Scholars Journal of Economics, Business and Management OPEN ACCESS
Abbreviated Key Title: Sch J Econ Bus Manag
ISSN 2348-8875 (Print) | ISSN 2348-5302 (Online)
Journal homepage: https://saspublishers.com/journal/sjebm/home

How Does Social Assistance Affect Family Expenditures? The Case of Urban China

Xiaolin Shi*

Research Director at CIPRUN Global; Adjunct Professor at Northeastern University, Boston, United States

***Corresponding author:** Xiaolin Shi
| **Received:** 05.03.2019 | **Accepted:** 10.03.2019 | **Published:** 30.03.2019
DOI: 10.36347/sjebm.2019.v06i03.003

Abstract **Original Research Article**

In this paper, I use national household survey data CHIP2007 (Chinese Household Income Project, 2007) to examine the effect of Social Alms on family's expenditures. The methodologies I use are propensity score matching and Altonji's bounding technique. I first adopt propensity score matching and find that people who received the social relief tend to spend statistically significantly more money (333.75 yuan) on the medical insurance and less money on the dwelling expenditure (-653.71yuan) and Durable goods (-493.15 yuan) than their counterparts who didn't receive the social benefits. Considering there might be selection bias to the estimates, I use Altonji's bounding technique, which is based on the idea that the amount of selection on the observed explanatory variables in a model provides a guide to the amount of selection on the unobservables to find the selection bias for the effects of social assistance on families' medical insurance expenditure. Once implement Altonji's bounding technique based on a non-linear OLS regression, I find that families that receiving social assistance in 2007 tend to spend 393 yuan more on medical insurance than those families who did not receive the social benefits. The policy implications of these findings are also discussed briefly in the paper.
Keywords: Social Relief, Social assistance, Social benefit, Family Expenditure, Medical Insurance, China.

Introduction

Social relief is a temporary or periodical provision of assistance (money, food, or other kind of help) intended for persons in poverty or need, usually financed and managed by the government. In China, social relief includes many programs such as the Minimum Living Standard Assistance (MLSA), which is the urban China's primary public assistance program; Relief Station (or rescue shelter), which provide food and shelters to the people who need help, especially those vagrants and beggars in the city; there are also other types of social relief aim to provide assistance to those army veterans and the families of servicemen who died while in service; Social aids also available for "household with special difficulties" and disaster relief means to provide assistance to the people who suffer the natural disasters such as, earthquakes, hurricanes, floods, tornadoes, transportation accidents and explosions and so on. The social relief studied in this article includes all kinds of assistance mentioned above in the form of money provided by the government and received by the persons in such dire material need that they are unable to meet their or their families' most basic needs.

Although a series of Chinese economic system reform, which began in October 1984 and in full swing in 1985, brings a lot more profits for the majorities of Chinese firms, higher standard of living for some of the Chinese citizens and much more rapid economic growth for China, it also results in a large growing gap between the rich and poor since on one hand, in order to motivate the company's' production of energy the new reform allows "a few people first rich"; on the other hand, a large amount of people got laid off by state-owned and collective enterprises after the reform. The consequence of the Chinese economic system reform also includes the emergence of a group of new urban poor because along with the reform of the health system, education system reform and housing reform system of multiple pressures make life more difficult for those people who got unemployed to become a major component of China's current urban poor. Moreover, in order to facilitate the economic system reform, a series of social policy changes have focused on shifting the welfare burden from employers to employees [1]. "The state-owned and collective enterprises, which were the major providers of social benefits, needed to lower costs and improve productivity. As a result, urban social benefits have transformed from their original broad coverage and generous provision to a more residual role in the lives of families, shrinking from 44 percent of the total household income in 1988 to only a quarter in 2002" [2]. Therefore, these new emerged large group of urban poor have been left behind by both market competition under market economy and social protection [1].

As I mentioned above, the Minimum Living Standard Assistance (MLSA) is the major and also the most important social assistance provided by the government. It initiated in Shanghai I 1993 and became countrywide (668 cities and 1,689 counties) in 1999. It aims to help a growing number of urban poor in China whose household per capita income was lower than the local minimum living standard line (for example, those unemployed, low wages, inadequate pension and so on). It has been regarded as a last resort for China's urban poor. The people who meet the criteria can get the money difference (local minimum living standard minus the actual income) from the local government and the central government may provide financial support to cities with difficulties [3, 4].

As the MLSA is the major social assistance program in China, concerning about China's social relief (or social assistance) program, most existing literatures studied the Minimum Living Standard Assistance (MLSA). The majority of the existing papers studied the effectiveness of this program MLSA, which include how effective it is to alleviate Poverty in China [5-7, 10, 8, 12]. Some studies concerned about other performance such as incentives and targeting of the MLSA [13, 14]. Gao, Garfinkel & Zhai, F [12] provides updated evidence on the participation rate, receipt amount, and anti-poverty effectiveness of MLSA.

In this article, I aim to examine the effectiveness of the China's social relief on family expenditures. And there is only one paper as of now studies the impact of the MLSA on family's expenditure for the case of urban China, which is written by GAO, Zhai and Garfinkel [1]. In their study, they use a Chinese national household survey data [15] and a Propensity Score Matching (PSM) method to examine the effects of the MLSA, which is the China's primary public assistance program on family expenditures. They found that families receiving MLSA prioritized human capital investment (i.e. paying for education and health) rather than making the ends meet (e.g. paying for food, clothing, rent and utilities).

And my study, to some extent, replicate this paper by Gao, Zhai and Garfinkel [1] using CHIPS2007 dataset in order to see if there are any changes in expenditure patterns for those families that received social relief after 5 years. It worth mentioning that there are two major differences between my study and theirs. One of them is that the social assistance programs we concerned about are different in terms of the definition. They studied the MLSA program; but I concerned all kinds of social assistance mentioned in the first paragraph in the form of money provided by the government and received by the persons in such dire material need that they are unable to meet their or their families' most basic needs [6] because there are not enough information about MLSA program in the newest 2007 CHIPS dataset. The other difference between my study and theirs is about the methodology we used, which is also considered as the main contribution of the current study to the existing literatures. Their study only adopted the Propensity Score Matching (PSM) method to identify comparable nonparticipants who have similar observed characteristics to those of MLSA participants and the effects of MLSA participation are estimated by comparing the expenditures of MLSA participants with those of their "matched" nonparticipant peers. However, in my study I first use the Propensity Score Matching (PSM), which has the same goal as theirs and then considering there might be some unobservable variables that might have some impact on the social relief's effects on some of the family expenditures, I adopted Altonji's Bounding technique based on the full sample Ordinary Least Square (OLS) with second order term interactions between some of the key control variables to get an idea of the magnitude of the selection on those unobservable variables so that I am able to obtain more accurate estimates of the key coefficients I am interested in. I will discuss more fully about the methods I am using in this paper in the "empirical strategy" part.

The rest of the paper is organized as follows. Section 2 and 3 describe the data and empirical strategy. Section 4 presents the estimation results. Section 5 discusses the policy implications of these findings and concludes the paper.

Data

CHIPS (Chinese Household Income Project Series)

The China Household Income Project (CHIP) started at the end of the 1988 and it was initiated and collectively designed by a group of researchers at the Australian National University and Beijing Normal University, and was supported by the China National Bureau of Statistics (NBS) and the Institute for the Study of Labor (IZA). It was conducted by scholars who at the time were based at the Institute of Economics, Chinese Academy of Social Science, Beijing. CHIP is focused on household income, which has taken advantage of working with the NBS (the National Bureau of Statistics) in many stages of the data generating process and it also collects detailed data on demographics, program participation, and expenditures. In the waves now available for researchers, income information refers to the years 1988, 1995, 2002 and 2007. CHIP survey consists of three parts: the Urban Household Survey, the Rural

Household Survey and the Migrant Household Survey. The 2002 surveys were carried out by the NBS. The 2007 urban and rural surveys were conducted by the NBS, but the rural-to-urban migrant survey was conducted by a survey company [1, 16].

All waves of CHIP consist of separate surveys on rural and urban households. Regarding survey design and sampling frame, CHIP have the broadest spatial coverage (It includes sample provinces from eastern, central, and western regions of China. More specifically, the Beijing municipality and the provinces Liaoning, Jiangsu, and Guangdong represent the eastern region; the provinces Shanxi, Anhui, Henan, and Hubei represent the central region; and the Chongqing municipality and the provinces Sichuan, Yunnan, and Gansu represent the western region) when it comes to sampling frame and are therefore from this perspective best suited to estimate nationwide income distribution [1, 16].

CHIP 2007

This study uses the CHIP 2007 urban survey data. CHIP 2007 was surveyed in the early 2008, and household income and expenditure was asked about information in 2007. For the surveys of urban local households, a total of same nine provinces were selected. They are Shanghai, Jiangsu, Zhejiang, and Guangdong from eastern China; Anhui, Henan, and Hubei from central China; Chongqing and Sichuan from western China. The CHIP 2007 urban sample contains 5000 households. Detailed information was collected on incomes and expenditures, employment status, family structure, and social and economic characteristics at both personal and household level.

Since this study examines how social relief affect family expenditures, I concerned all kinds of social assistance in forms of monetary term and received by the persons in dire material need that they are unable to meet their or their families' most basic needs. In CHIP 2007, the related question was directly asked about. Any families received any kind of social assistance in the year 2007 will give an amount to the survey question “how much of income have you received from social alms in 2007?” Still, it worth mentioning that it is undeniable that the majority of the money received by the poor people from social relief should come from MLSA program and those other forms of social assistance program are just complimentary to the MLSA. In CHIP2007, among 5000 households, only 236 (about 5 percent) families received social alms.

Family expenditures are classified into 5 major categories in CHIP 2007--- consumption expenditure; business expenditure; assets expenditure; transfer expenditure; social security expenditure. There are also some subgroups in consumption expenditure and social security expenditure. Consumption expenditure includes food expenditure; clothing expenditure; dwelling expenditure; durable goods/daily service expenditure (ex. Furniture, kitchen utensils, and electric appliances); medical expenses and health services expenditure; transportation and communication; education, culture and entertainment service expenditure and other commodities and serves. And there 5 subgroups in Social security expenditures ---pension insurance paid for by household member; housing fund paid for by household member; medical insurance paid for by household member; unemployment insurance paid for by household member and other social insurance expenditure. The sum of these expenditure items measures household total expenditure. Expenditures are assumed to be equally shared among family members and measured as household per capita values.

EMPIRICAL STRATEGY

Propensity Score Matching

The goal of our empirical strategy is to estimate the causal effect of receiving social assistance on households' expenditure tendencies. To do so, we first adopt a propensity score matching (PSM) method. The reason that I utilize the propensity score matching method (PSM) is that this method is able to address the issue of selection bias to some extent by mimicking randomization by creating a sample of units that received the treatment (here is to receive the social assistance) that is comparable on all observed covariates to a sample of units that did not receive the treatment, considering the household that receive the social assistance is typically not random and there is a large difference in the number of households who receive the social assistance and not receive the benefits (236 vs. 5000). And also, it has been increasingly used in studies about program evaluation in recent years, especially for those researches that evaluate the Chinese social assistance programs [1, 15, 6, 17, 18, 19, 5].

“A conventional PSM approach uses observed covariates to estimate the probability of receiving treatment (i.e., propensity score) and then, for members in the treatment group, identifies one or more “matched” members in the control group with the closest propensity scores using various ways of matching such as nearest neighbor, Kernel or local linear regression[1].”

In order to estimate the probability of receiving the social assistance for each household (i.e. receiving treatment), I estimate the following logistic regression for each household I and count c:

$$\text{Logit}\,(E[Y_{ic}|X_{1,ic,\ldots}X_{mic}]) = \beta_0 + \beta_1 X_{1,ic} + \ldots + \beta_m X_{m,ic} + \theta_c + \mu_{ic} = \beta_0 + \beta\, \Sigma X_{ic} + \theta_c + \mu_{ic} \quad (1)$$

Where, Y_{ic} is a binary variable; Y_{ic} is equal to one for those household that received social assistance in 2007 and zero otherwise; ΣX_{ic} is a sum of the factors that capture household social-demographics characteristics that might possibly influence the propensity score of receiving social assistance. These observed social-demographics variables include the household head's age, marital status, ethnicity, employment status, years of schooling, occupation, industry, health condition, hukou (i.e. a record in the system of household registration required by law in both mainland China and Taiwan) and some household characteristics including how many children (age 18 and under) in the household, whether there is at least one child in school, the household size, the average household income (income per person) prior to social assistance receipt ,whether the household has medical insurance and whether there is at least one person in the household has physical disability. θ_c is a county-specific fixed effect used to capture those omitted variables that vary over time but not within counties that might affect the probability of receiving the social assistance.

And then, according to their propensity scores predicted by equation (1), I identify a comparable control group, in which the household didn't receive any social assistance in 2007. Since I use the propensity score matching (PSM) with one-to-one nearest neighbor method, I identify the exact same number of households in the control group as that in the treatment group. After enforcing common support, I have 123 households in both treatment and control group so in order to see which expenditure category the household that received the benefit is more likely to spend more money on, I have total 246 households in my sample that allows me to do the following OLS regression analysis:

$$O_{ic} = \beta_0 + \beta_1\, \text{Treatment}_{ic} + \beta_2 X_{ic} + \theta_c + \mu_{ic} \quad (2)$$

Where, O_{ic} represents the outcome variables (the family expenditures) of each household I and county c; Treatment_{ic} is a binary variable, which indicate whether nor not a household received social assistance in 2007; Treatment_{ic} is equal to one for those household received the benefits and zero otherwise; X_{ic} is a vector of household social-demographics, which is the same as those variables in equation (1); I also include the county fixed effects, indicated by θ_c.

Altonji's Bounding Technique

It worth mentioning that the Propensity Score Matching (PSM) method can estimate the average treatment effect from only observational data. This exactly is one of the disadvantage of PSM since it only accounts for those observable covariates. Although like Gao, Zhai & Garfinkel [1], I've also take a substantial amount of observable factors into considerations, it is still possible that there are some factors that can affect assignment to treatment and outcome but that cannot be observed cannot accounted for in the matching procedure. As the procedure only controls for observed variables, any hidden bias due to latent variables may remain after matching [20, 21].

To deal with this problem, I adopt Altonji's bounding technique to estimate the selection bias caused by those unobservable variables because it is an estimation methods based on the idea that the amount of selection on the observed explanatory variables in a model provides a guide to the amount of selection on the unobservable [22].

As follows, I briefly discuss the theoretical foundation for using the relationship between an endogenous variable and the observables to make inferences about the relationship between the variable and the unobservables. Let the outcome of interest to be a function of a latent variable O*, which is determined as:

$$O^* = \alpha\, \text{Treatment} + X'\Gamma x + \varepsilon \quad (3)$$

Where Treatment is an indicator for whether the household received any social assistance, the parameter α is the causal effect of treatment on O*, X is a vector of the observable variables that determine O*, Γx is the corresponding coefficient of X, and the error component ε is an index of the unobserved variables. Because it is unlikely that the control variables X are all unrelated to ε, I work with:

$$O^* = \alpha\, \text{Treatment} + X'\gamma + \upsilon \quad (4)$$

Where γ and υ are defined so that $\text{Cov}(\upsilon, X) = 0$. Consequently, γ captures bothe the direct effect of X on O*, Γx, and the relationship between X and ε.

To argue the role of selection bias in a simple way, I ignore the fact that O is estimated by a probit or logistic regression and treat α as though it were estimated by a regression of the latent variable O* on X and Treatment. Let X'β and $\overline{Treatment}$ represent the predicted value and residuals of a regression of Treatment on X so that Treatment = X' β + $\overline{Treatment}$. Then

$$O^* = \alpha \overline{Treatment} + X'(\gamma+\alpha\beta) + \upsilon. \quad (5)$$

If the bias in a probit or logit regression is close to the bias in OLS applied to the model (5), then the fact that $\overline{Treatment}$ is orthogonal to X leads to the formula:

$$\text{Plim } \hat{\alpha} = \alpha + \frac{Cov(\overline{Treatment},\upsilon)}{Var(\overline{Treatment})}$$

$$= \alpha + \frac{Var(Treatment)}{Var(\overline{Treatment})}[E(\upsilon|\ Treatment=1) - E(\upsilon|\ Treatment=0)]. \quad (6)$$

Where, $\frac{Var(Treatment)}{Var(\overline{Treatment})}$ [E(υ| Treatment=1) - E(υ| Treatment=0)] measures the selection bias, which is caused by both observed and unobserved variables.

To apply this technique, I have to use the full sample with 5000 households instead of the matched sample, which only contains 246 households because the matched sample has already ruled out all the effects of any unobserved variables. Therefore, I apply Altonji's technique to estimate the bias of α based on the regular regression model with second order term and interactions between variables included (about this model will be discussed in a great detail in Result part). Thanks to Joseph G. Altonji's great generosity, I got his original code and apply them to this study. The results will be presented in the next part.

RESULTS

Results from Propensity Score Matching (PSM)

Balancing Test before and after PSM

Table 1 shows the balance changes on the mean differences in household social-demographics between households that received the social assistance (treated group) and those households that did not receive the social assistance (control group) before and after PSM based on two-tailed t-statistics. From the Table 1, we find that before PSM, the household in treatment group are significantly different from those households that in control group in many aspects. Compared to control group, the households that received the social assistance tend to have the following characteristics: household heads are older, unmarried, poorer health, lower education level; from the household characteristics, they are more likely to have family members with physical disabled and average income per person is lower. Those differenced above are all statistically significant. In contrast, after doing the PSM, those social-demographics characteristics between the households that in the treatment group and those in the control group are very similar in magnitude and the two-tailed t statistics shows that there are no statistically significant differences in any of them. This evidence suggests that the PSM method used in this study is able to identify a comparable control group for the household who receive the social assistance based on these observed covariates and therefore it is valid to use PSM to control the selection bias if we assume that all confounding covariates related to treatment status and outcomes have been observed.

Detailed expenditure patterns

After passing the balancing test, I implement the PSM and Table 2 reports the results from it. Since the goal of this study is to see if there is any change in the expenditure patterns of the households that receive the social assistance, comparing to those households without any social assistance, so the outcome variables include consumption expenditure, which contains food, clothing, dwelling, durable goods, medical and health expenditure, education and entertainment expenditure; business expenditure; assets expenditure; transfer expenditure and social security expenditure, which comprises pension, housing fund, medical insurance, unemployment insurance expenditures.

Table 2 shows that comparing to those households without any social assistance; those households with social assistance will have the similar expenditure pattern in most of the expenditure categories. For example, it shows that there are no statistically significant differences in either the expenditures on food, clothing, medical expenses, transportation or the expenditures on assets, pension insurance, housing fund and unemployment insurance. However, for those households that received the social assistance spent less money (-653 yuan) on dwelling expenditure and less (-493 yuan) money on durable goods expenditures compared to those families without any social assistance and theses differences are statistically significant in 2 and 5 percent for a two-tailed t test respectively. Moreover, it is also worth noting that the medical insurance paid for by the household is 333 yuan more for those families who received the social assistance than those did not receive the benefits and this number is statistically significant in 5 percent level for a two-tailed T test. For the following part, I turn my attention to show whether this is true because if it is, that implies that people who receive the social benefit are those people who care or concern their health condition more than those who didn't receive the social benefit. There is no any simultaneous causal relationship between the health condition and the medical insurance expenditure because the balancing test shows that there are no statistically significant differences in health condition between people in households in treatment and control group. However, the simultaneous causal relationship might still exist between the health condition and the medical insurance expenditure considering that there is still possibilities that some unobserved variables might affect the treatment status (i.e. who is going to receive the social assistance) since in order to use PSM we have to assume that all confounding covariates that related to treatment status and outcomes are those observed variables. That's why in the following part 4.2, I adopt Altonji's bounding technique to estimate the selection bias that is caused not only by those observed variables but also by those unobserved variables. This technique is based on the idea that the amount of selection on the observed explanatory variables in a model provides a guide to the amount of selection on the unobservable [22].

Results from Altonji's bounding technique

To get the selection bias through Altonji's bounding technique, I have to use the full sample (i.e. unmatched sample) instead of matched sample with only 246 observations because the matched sample has already been constrained to only observed covariates that are matched between the treatment and control group and there is no way to get any information about the effects of the unobservables if any. Therefore, in order to get the estimation of the impact of the treatment on the medical insurance expenditure, I first run an ordinary least square (OLS) regression of outcome (i.e. the medical insurance expenditure paid for by household member) on the treatment (i.e. whether or not the household received social assistance) and all the covariates, which are the same covariates (social-demographic characteristics) in equation (1). County fixed effects are also taken into consideration. Column (2) in Table 3 reports the coefficient of treatment. It shows that households who received the social assistance tend to spend about 331.6 yuan more than those households without any social assistance. This number is very close to what we get from PSM (about 333.7 yuan, which is shown in Column (1) of Table 3). The closeness of the magnitude of the coefficient can further improve that PSM is able to generate a reliable estimation of the average treatment effect in this case. However, the difference between these two model (PSM and OLS regression) lies on the statistically significance of these two estimation. PSM give a statistically significant estimation at 2 percent level for a two-tailed t test with lower standard errors. While, OLS regression yields a very similar estimation with much hiselegher standard errors. This difference in standard errors suggests an issue of power with OLS regression. To deal with this problem, I include second order terms for all the covariates, which are indicated in equation (1) and all the interaction term between any of the two covariates into the OLS regression. I present the estimation result from this specification model in Column (3) of Table 3. The point estimate is 381.6, which implies the household with social assistance will spend about 381.6 yuan more on the medical insurance. Since this number is statistically significant at 0.1 significance level for a two-tailed t test, I am allowed to do the Altonji's bounding technique based on this estimation result. After implementing this technique, I get the selection bias caused by both observed and unobserved variables is -11.38 (I present this selection bias in Column (4) of Table 3), which suggest a downward bias for the point estimation of the non-liner OLS regression in Column (3) of table 3. The true estimation of the effect of treatment should be about 392.99 yuan, according to Altonji's bounding technique. It suggests that when considering the selection bias caused by both the observed variables and those possibly unobserved variables, the households that received the social assistance will spend about 399 yuan more than those households that did not receive the social assistance in the year 2007. And for the dwelling and durable goods expenditures, PSM can also give very similar coefficient estimations to the results from regular OLS regression but with very small standard errors. However, under non-linear OLS regression with all the second order terms and interaction terms of covariates included, the standard errors of the effects of treatment on those expenditures (dwelling and durable goods expenditure) are still quite large, thus I rely on the estimation results from PSM regarding the effects of treatment on the dwelling and durable expenditures.

Table 1. Balancing tests before and after Propensity Score Matching (PSM)

	(1)		(2)	(3)	
	Untreated beofre Matcing		**Treated**	**Untreated after Matching**	
household head charactersitics					
Age	43	(2.4)***	44.9	45.67	(-0.17)
Marital Status					
married	0.92	(-2.76)***	0.85	1	(-0.73)
remarried	0.035	(-1.11)	0.016	0.01	(0.22)
divorced	0.032	(2.36)***	0.073	0.006	(0.48)
widowed	0.014	(4.04)***	0.065	0.059	(0.45)
health condition					
good	0.53	(-2.13)**	0.43	0.33	(0.33)
average	0.27	(2.84)***	0.39	0.33	(0.2)
poor	0.02	(3.46)***	0.07	0.06	(0.48)
very poor	0.00074	(3.66)***	0.016	0.009	(0.22)
Unemployed	0.007	(1.92)*	0.024	0.022	(0.27)
years of schooling	11.74	(-4.44)***	10.38	11.06	(-0.18)
medical insurance	0.137	(3.46)***	0.25	0.23	(1)
household characteristics					
number of children					
1	0.87	(1.09)	0.91	0.667	(1.42)
2	0.33	(1.79)*	0.65	0.067	(-0.08)
3	0.0067	(0.18)	0.008	0.0078	(0.16)
physical disability					
yes, but no impact on normal work, study and life	0.027	(1.4)	0.049	0.047	(0.39)
yes, affecting the normal work, study and life	0.0029	(2.21)**	0.016	0.014	(0.22)
whether child(ren) in school	0.7	(-0.58)	0.6748	0.67	(0.03)
household size	2.97	(0.21)	2.98	2.67	(0.85)
average income per person	20454	(-5.73)***	11592	13897	(1.41)

Notes: In Columns (1), the number in parentheses represent a t-value for the two-tailed T test, which test whether or not there are statistically significant differences between the coefficient for untreated before matching and the coefficient of treated group. In Columns (3), the number in parentheses also represent a t-value for the two-tailed T test, which test whether or not there are statistically significant differences between the coefficient for treated group and the coefficient of control group after matching. *** 2%, ** 5%, *10% for two-Tail T test.

Table 2. Effects of receiving social assistance on household expenditure patterns		
	(1)	(2)
	Coeff.	(s.e.)
expenditure categories		
consumption	-2380.5366	(2017.1611)
food expenditure	-188.7480	(674.5602)
clothing expenditure	13.1951	(316.8871)
dwelling expenditure	-653.7073	(284.3364)***
durable goods (furniture, kitchen utensils, electric appliances)	-493.1463	(232.6240)**
medical expenses an dhealth services expenditure	-817.4878	(1302.7598)
transportation and communication	-194.6016	(264.7698)
education, culture and entertainment service expenditure	-2.0163	(541.3849)
other commodities and services	-47.7642	(148.8743)
business expenditure	-162.6016	(162.6016)
asseets expenditure	-36.7236	(160.1946)
transfer expenditure	-6.2602	(236.4408)
social security expenditure	-30216.1626	(30869.2056)
pension insurance paid for by household member	114.9837	(267.4446)
housing fund paid for by household member	-16.1220	(303.3088)
medical insurance paid for by household member	333.7480	(155.5419)**
unemployment insurance paid for by household member	72.3984	(49.2973)
other social insurance expenditure	210.1951	(142.2056)

Notes: the numbers in parentheses stand for standard deviations.
*** 2%, ** 5%, *10% for two-Tail T test.

Table-3: Effects of receiving social assistance on the medical insurance expenditure

	(1)	(2)	(3)	(4)
MIE	Coef.	Coef.	Coef.	bias
treatment	333.748	331.562	381.608	-11.38
	(155.5419)***	(223.0887)	(226.885)*	
N	246	3006	3006	
Country FE	X	X	X	
Covariates	X	X	X	
2^{nd} order terms			X	
Interactions between covariates			X	

Note1: Treatment represent households who received the social assistance. Column (1) reports results from PSM; Column (2) reports results from the regular OLS regression of MIE on treatment and all the covariates and county fixed effects; Column (3) reports results from the OLS regression of MIE with including all covariates, county fixed effects and second order terms and interactions between covariates. Column (4) shows the selection bias caused by the unobserved variables, which is estimated by the Altonji's bounding technique. Numbers in parenthesis stand for standard error. *** 2%, ** 5%, *10% for two-Tail T test.

Note2:
$\frac{Var(Treatment)}{Var(\overline{Treatment})}$ [E(υ| Treatment=1) - E(υ| Treatment=0)] represent the selection bias of coefficient of MIA. After running the code Joseph G. Altonji provided, $Var(Treatment)$ is equal to 5.75e+08; [E(υ| Treatment=1) - E(υ| Treatment=0)] is equal to -1.45e-06; $var\ (\overline{Treatment})$ is equal to 73.23832. So the bias is equal to -11.37982

Conclusion

Although compared to Gao, Zhai & Garfinkel [1], I use the same methodology (PSM) with CHIP 2007 dataset in this study yet we find the different family expenditures pattern between households who received and did not received the social benefits. Gao, Zhai & Garfinkel [1] found that families receiving social benefits (only refers to Minimum Living Standard Assistance) in the year 2002 prioritized human capital investment (i.e., paying for education and health) rather than making the ends meet (e.g., paying for food, clothing, rent and utilities.) In this study, I find that there are no statistically significant differences in the expenditure patterns regarding both the education, culture and entertainment service and the food, clothing expenditure that helps them make ends meet between families with the similar social-demographic characteristics did not receive the social benefits (refers to all kinds of social assistance in monetary form) 5 years after (i.e., in 2007). Instead, in 2007, those families received the social benefit actually spend less money (817.48 yuan) on the medical expenses and health services, although this difference is not statistically significant. Part of the reasons for these differences lies on the fact that the urban MLSA (Minimum Living Standard Assistance), which is the major component of social assistance has been expanded since 2002 and has taken these factors (food, education, clothing, etc.) into consideration, making significant progress [1, 23].

I find that families that received the social assistance in the year 2007 spent less amount of money on dwelling expenditures (-654 yuan) and durable goods (furniture, kitchen utensils and electric appliances) expenditures (-493 yuan), compared to their comparable group of households that did not receive any social assistance in 2007. However, families that receiving social assistance in 2007 tend to spend 393 yuan more on medical insurance than those families who did not receive the social benefits.

Considering this expenditure priority on the medical insurance payment for those social assistance recipients, The Chinese policy makers should pay more attention to those poor citizens' health condition and try to enlarge the medical insurance coverage especially for those poor families. In fact, in 2007, the government initiated a medical assistance program to provide supplementary support to the poor families (especially for MLSA families) with difficulties to afford a basic health insurance [1, 8]. But clearly, the Chinese government still needs to make sure this policy can be implemented more efficiently.

REFERENCES

1. Gao Q, Zhai F, Garfinkel I. How does public assistance affect family expenditures? The case of urban China. World Development. 2010 Jul 1;38(7):989-1000.
2. Gao Q, Riskin C. Explaining China's changing inequality: Market vs. social benefits. Creating Wealth and Poverty in Contemporary China. Stanford University Press. Palo Alto, CA. 2009.
3. Gao Q. The social benefit system in urban China: Reforms and trends from 1988 to 2002. *Journal of East Asian Studies*. 2006; *6* (1), 31-67.
4. Leung JC. Social security reforms in China: Issues and prospects. International Journal of Social Welfare. 2003 Apr;12(2):73-85.
5. Jalan J, Ravallion M. Estimating the benefit incidence of an antipoverty program by propensity-score matching. Journal of Business & Economic Statistics. 2003 Jan 1;21(1):19-30.
6. Du Y & Park A. The effects of social assistance on poverty reduction: Evidence from household surveys in urban China. In *Paper presented at the international conference on policy perspectives on growth, economic structures and poverty reduction, Beijing, China*. 2007.
7. Guan X. China's social policy: Reform and development in the context of marketization and globalization. InTransforming the developmental welfare state in East Asia. Palgrave Macmillan, London. 2005; 231-256.
8. Wang M. Emerging urban poverty and effects of the Dibao program on alleviating poverty in China. *China & World Economy.* 2007; 15(2), 74-88.
9. Tang J. The situation and prospects of the MLSA. China's Social Situation Analysis and Prediction, Social Sciences Documentation Press, Beijing. 2004.
10. Hong D. The minimum living standard for urban residents. In Social Policy Research Center (Ed.), *Poverty and the minimum living standard assistance policy in urban China (in Chinese).* Beijing, China: Chinese Academy of Social Sciences. 2005a.
11. Gao Q, Garfinkel I, Zhai F. Anti-poverty effectiveness of the minimum living standard assistance policy in urban China. Review of Income and Wealth. 2009 Jul;55:630-55.
12. Chen S, Ravallion M, Wang Y. Di bao: a guaranteed minimum income in China's cities?. World Bank Publications. 2006.
13. Solinger DJ. Narratives of the Chinese Economic Reforms. Editor. Lewiston, NY: The Edwin Mellen Press. 2008.
14. Dehejia RH, Wahba S. Propensity score-matching methods for nonexperimental causal studies. Review of Economics and statistics. 2002 Feb;84(1):151-61.
15. Gustafsson B, Shi L, Sato H. Data for studying earnings, the distribution of household income and poverty in China. China Economic Review. 2014 Sep 1;30:419-31.
16. Heckman J, Ichimura H, Smith J, Todd P. Characterizing selection bias using experimental data. National bureau of economic research; 1998 Aug 1.
17. Blundell R, Dias MC. Alternative approaches to evaluation in empirical microeconomics. Portuguese economic journal. 2002 Aug 1;1(2):91-115.

18. Himaz R. Welfare grants and their impact on child health: the case of Sri Lanka. World Development. 2008 Oct 1;36(10):1843-57.
19. Garrido MM, Kelley AS, Paris J, Roza K, Meier DE, Morrison RS, Aldridge MD. Methods for constructing and assessing propensity scores. Health services research. 2014 Oct;49(5):1701-20.
20. Shadish WR, Cook TD, Campbell DT. Experiments and generalized causal inference. Experimental and quasi-experimental designs for generalized causal inference. 2002:1-32.
21. Altonji JG, Elder TE, and Taber CR. Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools. Journal of political economy. 2005 Feb;113(1):151-84.
22. Kaushal N, Gao Q, Waldfogel J. Welfare reform and family expenditures: how are single mothers adapting to the new welfare and work regime?. Social Service Review. 2007 Sep;81(3):369-96.