement may vary depending on individual situation.

To get more information on premium and entitlement, please read information in this brochure or alternatively, you can visit any of the branch of Dongguan human resources and social insurance bureau (see the first page for the addresses) or call on 0769-12333.

Detailed information:

1. Eligible Population:
   All employees and self-employed are eligible to purchase Dongguan social medical insurance and age pension insurance. When you leave in Dongguan, you can transfer your purchased social medical and age pension insurance to the new city if the new location accepts it.
2. Purchase Dongguan basic social medical insurance
   a) Premium: if you are an employee, the monthly rate is RMB 15.02 in 2015, your employer will deduct this from your salary and pay on your behalf. If you are self-employed, monthly rate is RMB 69.12 in 2015
   b) what's covered?
   Coverage of hospitalization cost (hospital and medical cost)in urban hospital

Hospital classification	Excess (RMB)	Coverage by Total Expenditure (Thousand RMB)			
		<= 50	50 to 100	100 to 150	> 150
Level 3	1300	85%	65%	45%	35%
Level 2	800	90%	70%	50%	40%
<=Level 1	500	95%	75%	55%	45%

   c) coverage for outpatient treatment: 70% expenditure at designated community health and medical clinic within your insured area. When a transfer is requested, 35% to 70% expenditure at transferred hospital. For some specific treatments, a 75% coverage applies, please visit your local social insurance office for more details.
   d) Serious illness treatment: during the insured calendar year, if your out of pocket hospital and outpatient payment is over RMB 35,000, extra coverage may apply. Please visit your local social insurance office for more details.
3. Sign up for Dongguan basic social age pension insurance
   a) Payment rate: if you are an employee, the monthly rate is 8% of your monthly salary, your employer will deduct this from your salary and pay on behalf. This will be paid to your personal withhold account. In addition, your employer and the government will pay extra to your personal withhold account. If you are self-employed, a few options are available . The minimum monthly rate in 2015 is RMB 505.68, partial of this personal payment will be accumulated in your personal withhold account, you can get a statement of your personal withhold account by visiting a local social insurance office.
   b) Benefits: anyone who purchased age pension insurance is entitled to receive a monthly pension from when they reaches the mandatory age for retirement until their death. The pension you received is calculated based on your payment rate, length of your payment, and your salary before retirement. The more and longer you pay for the insurance and the more of salary you receive at retirement, the more of pension you will receive.

A.4 Full Results of Equation 5 (Panel B of Table 2)

Full Results of Panel B of Table 2

	Health Insurance			Pension		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Treated	-0.030	-0.024	-0.028	-0.028	-0.020	-0.023
	(0.020)	(0.019)	(0.019)	(0.020)	(0.019)	(0.019)
Treated*No-Contract	0.062**	0.056**	0.060**	0.042	0.032	0.035
	(0.026)	(0.025)	(0.025)	(0.027)	(0.025)	(0.025)
No-Contract	-0.187***	-0.161***	-0.140***	-0.219***	-0.171***	-0.144***
	(0.023)	(0.026)	(0.026)	(0.024)	(0.027)	(0.026)
Lagged Dependent Variable	0.562***	0.545***	0.533***	0.519***	0.519***	0.504***
	(0.021)	(0.025)	(0.025)	(0.022)	(0.025)	(0.026)
Age		0.001	0.000		0.003**	0.003**
		(0.001)	(0.001)		(0.001)	(0.001)
Women Aged>40		-0.066***	-0.064***		-0.114***	-0.109***
		(0.023)	(0.023)		(0.025)	(0.025)
Men Aged>45		-0.034	-0.036		-0.082***	-0.082***
		(0.023)	(0.023)		(0.024)	(0.024)
Male		-0.013	-0.014		-0.028**	-0.030**
		(0.014)	(0.014)		(0.014)	(0.014)
Years of Schooling		0.013***	0.012***		0.017***	0.016***
		(0.002)	(0.002)		(0.002)	(0.002)
Lagged Willing to Stay Permanently		0.041***	0.041***		0.037***	0.039***
		(0.014)	(0.013)		(0.014)	(0.014)
Lagged Dummy for Being Working		0.036	0.044		0.083***	0.090***
		(0.039)	(0.040)		(0.021)	(0.021)
Lagged Self-employed		-0.018	0.014		-0.023	0.008
		(0.017)	(0.022)		(0.018)	(0.022)
Lagged Self-employed*Lagged Dep. Var		-0.055	-0.042		-0.092**	-0.077*
		(0.041)	(0.041)		(0.041)	(0.042)
Lagged Married		0.093***	0.086***		0.087***	0.079***
		(0.019)	(0.019)		(0.019)	(0.019)
Lagged Number of Children		-0.012	-0.011		-0.008	-0.007
		(0.010)	(0.010)		(0.011)	(0.011)
Lagged Dummies of Firm Size						
2-5 workers			0.015			0.034
			(0.025)			(0.027)
6-7 workers			-0.000			0.043
			(0.037)			(0.038)
8-20 workers			0.019			0.028
			(0.033)			(0.034)
21-49 workers			0.017			0.059
			(0.036)			(0.037)
50-99 workers			0.046			0.081**
			(0.038)			(0.039)
100-999 workers			0.038			0.083**
			(0.037)			(0.038)
1000 or above			-0.016			0.052
			(0.043)			(0.044)
not sure, maybe less than 50 workers			0.058			0.031
			(0.051)			(0.053)
not sure, maybe more than 50 workers			0.006			-0.007
			(0.046)			(0.048)
unknown			0.549***			-0.094
			(0.171)			(0.333)

continued on the next page

Full Results of Panel B of Table 2 (continued)

	Health Insurance			Pension		
	model 1	model 2	model 3	model 1	model 2	model 3
Lagged Ownership Dummies						
Domestic Private			-0.032			-0.033
			(0.025)			(0.024)
Foreign and Joint Venture			0.024			0.014
			(0.032)			(0.034)
Self-employed			-0.084***			-0.070**
			(0.027)			(0.027)
Other			0.035			0.108*
			(0.078)			(0.062)
City Dummies						
Shenzhen	-0.013	-0.043	-0.001	-0.019	-0.051	-0.013
	(0.043)	(0.041)	(0.045)	(0.044)	(0.042)	(0.046)
Luoyang	-0.116***	-0.155***	-0.121***	-0.151***	-0.190***	-0.165***
	(0.038)	(0.038)	(0.041)	(0.039)	(0.039)	(0.043)
Hefei	-0.185***	-0.220***	-0.182***	-0.156***	-0.192***	-0.155***
	(0.035)	(0.035)	(0.038)	(0.038)	(0.037)	(0.041)
Bengbu	-0.177***	-0.203***	-0.172***	-0.196***	-0.217***	-0.187***
	(0.041)	(0.041)	(0.043)	(0.039)	(0.040)	(0.043)
Chongqing	-0.036	-0.071*	-0.045	-0.056	-0.089**	-0.061
	(0.040)	(0.040)	(0.043)	(0.042)	(0.041)	(0.046)
Shanghai	-0.123***	-0.151***	-0.124***	-0.154***	-0.179***	-0.146***
	(0.040)	(0.039)	(0.040)	(0.042)	(0.040)	(0.043)
Nanjing	0.006	-0.028	0.002	0.006	-0.026	0.003
	(0.041)	(0.043)	(0.047)	(0.038)	(0.039)	(0.043)
Wuxi	0.037	-0.008	-0.010	0.031	-0.020	-0.023
	(0.037)	(0.036)	(0.036)	(0.038)	(0.037)	(0.037)
Hangzhou	-0.025	-0.040	-0.008	-0.027	-0.036	-0.002
	(0.034)	(0.033)	(0.037)	(0.035)	(0.035)	(0.040)
Ningbo	-0.008	-0.017	-0.011	-0.037	-0.044	-0.035
	(0.040)	(0.040)	(0.041)	(0.036)	(0.037)	(0.041)
Wuhan	-0.093***	-0.121***	-0.096**	-0.081**	-0.109***	-0.084**
	(0.035)	(0.035)	(0.037)	(0.036)	(0.035)	(0.040)
Chengdu	-0.044	-0.082**	-0.058	-0.051	-0.093***	-0.068*
	(0.035)	(0.036)	(0.038)	(0.035)	(0.036)	(0.040)
Observations	4,587	4,587	4,587	4,560	4,560	4,560
R-squared	0.505	0.519	0.524	0.479	0.501	0.506

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Note: The constant term is omitted. The omitted group for firm size in Model 3 is those workplaces with only one worker. The omitted group for the ownership is the state or collective owned. The omitted group for city is Dongguan. Robust standard errors clustered at workplace of household head are in parentheses. P-values are in brackets. Significance codes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A.5 Potential Wage Bargaining between Employers and Employees Non-Eligible for Full Pension Benefits

In the RUMiC cities, where the average employee contribution is 8% and the employer contributes between 14% and 21%, the magnitude of the "bargained" outcome makes intuitive sense: employers grant some higher return to employees, but generally less than half of the mandated employer contribution. Based on conversations with both migrants and their employers, researchers have believed that this bargaining outcome exists (Giles et al., 2013; Meng, 2017), but the observed increase in wages of older workers who cannot fully benefit from pension participation offers the first corroborating empirical evidence that informed workers may bargain with employers for higher wages. As both employers and employees lose contributions made to the urban employee pension fund on behalf of older employees, it seems to be incentive compatible for both older workers and their employers to engage in this type of bargaining.

ln(Wage) Regression Results for Pension Eligible and Non-Eligible Wage Earners

	Sample of "older" workers			Sample of "younger" workers		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Assigned to Treatment	0.072**	0.058*	0.072**	0.012	0.014	0.012
	(0.033)	(0.033)	(0.034)	(0.027)	(0.026)	(0.026)
Lagged ln(Wage)	0.343***	0.301**	0.294**	0.649***	0.584***	0.575***
	(0.123)	(0.123)	(0.121)	(0.049)	(0.051)	(0.051)
Individual Controls	No	Yes	Yes	No	Yes	Yes
Firm Level Controls	No	No	Yes	No	No	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	381	381	381	705	705	705
R-squared	0.476	0.499	0.517	0.436	0.462	0.468

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Notes: "Older" workers are those workers within fifteen years of retirement age (men over 45, and women over 40), and who cannot expect to receive the employer contribution as part of their pension. "Younger" workers (men and women who are under 45 and 40, respectively) can expect to receive full benefits at retirement. The additional variables included in Model 1 are a vector of city fixed effects; in Model 2 we also add individual level controls (age, age squared, gender, education, marital status, number of children), while Model 3 adds firm level controls (pre-treatment firm size and ownership indicator variables) as well. Robust standard errors clustered at workplace of household head level are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

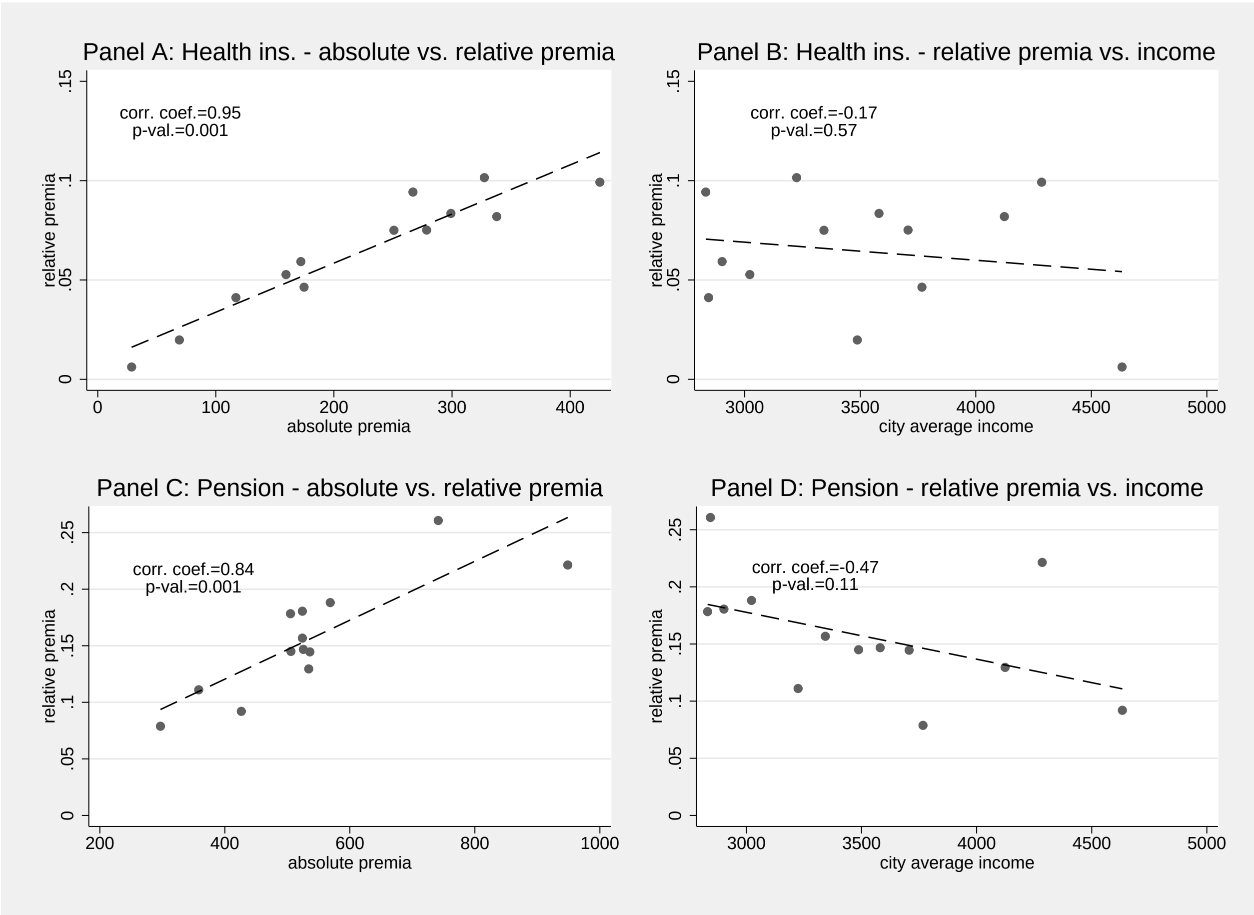
A.6 Estimation of the Extensive Margin

Treatment Effects on Employment Transition

Multinomial Model	Model 1		Model 2		Model 3	
	Employee w.o. a contract	Self-employed	Employee w.o. a contract	Self-employed	Employee w.o. a contract	Self-employed
Treated	0.022*	0.001	0.021*	0.001	0.020*	0.002
	(0.012)	(0.008)	(0.012)	(0.008)	(0.012)	(0.008)
No. of Observations	4,444	4,444	4,444	4,444	4,444	4,444

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Notes: The base dependent variable is the employee with a contract. The additional control variables included in Model 1 are a lagged contract indicator, lagged self-employment indicator and a vector of city fixed effects; Model 2 adds individual level controls (age, gender, education, marital status, number of children, dummy for working and dummy for "willingness to remain in the city permanently if policy permits".), while Model 3 adds firm level controls (pre-treatment firm size and ownership indicator variables) as well. Robust standard errors clustered at workplace of household head are in parentheses. P-values are in brackets. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

A.7 Unconditional Relationship between Relative Premia and City Average Earnings



A.8 Patience and Social Insurance Participation

	Health Insurance			Pension		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Treated	-0.008	-0.001	-0.001	0.009	0.013	0.012
	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Discount Rate	-0.116*	-0.130*	-0.118*	-0.078	-0.100	-0.097
	(0.070)	(0.067)	(0.067)	(0.068)	(0.067)	(0.067)
R-squared	0.487	0.534	0.540	0.523	0.553	0.557
No. of Observations	2,729	2,729	2,729	2,734	2,734	2,734

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Notes: The other covariates includes are the same as those in Panel A of Table 2. Only one person from a household participated in the patience experiment. Robust standard errors clustered at workplace of household head are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

A.9 Estimation of Demand Curves

	Eq (6): Price Interaction		Eq (7): Price and Contract Interactions	
	With City FEs	W/t City FEs	With City FEs	W/t City FEs
Treated	0.078**	0.079**	0.027	0.029
	(0.032)	(0.032)	(0.041)	(0.041)
Treated*No-contract			0.128**	0.125*
			(0.064)	(0.065)
Treated*Price	-1.020**	-1.042**	-0.917	-0.926
	(0.434)	(0.434)	(0.597)	(0.594)
No-contract Dummy			-0.146***	-0.148***
			(0.046)	(0.046)
No-contract*Price			-0.725	-0.864
			(0.635)	(0.607)
No-contract*Price*Treated			-0.798	-0.785
			(0.859)	(0.86)
Price		-0.786**		0.093
		(0.342)		(0.438)
Lagged Dependent Variable	0.655***	0.676***	0.557***	0.567***
	(0.016)	(0.015)	(0.021)	(0.021)
City FE	Yes	No	Yes	No
Observations	4,587	4,587	4,587	4,587
R-squared	0.489	0.481	0.507	0.502

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Notes: In the specifications without city fixed effects, city public finance expenditure, GDP level and its growth rate are included as covariates. Robust standard errors clustered at workplace of household head are in parentheses. P-values are in brackets. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

A.10 Calculation of the Social Insurance Management Cost

The total social insurance management expenses are collected from the final financial reports published by each of the 13 cities' local social security bureaus in 2016. There are two major inconsistencies in the information across cities. First, the information in 2016 was published by the city level social security bureaus in all cities but Wuhan. The information in Wuhan was published by the district level bureaus. While financial reports with expenditure information were available for 11 districts in Wuhan, they were unavailable for Qingshan and Hannan districts. We thus assign the average management expenses of the other 11 districts to Qingshan and Hannan districts. Second, the information on social insurance related management expenses was reported as the sum of management expenses related to social insurance and employment policies in all cities but Dongguan. However, there are sub-categories, some of which can easily be identified as either employment-related or social-insurance-related expenses while others may not be clearly identified. Thus, for these 12 out of 13 cities the calculations exclude the easily identified employment-policies-related sub-categories, while kept social-insurance-related categories and not-easily-identified categories. So we may overestimate the management expenses of social insurance in all cities but Dongguan.

A.11 Sample Selection Bias Tests

To test potential attrition bias, we adopt the Heckman sample selection model. First, we estimate an attrition equation. The instruments used are drawn from two questions answered by enumerators in the 2015 survey regarding the reliableness and trustworthiness of the respondents following a strategy used in Mu (2006). The first question is "Do you think the respondent was careful and serious in answering the questions? 1. very serious throughout the survey; 2. fair; 3. not very serious." An indicator variable is set equal to one if the enumerator reported that the respondent was "very serious throughout the survey" or "fair." The second question asked "To what extent do you think the respondent's answers are reliable? 1. very reliable; 2. relatively reliable; 3. fair; 4. relatively not reliable; and 5. not reliable." For this instrument, an indicator variable is set equal to one if the response was 'very reliable', 'relatively reliable' or 'fair,' and zero otherwise. These two variables reflect individuals' engagement with the survey, which, we argue, should not be directly related to the decision to participate in insurance, but should be related to attrition. The first step results are reported in the Table A.11.1 below and the F-tests show that the IVs are jointly strong predictors of the attrition for the health insurance equations and marginally strong for the pension equations.

The results obtained from the first step estimations are then used to calculate an Inverse-Mills ratio, which, in turn, is included in the estimation of equations (4), (5), (6a) and (7a) to control for potential sample selection bias. Confidence intervals are estimated using a bootstrap with 1,000 replications. The results for equations (5) and (6a) are presented in Panel B of Table 5, while the remaining results are presented below in Table A.11.2.

Table A.11.1: Selected First-Step Results from Heckman Selection Model

	Health Insurance with Full Sample					Pension with Restricted Sample				
	Eq (4)	Eq(5)		Eq (6a)	Eq (7a)	Eq (4)	Eq (5)		Eq (6a)	Eq (7a)
		One Int.	Two Int.				One Int.	Two Int.		
Trustworthiness	0.333***	0.333***	0.333***	0.331***	0.329***	0.327**	0.327**	0.327**	0.325**	0.326**
	(0.126)	(0.126)	(0.126)	(0.126)	(0.127)	(0.146)	(0.147)	(0.147)	(0.147)	(0.147)
Reliableness	0.143	0.143	0.143	0.144	0.145	0.118	0.118	0.118	0.119	0.120
	(0.0907)	(0.0907)	(0.0907)	(0.0907)	(0.0909)	(0.103)	(0.103)	(0.103)	(0.103)	(0.103)
Treated	0.0843*	0.108		0.127	0.0122	0.108**	0.112		0.0328	0.344
	(0.0441)	(0.0689)		(0.113)	(0.153)	(0.0516)	(0.0773)		(0.185)	(0.267)
Treated*Contract			0.108					0.112		
			(0.0689)					(0.0773)		
Treated*No-Contract		-0.0375	0.0706		0.211		-0.00670	0.105		-0.538
		(0.0847)	(0.0543)		(0.213)		(0.100)	(0.0668)		(0.352)
Treated*Price				-0.625	1.570				0.478	-1.513
				(1.531)	(2.245)				(1.148)	(1.694)
Treated*No-Contract*Price					-3.661					3.398
					(2.913)					(2.207)
No-Contract*Price					-0.262					-0.382
					(1.933)					(1.323)
No. of Observations	6,396	6,396	6,396	6,396	6,396	4,255	4,255	4,255	4,255	4,255
F-Test for joint sig. of IVs	14.56	14.56	14.56	14.48	14.42	9.1	9.1	9.1	9.06	9.08

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Notes: Individual characteristics of Model, firm size and onwership controls and city fixed effects are also included in the regression. Robust standard errors clustered at workplace of household head are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

Table A.11.2: Additional 2nd Step Results from Heckman Selection Model

	Eq (4)	Eq (5): Two Int.	Eq (7)
Panel A: Health Insurance with Full Sample			
Treated	0.017		0.028
	[-0.011, 0.045]		[-0.058, 0.110]
Treated*Contract		-0.018	
		[-0.060, 0.026]	
Treated*No-Contract		0.037	0.150
		[0.001,0.071]	[0.017, 0.288]
Treated*Price			-0.749
			[-1.987, 0.524]
No-contract*Price*Treated			-1.222
			[-3.000, 0.604]
F-statistics	14.56	14.56	14.42
No. of Observations	4,587	4,587	4,587
Panel B: Pension with Restricted Sample			
Treated	0.010		0.023
	[-0.024, 0.050]		[-0.137, 0.184]
Treated*Contract		-0.033	
		[-0.081, 0.019]	
Treated*No-Contract		0.038	-0.026
		[-0.007,0.086]	[-0.264, 0.214]
Treated*Price			-0.367
			[-1.399, 0.665]
No-contract*Price*Treated			0.605
			[-0.873, 2.024]
F-statistics	9.1	9.1	9.08
No. of Observations	2,925	2,925	2,925

Source: RUMiC Migrant Survey 2015 and 2016, RUMiC Information Intervention Field Experiment, 2016.
Notes: All regressions are using the Model 3 specification (see note to Table 2). The 95% bootstrapping percentile confidence intervals are in the square brackets, which are calculated by pair cluster bootstrap with 1000 replications.