Consequence and Policy Response of Health-Induced Poverty among Older Adults:

Evidence from the United States and China

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Abstract

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This dissertation aimed to examine the consequence of health-induced poverty and two policy responses to address this issue among older adults in the United States and China. Specifically, Paper I investigates whether public transfers crowded out private transfers among rural and urban Chinese older families and if this dynamic would change when health care expenses were high. Paper II examines the effect of New Rural Cooperative Medical Insurance, a national health insurance program for rural residents in China, on changing the incidence of health-induced poverty among middle-aged and older beneficiaries. Paper III tests the effects of closing the Medicare Part D donut hole (coverage gap) through the Affordable Care Act (ACA) on changing prescription drug cost-induced poverty. Overall, the findings obtained from these three papers provide empirical evidence that health-induced poverty is prevalent among older adults in both China and the United States and the current public transfers and health policies are either ineffective or insufficient to reduce health-induced poverty as intended.

Table of Contents

List of Tables iii

List of Figures v

Acknowledgments vi

Dedication viii

Introduction 1

PAPER I: The dynamic relationship between public and private transfers among older adults in China: Does experiencing higher health care spending change the relationship? 5

- Introduction 5
- Policy Background: Public and Private Transfers for Older Adults in China 8
- Conceptual Framework 10
- Empirical Evidence 11
- Methods 15
- Results 23
- Conclusion and Discussions 28

PAPER II: Does participating in New Rural Cooperative Medical Insurance change catastrophic health expenditure? Evidence from the China Household Income Project 40

- Abstract 40
- Introduction 40
- Literature Review 43
- Methods 48
- Results 54

Discussion and Conclusion 56

PAPER III: Does closing the donut hole under the Affordable Care Act reduce financial burdens of prescription medication expenses among Medicare Part D beneficiaries? 67

Abstract 67

Introduction 68

Background 70

Literature Review 73

Methods 79

Results 86

Discussion and Conclusion 89

Conclusion 104

Conclusion 104

Implications for Social Policy, Practice, and Research 105

References 109

List of Tables

Table 1-1: Public financing and beneficiaries of Dibao, Wubao, and Medical Assistance programs: 2011-2015. 31

Table 1-2: Descriptive analysis of public and private transfers and health spending among rural and urban older adults: 2011-2015. 32

Table 1-3: Sample characteristics at the individual, household, and community levels by rural and urban: 2011-2015. 33

Table 1-4: OLS and FE results for rural and urban older adults. 34

Table 1-5: Arellano-Bond Model results for rural older adults. 35

Table 1-6: Arellano-Bond Model results for urban older adults. 37

Table 2-1: Descriptive results of the village-, household-, and individual-level factors by NRCMI implementation and participation. 60

Table 2-2: Instrumental variable estimations of effects of NRCMI participation on CHE incidence and medical expense amount among adults aged 45 and above in Anhui and Sichuan provinces using 40% as the threshold of CHE. 62

Table 2-3: Instrumental variable estimations of effects of NRCMI participation on CHE incidence and medical expense amount among adults aged 45 and above in Anhui province using 40% as the threshold of CHE. 63

Table 2-4: Instrumental variable estimations of effects of NRCMI participation on CHE incidence and medical expense amount among adults aged 45 and above in Sichuan province using 40% as the threshold of CHE. 64

Table 3-1: The design of treatment and comparison groups for the four scenarios. 93

Table 3-2: Descriptive statistics of prescription drug utilization, CHE, CHE-Rx, demographic characteristics, and health conditions. 94

Table 3-3: Effects of donut hole closing policy on prescription drug utilization, CHE, and CHE-Rx using the panel DID methods among all the analytical samples. 95

Table 3-4: Effects of donut hole closing policy on prescription drug utilization, CHE, and CHE-Rx using the panel DID methods among those whose prescription drug costs reached the donut holes. 96

Table 3-5: Effects of donut hole closing policy on prescription drug utilization, CHE, and CHE-Rx using the panel DID methods among those whose prescription drug costs were between donut holes and catastrophic coverages. 97

Table 3-6: Effects of donut hole closing policy on prescription drug utilization, CHE, and CHE-Rx using the panel DID methods among those whose prescription drug costs reached the catastrophic coverages. 98

Table 3-7: Effects of donut hole closing policy on prescription drug utilization, CHE, and CHE-Rx using the aggregated DID results among four study groups. 99

List of Figures

Figure 1-1: Dynamic relationships between public and private transfers..................................... 38

Figure 3-1: Descriptive connected graph for average out-of-pocket payment on prescription drugs and health care by the treatment between 2009 and 2016. 100

Figure 3-2 Trends of prescription use, CHE, CHE-Rx among Medicare Part D enrollees, those who reached donut hole, and those who reached catastrophic coverage from 2008 to 2017. 101

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Dedication

For my parents, Yunze, Lucas, and Chris, who are the heart of my world.

Introduction

Concerns among the public, policy makers, and scholars are rising regarding the high prevalence and negative consequences of health-induced poverty. For people with limited financial resources, out-of-pocket health care expenses and other indirect health-related costs could lead to financial hardships at both individual and household levels (Wagstaff, Lindelow, Jun, Ling, & Juncheng, 2009). Some studies have found that impoverished households that anticipate undergoing or already have experienced health-induced poverty are highly likely to adopt risky coping strategies such as delayed treatment or skipped medications (Altice, Banegas, Tucker-Seeley, & Yabroff, 2017; Kavosi et al., 2012). Such strategies can worsen health, which could eventually worsen poverty if illness interferes with employment among people with poorer health and fewer financial resources.

The three papers in this dissertation examine the consequence and effects of policy responses on health-induced poverty among Chinese and U.S. older adults. The first paper tests whether public transfers crowded out private transfers among rural and urban Chinese older families and if this dynamic would change when health care expenses were high. The second and third papers examine the effects of national health insurance programs in China and the United States, respectively, on changing the likelihood of experiencing catastrophic health expenditures among older beneficiaries.

In the literature, the primary argument on the definition and measurement of health-induced poverty focuses on the values and percentages used as thresholds, such as what earnings should be counted as income, what should be regarded as wealth, and how many people should be counted when calculating household income per capita. Overall, health-induced poverty is defined in three ways: First, when a household spends a greater proportion of income on health-related expenses than a certain threshold, usually between 5% and 40%, the household is considered to have limited ability to pay for health care services. This is referred as catastrophic health expenditure (Ke Xu et al., 2003). The calculations vary in the United States and China and therefore, the thresholds are different in these two countries. For example, in paper II, the calculation of catastrophic health expenditure in China used disposable household income as the denominator, which excluded expenditures on basic needs such as food. In paper III, the calculation of catastrophic health expenditure used total household income as the denominator, which did not take into account the cost of basic needs. Second, if a household's income falls below a particular poverty line, defined using an absolute value after subtracting out-of-pocket medical payments and other health-related payments, the household is regarded as undergoing health-induced poverty (Habib, Perveen, & Khuwaja, 2016). Prior literature adopted many different poverty lines in the calculations, such as federal poverty line and supplemental poverty measure in the United States; Dibao, standard poverty threshold, and regional poverty lines in China; and $1.9 or $2.5 U.S. dollars per day in the global context. Third, for households already below a particular poverty line before subtracting basic needs such as food or health-related direct and indirect payments, health-induced poverty is defined as the increased intensity of poverty (also referred as the poverty gap) that is induced by health-related payments (W. Yang, 2014).

This dissertation builds on and extends the limited existing literature on health-induced poverty by investigating this issue among older adults, particularly by adopting the measure of relative financial burden (the percentage of health care expenses in total income) and catastrophic health expenditure (when the percentage of health care expenses exceeds 10% or 40% of household total income in the United States and China, respectively) to capture health-induced poverty and using more recent nationally representative datasets and rigorous study designs. Specifically, Paper I, titled “The dynamic relationship between public and private transfers among older adults: Does experiencing higher health care spending change the relationship?” examined the dynamic relationship between public transfers and interfamily private transfers in China using the China Health and Retirement Longitudinal Study (CHARLS) 2011, 2013, and 2015 data and the Arellano-Bond model. The relationship was found to be different among rural and urban older adults. More specifically, public transfers did not induce any crowding-out or crowding-in effects on private transfers among rural older adults. Instead, their private transfers were more likely to be determined by their private transfer behaviors in the past. In contrast, urban older adults’ private transfers were significantly crowded out by public transfers. Such crowding effects were greater for those who had a higher level of health care spending.

Paper II, titled “Does New Rural Cooperative Medical Insurance (NRCMI) reduce catastrophic health expenditure? Evidence from the China Household Income Project,” examined to what extent participating in NRCMI was associated with the incidence of catastrophic health expenditure (CHE) among middle-aged adults and older adults. This paper used China Household Income Project 2007 rural data and the methods of the instrumental variable to answer this research question. Taking advantage of the gradual rollout of the NRCMI policy at the village level, this paper used village-level NRCMI rollout time and participation rates as the instruments. The results show that NRCMI participation did not change the incidence of CHE among middle-aged and older adults in Sichuan and Anhui provinces. This finding is consistent with findings of prior studies, especially those obtained using quasi-experimental designs (Ministry of Health Statistical information center, 2007; Wagstaff, Lindelow, Jun, Ling, & Juncheng, 2007). It provides empirical evidence to policy makers that the impacts of NRCMI participation on financial protection are limited.

Paper III, titled "Does closing the donut hole under the Affordable Care Act reduce financial burdens of prescription medication expenses among Medicare Part D beneficiaries?" examined the effects of the donut hole closing policy on prescription drug usage, catastrophic health expenditure, and prescription drug cost-induced catastrophic health expenditure in the United States. This study used Medical Expenditure Panel Survey 2008-2017 longitudinal nationally representative data and the method of difference-in-differences. The findings suggest that the donut hole closing policy was associated with more usage of prescription drugs and a higher likelihood of experiencing catastrophic health expenditure induced by prescription drugs among enrollees who fell in the donut holes.

Overall, the findings obtained from these three papers provide empirical evidence that health-induced poverty among older adults in both China and the United States is prevalent and the current public transfers and health policies are either ineffective or insufficient to reduce health-induced poverty as intended. The dissertation overall alerts policy makers that older adults with greater health care needs and more health care spending but limited financial resources should receive particular attention future policy reforms in both China and the United States.

PAPER I: The dynamic relationship between public and private transfers among older adults in China: Does experiencing higher health care spending change the relationship?

Abstract

Using the panel data of the China Health and Retirement Longitudinal Study (CHARLS) 2011, 2013, and 2015 and the Arellano-Bond model, this paper, for the first time, examines the dynamic relationship between public and private transfers among rural and urban older adults in China. The relationship was found to be very different in rural and urban settings. The results show that public transfers did not induce any crowding-out or crowding-in effects on private transfers among rural older adults. Their private transfers were more likely to be determined by the private transfers they received in the last two years. In contrast, public transfers crowded out private transfers for urban older adults. By including health care spending as the key control variable, the magnitude of the crowding-out effect increased for urban older adults.

Introduction

Many countries are undergoing an unprecedented challenge to provide financial support to the older generation and guarantee their livelihood and well-being. China is no exception. The population in China has been aging rapidly over the past two decades. Specifically, the proportion of Chinese aged 60 or older reached 10% of the total population in 2006, and it is projected that this proportion will rise to 30% by 2030 (Textor, 2020b, 2020a). In particular, rural older adults have been becoming even more vulnerable due to lack of care and inadequate financial resources related to intensified growth of urbanization and labor migration. Therefore, it is increasingly difficult to follow the traditional family-supporting model for older adults.

China has implemented several cash-transfer programs to respond to these challenges since 1999, especially in rural areas where public benefit programs were previously lacking, such as the Minimum Livelihood Guarantee program (Dibao), the New Rural Cooperative Medical Scheme, and the New Cooperative Pension Scheme. These programs were found to be effective or ineffective in certain aspects. For example, the Dibao program was found to be effective in decreasing poverty depth and severity, but less effective in reducing poverty rates (Gao, 2017). It also boosted households' consumption on health care and education for urban beneficiaries but only on health care for rural beneficiaries (Gao, Zhai, Yang, & Li, 2014; Han, Gao, & Xu, 2016). The New Rural Cooperative Medical Scheme was found to be effective in improving the health status of low-income older enrollees (Cheng, Liu, Shen, Zhang, & Zeng, 2013) but not among enrollees in general (Lei & Lin, 2009).

One concern raised by scholars is that public and government transfers affect family relationships and living arrangements in a negative way in many high-income countries (Cong & Silverstein, 2011; Wu & Ramesh, 2014). In China, studies found that the New Rural Pension Scheme did not significantly crowd out private transfers from noncoresident children to their parents (Ning, Liu, Gong, & Liu, 2019). The Dibao program was found to crowd out nearly 1,100 yuan (equivalent to $157 in U.S. dollars) of older parents from their adult children in rural areas in 2015. The New Rural Cooperative Medical Scheme was found to crowd out nearly 8% of private transfers from migrated workers to their parents (L. Zhao & Zhao, 2014). All studies examining the relationship between public transfers and private transfers focused on rural residents. No studies have investigated this relationship among urban older adults yet. The topic is particularly important because it can provide evidence to policy makers whether the antipoverty effects of the public transfer programs were reduced by crowding out interfamily private transfers.

The relationship between public and private transfers may vary depending on health-related spending. Health care spending can account for as much as 65% of per capita income in some counties with low GDP (T. Yang et al., 2016). By decomposing the leading factors of poverty among older adults in China, official reports found that even though the poverty rate has steadily reduced from 10.2% to 4% since 2012 in China, the proportion of health payment-induced poverty increased from 42% in 2014 to 44% in 2017 (The State Council Leading Group Office of Poverty Alleviation and Development, 2017). Therefore, it is important to understand whether the relationship between public and private transfers would change if controlling for health care spending.

Using a nationally representative, longitudinal dataset and the Arellano-Bond model, this study addressed three research questions: (1) What were the trends in the levels and percentages of public and private transfers between 2011 and 2015 in rural and urban areas? (2) Did public transfers crowd out (substitute) or crowd in (supplement) private transfers among older adults in rural and urban China? (3) Did controlling for health care spending reduce the crowding-out or crowding-in effect among rural and urban older adults? It is essential and meaningful to have an evaluation paper on public transfers at this stage for further policy-making references, because many policy changes concerning public transfers have been made in recent years. By utilizing a rich array of control variables at different levels and rigorous empirical strategies, this study can enable a timely discussion on the dynamic relationship between public and private transfers among Chinese older adults.

Policy Background: Public and Private Transfers for Older Adults in China

The public transfer system in China can be generally clustered into two categories: social insurance and social assistance. Pension income is one primary component of social insurance and income resources for older adults in China. The contribution structures and benefit levels vary considerably between rural and urban areas. Urban retirees receive a monthly sum of the basic pension (1% of the province-wide average earnings and individual indexed average wage) and a certain percentage (depending on a government-determined annuity factor, 1/139 if retiring at 60 years old) of individual accumulation funds (8% of employees' wages). Urban unemployed residents and rural residents are eligible for the Minimum Pension program[1] by contributing to individual pension accounts or taking a pension once they reach the 60-year-old requirement. The monthly pension payment features two parts for these two groups of older adults: a fixed amount (55 yuan from the central government plus a top-up from local governments) and a 1/139 share of total individual contributions. Given the vast disparities in regional economic development and household financial capabilities in contributing to personal pension accounts, huge discrepancies exist in the benefit level (Zhu & Walker, 2018).

The other category, social assistance, consists of two parts: cash subsidies, such as Dibao, rural Wubao, or urban Sanwu, and cash reimbursement, such as medical assistance, injury or disaster relief, and vagrant assistance.[2] The cash subsidies are usually means-tested programs, the eligibilities of which are determined by all sources of income compared to local poverty

[1] For more details, please refer to Appendix 1.
[2] For more details of these public transfer programs, please refer to Appendix 1.

lines, assets, and family structure. The subsidy standards and poverty lines are guided by the central government but administered by local governments and therefore, the eligibility and subsidy standards vary not only between rural and urban areas but also across localities. Dibao, the largest conditional cash transfer program in China, was implemented nationwide in urban and rural areas in 1999 and 2007, respectively (Gao, 2017). Wubao (translated as Five Guarantees) was provided in rural areas. Sanwu (translated as Three Nones) was offered in urban areas. Since 2014, these two programs have been gradually combined and unified as Tekun (translated as Extreme Poverty). The eligibilities of these programs are not as standardized as the Dibao program—local leaders have the authority to decide the qualifications according to their own observations and judgments regarding the poverty level of a household. The cash reimbursements are transferred to those who had unexpected fees or payments that occurred, usually after disasters, critical illnesses, land seizures, and so on.

As shown in Table 1, in general, both the fiscal budgets and average receipts increased, with the exception of public financing on urban Dibao, which decreased from 2013 to 2015. However, the number of beneficiaries in programs of Dibao, Wubao, Tekun, and medical assistance steadily decreased between 2011 and 2015. It is also noted that discrepancies exist between the average local standards and average receipts in both rural and urban Dibao, and the gap had enlarged between 2011 and 2015. Comparatively, rural China has many more beneficiaries of public transfers, except pension income, whereas the average subsidy amounts are much smaller than in urban areas.

[Table 1 here]

Conceptual Framework

Theoretically, the occurrence of interfamily private transfers is, in general, motivated by two reasons: altruism and exchange. The altruistic framework hypothesizes that transfer givers care about recipients' well-being and make transfers to maximize or increase the utility of recipients (Barro, 1974; Becker, Drachman, & Kirscht, 1974; Cox, 1987). In this case, interfamily transfers are more likely to happen if transfer recipients' financial status is lower than nonrecipients, and the amount is expected to be higher for recipients with lower permanent income (Cox, Eser, & Jimenez, 1998). The empirical evidence shows that public transfers, such as social security and private transfers, crowded out interfamily transfers if transfers were motivated by givers' altruistic feelings in Peru in the mid-1980s (Cox & Jimenez, 1992). In that situation, the interfamily transfers decreased the redistribution effect of public transfers.

The second motivation, exchange, hypothesizes that both transfer recipients and givers realize that the transferred money will be paid back later (Bernheim, Shleifer, & Summers, 1986). This framework does not necessarily predict negative associations between recipients' financial status and transfer occurrence. In contrast, the association could be positive as well—the initial transfer(s) could be motivated even though recipients' income is increasing or higher than nonrecipients (Cox & Rank, 2016). The exchange framework hypotheses are related to the mechanisms between public and interfamily private transfers. Cox and Jimenez (1992) they found that public transfers could crowd in interfamily transfers, and the redistribution effect of public transfers on well-being and financial status is therefore, reinforced by interfamily transfers in Peru.

Empirical Evidence

The crowding-out effects of public transfers on private transfers have been widely investigated in the global context, including both developing and developed countries (Cox & Jimenez, 1992; J. Lee & Lee, 2009; Nikolov & Bonci, 2020). The vast majority of such studies found that the public transfers either had crowding-out or nonsignificant effects on private transfers, and only one found a significant crowding-in effect (Kang, 2004). In China, the findings were similar—the rural pension programs and Dibao were found to either crowd out private transfers from children to their older parents or have a nonsignificant impact on private transfers. The methodologies adopted in these studies included linear regressions, logistic regressions, fixed effects, first difference, propensity score matching, and regression discontinuity, which all captured the static relationship between public and private transfers. None of the studies so far has examined the dynamic relationship.

The crowding-out effect of public transfers on private transfers was found in the global context. Cox (1992) discovered that social security benefits in Peru crowded out about 20% of private transfers from adult children to parents. Similarly, Orraca-Romano (2015) found that free health insurance in Mexico reduced the probability of private-transfer behaviors by 6% while not significantly driving down the transfer amount. In Ghana, Strupat and Klohn (2018) had similar findings that public health insurance significantly crowded out the incidence of making informal transfers by 12%. Lee and Lee (2009) examined the crowding-out impact of the Basic Old-Age Support Pension program in South Korea on private transfers. They found that the crowding-out effect was more intense among middle-income families than in low-income ones.

Only one empirical study found that public transfers significantly crowded in private transfers in the global context. Using Nepal Living Standards Survey 1995/96 data and descriptive analyses, Kang (2004) concluded that public transfers in Nepal could crowd in private transfers by 21%. However, the results should be interpreted with caution because the public transfer program was not expanded nationwide and the generosity of the programs was limited (Nikolov & Bonci, 2020). Additionally, the study did not control for confounding variables nor account for bidirectional relationships.

In China, most studies that explored the relationship between public and private transfers focused on the effects of the pension programs. The findings were mixed. Chen et al. (2017) used a semiparametric method and found that the pension program in urban China crowded in private transfers from children to older parents, especially among older adults with middle or high pension income. Nikolov and Adelman (2019) examined the effect of the New Rural Pension Scheme on private transfers using a difference-in-difference-in-differences method. They found that this program crowded out private transfers from children to their older parents, even though the effect size was much smaller than the results found in high-income countries. Ning et al. (2019) examined the effects of the same program using a combined method of regression discontinuity and difference-in-differences and the China Health and Retirement Study 2011 and 2013 data. They found, however, no significant crowding-in or crowding-out effect of the New Rural Pension Scheme on private transfers from noncoresident children to their parents.

In addition to the pension programs, one study examined the crowding-out effect of another large public transfer program in China, Dibao, on private transfers (Han, 2020). It used China Health and Retirement Longitudinal Study 2015 data and the propensity score matching method. The results show that Dibao crowded out irregular private transfers from children to their older parents in rural areas, but not regular private transfers. No other studies investigated the relationships between Dibao or other public transfer programs and private transfers.

This body of existing literature has several limitations that can be addressed by future research. First, most studies used cross-sectional data, which did not capture changes in public and private transfers over time. Second, many studies examined one specific public transfer. However, low-income families are usually the beneficiaries of multiple public transfer programs at the same time. The total crowding-out effect could be shared by various public transfers, instead of the one specific public transfer. Therefore, the crowding-out effect in such studies may be overestimated. Third, regarding upstream transfers (from the younger generation to the older generation), given that the life expectancy has been increasing in most countries, older parents as recipients of their children's transfers could also be transferring support to their parents, the children's grandparents. So far, no study has discussed private transfers that occurred between older adults and their older parents. Prior studies focused on either transfers from adult children to their older parents or transfers from older adults to their adult children. Last, most studies addressed how pretransfer income and socioeconomic status would determine the relationship between public and private transfers. However, given interfamily transfer is not a static behavior, it could also change depending on other events or needs, such as health care spending.

Prior literature found factors including culture, resources, financial market status, socioeconomic status, family structure, and demographic characteristics are associated with the occurrence and amount of private transfers. Adult children in Asian cultures, such as Japan and China, are more likely to financially support their older parents (Horioka, 2014; Horioka, Gahramanov, Hayat, & Tang, 2018). Additionally, interfamily transfers occur more when and where the financial market is more imperfect (Cox et al., 1998). Interfamily transfers are associated with demographic and socioeconomic factors, such as age, gender, marital status, and recipients' and givers' income, assets, and homeownership (Reil-Held, 2006). Living arrangements—for instance, coresidence and labor migration—have also been found to be significantly associated with interfamily transfers (Cong & Silverstein, 2011; Y. Li et al., 2014).

Building on the existing literature, this study used three-wave panel data with comprehensive questions regarding both public and private transfers to investigate the effect of public transfers on interfamily transfers over 5 years. Specifically, this study explored the crowding-out and crowding-in effects of public transfers on interfamily private transfers among rural and urban older adults in the Chinese context. Both upstream (from the younger generation to the older generation) and downstream (from the older generation to the younger generation) were included in the analyses. This study additionally compared the models with and without controlling for health care spending to investigate the relationship between public and private transfers.

Based on the conceptualization and empirical evidence, I hypothesize that interfamily private transfers are crowded out by public transfers for older adults in China. The patterns and magnitudes of the crowding-out effects are hypothesized to be different between rural and urban older adults.

To build on prior studies, this study made contributions in four aspects. First, it contained a rich array of measures to capture private transfers. The prior studies focused on private transfer-in (receiving from others) only. This study additionally assessed private transfer-out (giving to others). Besides, this study included both upstream (from children to parents) and downstream (from parents to children) private transfers. In addition, transfers that occurred among multiple generations were also reflected in this study, including older adults' (second generation) transfer-in from or transfer-out to their parents (first generation) and their children (third generation). Second, most of the public transfer recipients were eligible for multiple public transfer programs. Unlike prior studies that examined a specific public transfer program, this study examined public transfers as a whole. The advantage of doing this is that it reduced the possibility of overestimation of a single public transfer program. Third, all prior studies focused on the crowding-out effect of public transfers among rural residents. This study added empirical evidence on the relationship between public and private transfers among urban older adults in the Chinese context. Last, this study, for the first time, used the Arellano-Bond model to examine the dynamic relationship between public and private transfers. The usage of the Arellano-Bond model enabled this study to reduce omitted variable bias and the reverse causality issue and capture private transfer behaviors in the past.

Methods

Data and sample

This study used nationally representative longitudinal data, the China Health and Retirement Longitudinal Study (CHARLS), collected in 2011 (Wave I), 2013 (Wave II), and 2015 (Wave IV) in China.[3] Most of the questions in this dataset are consistent with many other influential aging studies in the world, such as the Health and Retirement Study (HRS) in the U.S., the Survey of Health, Ageing, and the Retirement in Europe (SHARE), and the English Longitudinal Study of Ageing (ELSA). The CHARLS specifically added many culturally

[3] This paper does not use Wave III data, collected in 2014, which is a life-course survey and does not cover the same questions and variables this paper needs.

adapted survey questions to better capture norms, values, and cultural practices in China. The CHARLS, additionally, is the only nationally representative longitudinal survey to comprehensively collect information on Chinese older adults' public and private transfers, as health status, and health care costs.

The CHARLS Wave I, II, and IV surveys interviewed 17,708, 19,666, and 20,258 individuals, respectively, in more than 10,000 households in 450 villages or neighborhoods selected through probability proportional to size sampling in 28 provinces in China. The dropout rates in Wave II and IV were 20.5% and 13.59%, respectively.

This study limited the analytic sample to households with at least one main respondent and their spouse being 55 years old or older when interviewed. The current retirement ages in China are 60 (for men) and 55 (for women) for civil servants and 55 (for men) and 50 (for women) for workers. This study adopted the age of 55 as the cutoff for simplicity purposes. To better capture the dynamics of interfamily private transfers, this study adopted individuals, including both respondents and spouses, if married, as the analytic unit. To meet the requirement of running the Arellano-Bond model, only individuals who participated in all three waves were included in the analysis. The analytic sample size is 9,496 individuals, including 6,112 with rural Hukou (i.e., household registration status) and 3,384 with urban Hukou.[4]

Measurement

The information about interfamily private transfers collected in the survey contains both transfer-in (received from others) and transfer-out (giving to others). This study adopted the amount and incidence of transfers as dependent variables for both transfer-in and transfer-out.

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[4] In this analytic sample, 276 individuals had urban Hukou but lived in rural regions as defined by National Bureau of Statistic of China, and 1,709 individuals had rural Hukou but lived in urban regions.

The amounts of private transfer-in were the sum amounts of transfers received from children, parents, other relatives, and friends. The amounts of private transfer-out were the sum amounts of transfers given to children, parents, other relatives, and friends. The incidence of interfamily transfers captures whether the respondents had any private transfer activities in the last year. It was coded as 1 if either or both transfer-in or transfer-out occurred, and coded as 0 otherwise. In the descriptive analysis, to clearly show the pattern and size of private transfers, the net transfers were also calculated, which are the sum amounts of private transfer-ins (positive values) and private transfer-outs (negative values) between older adults and their children, their parents, other relatives, and friends.

The independent variable, public transfer income, reflected the total amount a household received from programs including unemployment compensation, pension subsidy, medical assistance, Dibao, worker's compensation from an industrial accident, compensation insurance including wage-replacement benefits, disability and survivor benefits, older adult family planning subsidies, subsidies from reforestation, Wubao, Tekun, work injury subsidies to the immediate family members, and emergency or disaster relief.

This study took the natural logarithms of the amounts of private transfer-in, private transfer-out, and public transfers in the regression analyses, because the private transfers were highly right-skewed. All transfers reported in the survey were either 0 or positive values. Given that the natural logarithms of 0 are undefined, I added a constant value of 1 to the numbers for the log transformation, which would not affect the use of the data.

The key control variable, health care spending, was controlled for in the second set of analyses, given that the private transfers are also likely to be affected by health care spending. It was measured by the level of health care spending. This refers to the concept of catastrophic health expenditure, which reflects the relative financial burden induced by health-related spending. Prior studies used 5% to 40% as cutoffs to determine the incidence of catastrophic health expenditure, depending on the included categories of expenditure, sources of income, and the wealth level of the studied regions (Ke Xu et al., 2003). In this study, more specifically, I calculated the ratio of health care spending of the main respondent and his or her spouse, if married, to their income in the last year. Then I categorized the ratios into three groups—coded as 1 if the ratio was below 5% and above 0%, coded as 2 if the ratio was between 5% and 40% (not including 40%), and coded as 3 if the ratio was at or above 40% or under 0%. The higher the coding number, the more intensified the level of health care spending. The total amounts of health expenses were the summed amounts of direct costs for doctor visits, hospitalizations, and dental care on a yearly basis. Respondents were asked how much they spent on doctor visits in the last month and how much on hospitalizations and dental care in the previous year. The yearly health expenses were calculated by summing the costs of hospitalizations, dental care, and 12 times the costs of doctor visits.

Based on the prior analysis, this study controlled for a rich set of characteristics at the main respondent, household, and community levels. At the individual level, the main respondents' age, educational attainment, marital status, self-reported health (range = 1–5; a higher number indicates better health condition), and retirement status (dummy coded as 1 if retired and 0 otherwise) were controlled. At the household level, this study controlled for the total number of living parents of a couple, total number of children of a couple, living arrangement with their children (living nearby or coresiding), the couple's total earnings and financial assets, total number of people in the household, and total amount of household consumption. This operationalization was based on the assumption that each couple had access to their total earnings and financial assets if needed. Similarly, the human capital resources they could obtain from their parents and children and caregiving responsibilities they could provide to their parents and (grand)children were both potentially doubled for a couple. Children or parents, no matter if they lived in the same household as the couple or not, would be treated the same if they had cash or in-kind transfer activities with the couple. At the community level, this study controlled for the type of community (categorized as village, community, or both), population size, and the net income per capita.

Empirical strategies

Private transfer behavior is not static but can change over time or be triggered by certain reasons. This study aimed to go beyond the static relationship and explore the dynamic relationship between public and private transfers. A simple ordinary least squares estimation or a fixed-effect method could not capture the effects of the changing public transfers on the varying private transfers. Following the study design of Meraya et al. (2018), this study tested the relationship between public and private transfers by using three methodologies to compare the results.

I. Ordinary least squares (OLS) estimates

Based on the indicators affecting the incidence and amount of interfamily private transfers found in the prior literature, this study, in the first step, involved a simple cross-sectional OLS regression to estimate the rough correlation between public transfers and private transfers by controlling for observable variables along with the key control variable, health care spending. The OLS estimation specification is as follows:

$$PRT_{it} = \beta_0 + \beta_1 PUT_{it} + \beta_2 EXP_{it} + \beta_3 X_{it} + \mu_{it} \qquad (1)$$

In this equation, PRT_{it} is the incidence or logged amount of private transfers, PUT_{it} is the incidence or logged amount of public transfers, EXP_{it} stands for the level of health care spending, and X_{it} is the vector of other control variables. A strong positive association between public and private transfers is expected in this model, which will provide the foundation for further estimations.

II. Fixed-effects (FE) model

One of the major concerns of using simple cross-sectional OLS estimation is that variables that are not observable or measurable, such as family culture or differences in household characteristics over time, are potentially correlated with the incidence or amount of private transfers. Therefore, a fixed-effects model was applied in the second step to remove the omitted variable bias that is induced by time-invariant characteristics in households (McGarry, 2016). The model specification is as follows:

$$PRT_{it} - \overline{PRT_{\iota}} = \beta_1(PUT_{it} - \overline{PUT_{\iota}}) + \beta_2(EXP_{it} - \overline{EXP_{\iota}}) + \beta_3(X_{it} - \overline{X_{\iota}}) + \epsilon_{it} \quad (2)$$

Where $\overline{PRT_{\iota}}, \overline{PUT_{\iota}}, \overline{EXP_{\iota}}$, and $\overline{X_{\iota}}$ represent the average private transfer, average public transfer, the average level of health care spending, and average value of other control variables, respectively, for individual *i* over time *t*. The error term ϵ_{it}, stands for the time-variant residuals that were not canceled out by the subtraction. Compared to the cross-sectional OLS regression, the fixed-effects model improved the accuracy of estimations of the correlation between public and private transfers. The results, including both coefficients and statistical significance, obtained from OLS regressions and fixed-effect models are expected to differ. Nevertheless, the fixed-effects method does not deal with the endogeneity between private and public transfers, such as unobserved time-variant characteristics, dynamics of households, and the consistency of private-transfer behavior in certain households.

III. Arellano-Bond model

As mentioned, the primary aim of this study was to investigate the dynamic relationships between public and private transfers among older adults in the Chinese context. I choose the Arellano-Bond model, a systematic generalized methods of moment (GMM), to detect whether interfamily private transfers were crowded out by increased public transfers in both the current year and the following 2 years[5] as hypothesized. For example, this paper examined if the interfamily private transfers in 2013 were crowded out by public transfers in 2013 while accounting for public transfers in 2011.

The first difference in the Arellano-Bond estimation reduced the omitted variable bias that was induced by the unobservable time-invariant characteristics of individuals, households, and communities by subtracting the differences of both outcome and explanatory variables across waves (Roodman, 2006). In addition, the lags of private transfers were used as instruments for differenced lags of private transfers, which were endogenous and different than how they are conceptualized and used in instrumental variable methods (Bhargava & Sargan, 2006). The inclusion of the lags of the private transfers in the model enabled the study to better capture the potential consistent behaviors of interfamily transfers. More specifically, the amounts of private transfers at time t (current analytic time period) were correlated with the amounts of private transfers in time $t-1$ (last analytic time period). This allowed more accurate estimations for families that had more occurrences or amounts of interfamily transfers due to closer relationships and increasing transfer habits in households over time, even though they did not have higher earnings or other related predictors.

[5] The interval of two waves of data is 2 years.

The Arellano-Bond model specification used the lagged levels of the endogenous regressor, public transfer, in this case, to make the endogenous variables not correlated with the error terms (Meraya et al., 2018; Mileva, 2007; Roodman, 2006). In the model specifications, public transfers were assumed to be endogenous. The causality might run in both directions. The amounts of private transfers an older adult received may affect whether the older adult was eligible for certain public transfers, especially the means-tested programs. Conversely, the amounts of public transfers an older adult obtained might also affect how likely or how much this older adult received interfamily private transfers.

[Figure 1 here]

The Arellano-Bond model estimation requires at least three waves of data[6] and satisfying a condition wherein the data have a large sample size and a short time dimension. The sample size was 9,496 individuals and the time dimension was 4 years, from 2011 to 2015. Therefore, this study satisfied both requirements.

The model specification to answer this research question is as follows:

$$\Delta PRT_{it} = \Delta\beta_1 PRT_{i,t-1} + \Delta\beta_2 PUT_{it} + \Delta\beta_3 PUT_{i,t-1} + \Delta\beta_6 X_{i,t} + \Delta\mu_{it} \quad (3)$$

wherein t is the indicator at the current period, $t-1$ is the indicator at last period, PRT_{it} and $PRT_{i,t-1}$ are the incidence or amounts of private transfers at the current and the last periods, respectively, PUT_{it} and $PUT_{i.t-1}$ represent the incidence or amounts of public transfers at the current and last periods, respectively, and X_{it} is the vector of control variables. The error term, μ_{it}, is constituted of unobserved effects, v_i, and observed errors, ε_{it}.

[6] It should be noted that the Arellano-Bond test for correlations in first differences requires at least four waves of data. Therefore, this study was not able to conduct the Arellano-Bond test for correlations in first differences and referred to the Sargan and Hansen tests of overidentification restrictions only.

Another purpose of this study was to examine whether the effect size could change when accounting for health care spending in examining the dynamic relationship between public and private transfers among Chinese older adults. To achieve this goal, this study compared the coefficients and statistical significance of the two models with (Equation 4) and without (Equation 3) controlling for health care spending in the current and the prior wave of survey.

$$\Delta PRT_{it} = \Delta\beta_1 PRT_{i,t-1} + \Delta\beta_2 PUT_{it} + \Delta\beta_3 PUT_{i,t-1} + \Delta\beta_4 EXP_{it} + \Delta\beta_5 EXP_{i,t-1} + \Delta\beta_6 X_{it} + \Delta\mu_{it} \quad (4)$$

where EXP_{it} and $EXP_{i,t-1}$ are the levels of health care spending at the current and the last periods, respectively.

Results

Descriptive statistics

Table 2 presents the trends and patterns of public and private transfers in rural and urban areas between 2011 and 2015. Overall, a higher proportion of older adults in rural areas had private transfer activities than their urban peers. Interestingly, rural older adults had positive private net transfers across three waves, whereas urban older adults had all negative values across these waves. This means that rural older adults had more transfer-in from children, parents, relatives, and friends than transfer-out to these people. In contrast, urban participants had more transfer-out than transfer-in. In terms of public transfers, a far higher proportion of rural participants received public transfers than urban participants.

In most cases, the amounts of public transfer income received by rural older adults were slightly larger than or similar to their urban peers. For rural older adults, a higher percentage of the public transfer income was from cash subsidies, such as Dibao, Wubao, Tekun, subsidies from reforestation, and agricultural subsidies. For urban older adults, however, the difference between the amounts received from social assistance and cash subsidies were not remarkably large (about 100 yuan in each wave). Consistent with findings from the administrative data, the public transfer income for both rural and urban participants steadily increased between 2011 and 2015, yet the number of beneficiaries decreased during this period. In addition, both the occurrence of hospitalizations and health care spending for rural and urban older adults increased from Wave I to Wave IV.

[Table 2 here]

About 80% of the sample had rural Hukou. The average age was 63 years old in the baseline interview. More than 40% of the participants in rural areas did not have any form of education, and less than 1% of rural respondents had a vocational school degree or above. In contrast, 12% and 15% of urban respondents had no formal education and vocational degree or above, respectively. This is because, in most cases, older adults with rural Hukou, no matter if they lived in urban or rural areas when interviewed, had received their education in rural areas when they were young. Not surprisingly, more than 80% of the sample was married or partnered. Urban older adults reported poorer health status than rural older adults. Around 30% of the rural sample and 70% of the urban sample formally retired from employment by the year they were interviewed. This is consistent with the findings in prior literature—older adults in rural areas usually continue their farm or fishery working until unbearable physical limitations (Y. Zhao et al., 2013).

[Table 3 here]

Although the CHARLS gathered much detailed information on public and private transfers, individual-, household-, and community-level characteristics, limitations of this dataset may affect the accuracy of the analysis results. First, some categories of public transfers and questions relating to parents' and children's income have more than 20% missing values. Given that it is uncertain whether the missing values were missing at random, in this study, I dropped these 20% cases and focused on the cases with completed information on income, health spending, and financial transfers. Second, as one part of the private transfers, premium payment amounts made by children or relatives were not surveyed in 2015. Third, as mentioned, health care expenditures, which could be affected both by public and private transfer and could also affect private transfers in later waves, cannot be precisely calculated from the current questions. For example, the amounts an individual spent on doctor visits in clinics or outpatient departments and self-treatment were reported for the prior month, but the amounts paid on hospitalization and dental visits were reported for the previous year. Additionally, expenditures on dental visits were missing in Wave 1, and the number of dental visits for spouses if married were missing across all three waves.

OLS and FE estimations

Among rural older adults, the simple OLS results show that public transfers were positively associated with private transfers when controlling for other individual, household, and community characteristics. This means public transfer recipients in rural areas were more likely to receive private transfers (2.8%) and to give private transfers (2.7%) at the same time (Table 4). On average, every 1% increase in receiving public transfers was associated with a 3.3% increase in private transfer-in and a 3.5% increase in transfer-out. Similarly, the incidence of hospital stays was associated with a greater likelihood of receiving private transfers (1.8%), and every 1% of increased health-related spending was associated with 6.6% and 6.1% increases in private transfer-in and transfer-out, respectively.

[Table 4 here]

As discussed, the results obtained from the simple OLS regressions could be biased due to omitted variable bias. The FE models partially corrected this issue by removing the impacts of time-invariant variables. The incidence of public transfer and an increase in amounts of public transfers were no longer significantly associated with the likelihood and amounts of receiving and giving private transfers for rural older adults. The magnitudes of receiving and providing private transfers were statistically associated with the increase in amounts of health spending, increasing to 10.4% and 11.7%, respectively, among rural older adults.

Surprisingly, results for urban older adults did not indicate any statistically significant correlations between public and private transfers using simple OLS regressions. The later corrections made by FE estimations did not alter the results: All associations among urban older adults were not significant at a 90% confidence level. Again, the results of simple OLS and FE for both rural and urban older adults should be interpreted and applied cautiously because neither of the estimations dealt with the endogeneity between public and private transfers.

Arellano-Bond estimations

As shown in Table 5 and Table 6, the estimations of the Arellano-Bond model present the relationship between public and private transfers. For rural older adults (Table 5), without controlling for the level of health care spending in both current and prior waves, every 1% increase in prior private transfer-in predicted a 6.8% increase in current private transfer-in. This model did not pass the overidentification test at a 95% confidence level (p = .04). However, when controlling for the level of health care spending, this relationship between previous and current waves of private transfer-in was no longer significant. An increase in the level of health care spending is expected to cause a 2.3% decrease in the likelihood of private transfer-in.

The amounts of public transfers in both prior and current waves did not significantly cause the changes in private transfer-in and transfer-out at a 95% confidence level for rural older adults. Increases in current and prior public transfers were related to increases in incidences of private transfer-out by 5.9% when not controlling for health care spending. However, this result did not pass the Sargan and Hansen overidentification tests. Both current and prior incidence of the level of health care spending were not significantly associated with transfer-out. Furthermore, the incidence and amount of transfer-out at the previous wave were not significantly associated with the current wave of transfer-out.

[Table 5 here]

For urban older adults, the dynamic relationship between public and private transfers was remarkably different than rural older adults (Table 6). Public transfers had a crowding-out effect on private transfers-in and transfer-out, except one case. A higher level of health care spending reduced the likelihood of private transfer-out. Moreover, the amounts of private transfer-in in prior waves played a strong indicating role in the amount of private transfer-in in current waves. All these outcomes were reflected in models with instruments that passed overidentification tests at a 95% confidence level.

More specifically, every 1% increase in the incidence of public transfer in prior waves caused a decrease in the incidence of private transfer-in by 11.9% and 13.7% without and with the inclusion of health care spending as a control variable, respectively. On average, every 1 yuan increase in public transfer receipt predicted a decrease of 0.36 and 2.22 yuan, respectively, in private transfer-in without and with the inclusion of health care spending as a control variable.

One higher level of health care spending in prior waves was associated with a decrease in private transfer-in by 3,312.43 yuan. Furthermore, participants in our sample were predicted to receive 1.01 yuan more in the current wave if they had private transfer-in in prior waves. Each 1 yuan increase in current public transfer was associated with a 0.36 and 0.39 yuan decrease in public transfer-out, respectively. Similarly, the increase in the previous public transfer was related to a reduction in public transfer-out by 0.38 and 0.39 yuan, respectively, in the two models (Equation 3 and Equation 4).

[Table 6 here]

Conclusion and Discussions

Using panel data from the CHARLS in 2011, 2013, and 2015 and the Arellano-Bond model, this paper examined the dynamic relationship between public and private transfers among rural and urban older adults in China. The results show that public transfer did not induce any crowding-out or crowding-in effects on rural older adults' private transfer receipt and giving. The incidence and amount of private transfers that occurred among rural older adults were more likely to be determined by the private transfers they received in the last 2 years. In contrast, public transfers were found to have crowding-out effects on private transfer receipts, but not private transfer giving, among urban older adults. By including the level of health care spending, the magnitude and significance level of the dynamic relationship between public and private transfers were found to increase among urban older adults.

The results for urban older adults generally follow the hypothesis, but not for the rural older adults. This is probably because the incentives of private transfers in rural families and urban families could be different. Rural older adults were more financially or capably vulnerable in terms of demographic factors than their urban peers, as shown in Table 3, including lower educational attainment, retirement rate, parents' income, and household earnings, assets, and consumption. This could result in rural older adults primarily or largely relying on interfamily transfers to sustain their basic living or meet urgent needs. Comparatively, the small amounts of public transfers would not be able to fully meet their needs, and private transfers, therefore, would occur regardless of the incidence of public transfers.

This paper, for the first time, used the Arellano-Bond model to explore the dynamic relationship between public and private transfers in China. Public transfers had various impacts on interfamily private transfer-in and transfer-out among rural and urban older adults. The finding of a nonsignificant crowding-out effect for rural older adults is consistent with the results of Ning (2019). The findings of a crowding-out effect for urban older adults added empirical evidence of the dynamic relationship between public and private transfers among urban older adults, who were not studied before.

However, this study also bears a few limitations that should be noted. First, as mentioned, more than 20% of data on parents' and children's incomes was missing. To avoid biased results from multiple imputations, this study only focused on complete cases, which could miss participants who did not report their parents' or children's income on purpose, such as those at the high end or low end. Second, given that the instruments did not pass the overidentification tests in some models for rural older adults, this study could not thoroughly detect the dynamic relationship between public and private transfers. It leaves some remaining questions for further studies, such as the dynamic relationship between public transfer and private transfer-out among rural older adults. Third, due to data limitations, this study could only examine the dynamic relationship between public and private transfers for 4 years. A more extended period with more waves of data could improve the accuracy of the estimations and also enable Arellano-Bond tests in the first differences.

This study, on the one hand, confirmed that public transfers do not crowd out private transfers among rural residents, which many policy makers have been concerned about. However, on the other hand, it also revealed the shortcoming of current public transfer policies—the relatively low generosity of public transfers did not enable rural older adults to be financially independent of interfamily transfers. Future policies could consider increasing public transfers in rural areas. Also, targeted populations, such as rural older adults with a higher financial burden of health-related expenditures, could be considered for more types of more generous public transfers.

To further explore the reasons for the crowding-out effects of public transfers on both private transfer-in and transfer-out among urban older adults, future studies could decompose private transfers into various recipients or givers, such as children, parents, other relatives, and friends. Additionally, future studies could also compare migrated older adults with rural and urban older adults, considering the increasing number of migrants in China. Furthermore, when more waves of CHARLS or other qualified datasets are available, future studies could expand the instrument groups by involving more lags of public transfer and level of health care spending in the model to verify the dynamic relationship between public and private transfers among Chinese older adults in the long term.

Table 1-1: Public financing and beneficiaries of Dibao, Wubao, and Medical Assistance programs: 2011-2015.

	Beneficiaries (million)		Fiscal budget (billion yuan)		Average standard (yuan/year)		Average receipts (yuan/year)	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
	2011							
Pension	326.43	5.39						
Dibao	53.1	22.8	66.8	66.0	1718.4	3451.2	1273.2	2883.6
Medical Assistance	63.0	22.2	12.0	6.8	-	-	-	-
Wubao (Rural)	5.5	-	12.2	-	2781.6	-	-	-
	2013							
Pension	497.5							
Dibao	53.9	20.6	86.7	75.7	2434.0	4476.0	1392.0	3168.0
Medical Assistance	21.3	14.9	3.0	1.4	-	-	-	-
Wubao (Rural)	5.4	-	17.2	-	3904.0	-	-	-
	2015							
Minimum pension	504.7							
Dibao	49.0	17.0	93.2	71.9	3177.6	5413.2	1766.5	3799.2
Medical Assistance	6.1	66.3	-	-				
Wubao (Rural)	5.2	-	21.0	-	4792.4	-	-	-

Notes: Beneficiaries of Sanwu in urban areas are included in the Dibao beneficiaries in statistical yearbooks. The total number of Sanwu beneficiaries accounted for about 3%. After 2014, in some regions, the Sanwu program in urban areas and the Wubao program in rural areas were unified as the Tekun program.

Table 1-2: Descriptive analysis of public and private transfers and health spending among rural and urban older adults: 2011-2015.

	2011			2013			2015		
	Freq.	Mean/%		Freq.	Mean/%		Freq.	Mean/%	
	Rural (n=6,112)								
Dependent Variables									
Private Net Transfers	0.61	1.27	(12.11)	0.91	2.14	(12.55)	0.93	2.93	(15.01)
Transfer-In	0.49	1.96	(8.89)	0.84	3.53	(8.44)	0.88	5.36	(9.37)
Transfer-Out	0.30	0.87	(7.52)	0.62	2.07	(7.69)	0.62	3.12	(12.07)
Independent Variables									
Public Transfer Income	0.74	0.66	(1.30)	0.69	0.82	(1.93)	0.59	0.86	(1.93)
Health spending	0.28	1.07	(4.67)	0.45	1.98	(6.86)	0.49	2.36	(8.05)
	Urban (n=3,384)								
Dependent Variables									
Private Net Transfers	0.54	-0.88	(18.23)	0.89	-1.02	(22.57)	0.92	-1.96	(40.13)
Transfer-In	0.31	1.85	(11.21)	0.75	5.29	(21.91)	0.78	7.15	(28.09)
Transfer-Out	0.37	3.14	(14.49)	0.73	7.50	(24.06)	0.78	9.72	(30.15)
Independent Variables									
Public Transfer Income	0.27	0.55	(1.78)	0.28	0.67	(2.17)	0.31	0.70	(2.62)
Health spending	0.37	1.62	(6.16)	0.56	2.62	(7.66)	0.64	4.41	(14.57)

Notes: 1. The frequency of health spending is the total frequencies of an older adult; 2. The mean of health spending is the average amount a couple spends out-of-pocket on a doctor visit, hospitalization, dental care; 3. The unit of all the mean value and standard deviation in this table is thousand yuan; 4. The t-test results of each variable by Hukou status shows that only the mean of Transfer-in in 2011, the frequency of Social assistance in 2011, and the frequency of Private net transfers in 2015 are not significant at 95% CI between rural and urban Hukou. All others are significant at least at 95% confidence level. Standard deviations are in parenthesis.

Table 1-3: Sample characteristics at the individual, household, and community levels by rural and urban: 2011-2015.

	Rural						Urban					
	2011		2013		2015		2011		2013		2015	
	Mean/%	S.D.	Mean/%	S.D.	Mean/%	S.D.	Mean/%	S.D.	Mean/%	S.D.	Mean/%	S.D.
Individual-level												
Age	62.44	8.00	64.40	7.98	66.25	8.18	63.12	8.23	64.93	8.30	66.94	8.37
Edu attainment												
No formal education	40.08						12.06					
Elementary school	44.94						33.24					
Middle school	11.65						27.48					
High school	2.71						11.79					
Vocational or above	0.62						15.42					
Marital status												
Married/partnered	83.13		81.13		78.66		85.37		83.55		82.06	
Separated/widowed	15.45		17.50		20.08		14.20		16.05		17.40	
never married	1.42		1.37		1.27		0.43		0.41		0.54	
Self-reported health	3.97	0.89	3.94	0.89	3.95	0.92	3.78	0.92	3.77	0.88	3.79	0.90
Retirement status	0.24	0.43	0.29	0.45	0.36	0.48	0.63	0.48	0.64	0.48	0.71	0.45
Household-level												
Parent living status	0.47	0.77	0.37	0.68	0.28	0.58	0.53	0.84	0.44	0.77	0.33	0.65
# of children	3.00	1.51	3.14	1.53	3.28	1.55	2.40	1.40	2.48	1.41	2.59	1.42
If any child lives nearby	0.92	0.27	0.91	0.29	0.90	0.30	0.94	0.24	0.90	0.29	0.89	0.31
If any child co-resides	0.55	0.50	0.47	0.50	0.53	0.50	0.50	0.50	0.44	0.50	0.45	0.50
Couple's total earnings	1.75	7.70	1.79	6.52	1.40	5.53	5.41	51.41	4.29	13.17	3.67	11.08
Couple's total asset	2.56	35.47	7.45	37.30	14.60	62.49	17.83	75.35	39.25	139.61	64.02	291.76
# of people in the hhold	3.65	1.96	3.67	1.99	2.90	1.37	3.07	1.62	3.21	1.64	2.71	1.11
Total consumption	18.13	20.03	28.77	51.05	29.38	42.82	30.79	57.79	39.50	48.12	46.45	70.45
Community-level												
Community type												
Village	93.49						17.92					
Community	5.38						79.92					
Both	1.13						2.15					
Total population	2.35	2.42	2.34	2.39	2.37	2.47	5.78	4.71	5.64	4.64	5.74	4.71
Per capita net income	4.32	4.78	4.32	4.77	4.35	4.86	6.58	7.91	6.45	7.79	6.55	7.89

Notes: Sample sizes in rural and urban are 7,603 and 1,874 respectively; The units of parent's, child's, couple's income, couple's asset, household consumption, and total population per capita net income (in the village) are in a thousand; The t-test results show that only the difference of the mean of Parent health status between rural and urban hukou in 2013 is not significant at 95% confidence level.

Table 1-4: OLS and FE results for rural and urban older adults.

	Private Transfer-In				Private Transfer-Out			
	Incidence		Amount		Incidence		Amount	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
				Rural				
Incidence of public transfer	0.028***	0.035			0.027**	0.040		
	(0.011)	(0.024)			(0.013)	(0.029)		
Amount of public transfer			0.033***	0.032			0.035***	0.028
			(0.013)	(0.027)			(0.013)	(0.030)
Level of healthcare spending			0.066***	0.104***			0.061***	0.117***
			(0.013)	(0.029)			(0.014)	(0.033)
Obs.	6356	6356	6987	6987	6354	6354	7001	7001
R-squared	0.237	0.354	0.280	0.388	0.200	0.194	0.250	0.255
				Urban				
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Incidence of public transfer	0.017	0.035			0.009	0.027		
	(0.017)	-0.037			(0.018)	-0.039		
Amount of public transfer			-0.006	-0.006			-0.008	0.038
			(0.020)	-0.043			(0.020)	-0.043
Level of healthcare spending			0.023	0.022			0.029	-0.02
			(0.022)	-0.048			(0.022)	-0.052
Obs.	2733	2733	2969	2969	2719	2719	2954	2954
R-squared	0.272	0.359	0.281	0.389	0.230	0.239	0.297	0.308

Notes: Standard errors are in parenthesis; All amounts (x) shown in this table, including private transfer-in, private transfer-out, and public transfer, were plus the value of one and taken natural logarithms, which is ln(x+1); Besides the variables shown in the table, all models control for variables including age, educational attainment, marital status, self-reported health status, retired employment status, number of people living in the household, the total number of living parents, number of living children, number of co-resident children, number of children living nearby, informal child care provision, amount of after-tax earnings, total non-housing financial wealth, and the total amount of household consumption.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 1-5: Arellano-Bond Model results for rural older adults.

	Private Transfer-In				Private Transfer-Out			
	Incidence		Amount		Incidence		Amount	
	M(1)	M(2)	M(1)	M(2)	M(1)	M(2)	M(1)	M(2)
Incidence of current public transfer	0.012	0.006			0.059**	0.045		
	(0.019)	(0.025)			(0.027)	(0.034)		
Lagged incidence of public transfer	-0.018	-0.008			0.059*	0.027		
	(0.022)	(0.031)			(0.033)	(0.042)		
Amount of current public transfer			0.074	0.005			0.214	0.004
			(0.082)	(0.072)			(0.301)	(0.136)
Lagged amount of public transfer			0.396	0.443			0.509	0.423*
			(0.373)	(0.421)			(0.313)	(0.228)
Current level of healthcare spending		-0.007		303.068		0.008		-517.138
		(0.012)		(715.192)		(0.022)		(609.695)
Lagged level of healthcare spending		-0.023*		1404.604		-0.035		272.299
		(0.014)		(896.425)		(0.024)		(717.046)
Lagged incidence of private transfer-in	0.068**	0.047						
	(0.028)	(0.035)						
Lagged amount of private transfer-in			0.102	-0.096				
			(0.074)	(0.145)				
Lagged incidence of private transfer-out					-0.046	0.006		
					(0.033)	(0.042)		
Lagged amount of private transfer-out							-0.512	-0.152
							(0.341)	(0.136)
Obs.	4003	3036	3981	3021	4005	3037	3988	3024
d.f.	3	6	3	6	3	6	3	6
Sargan Test Chi2	13.49	10.87	5.96	12.63	9.19	10.16	397.93	79.65
Sargan Prob>chi2	0.04	0.092	0.114	0.049	0.027	0.118	0.000	0.000
Hansen Test Chi2	12.56	11.27	10.17	11.07	9.02	10.92	6.55	11.82
Hansen Prob>chi2	0.06	0.08	0.017	0.086	0.029	0.091	0.088	0.066

Notes: Standard errors are in parenthesis; The M(1) model uses current and lagged public transfers as instruments. The M(2) model adds current and prior catastrophic health expenditure or hospital stays in the instrumental group. Besides the variables shown in the table, all models control for variables including age, educational attainment, marital status, self-reported health status, retired employment status, number of people living in the household, the total number of living parents, number of living children, number of co-resident children, number of children living nearby, informal child care provision,

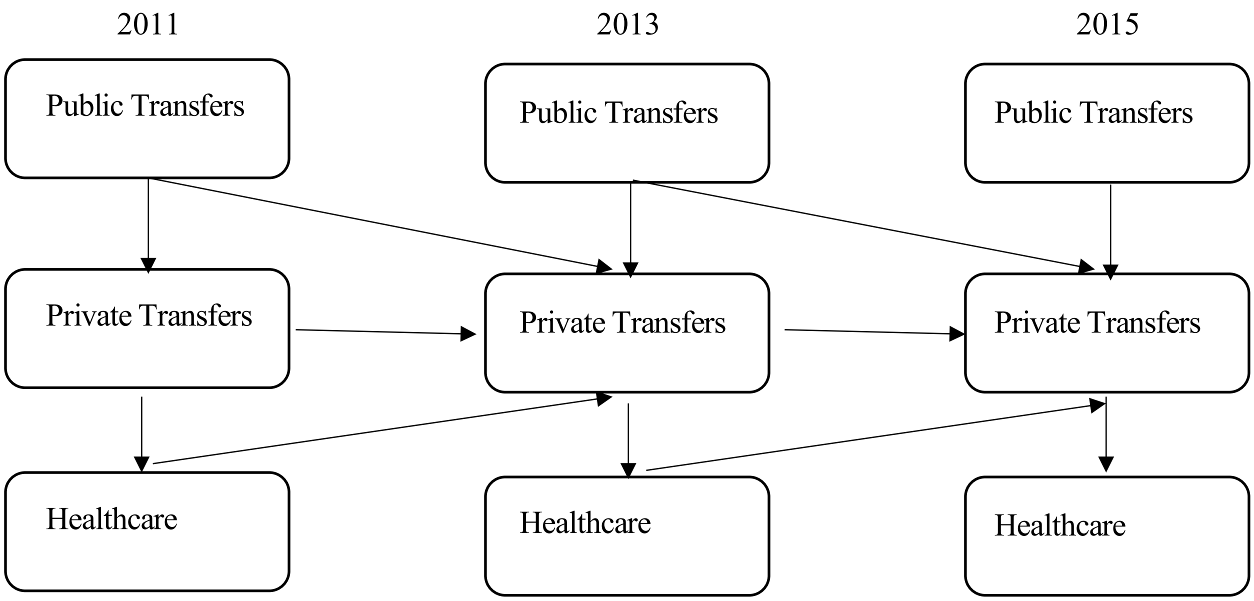
amount of after-tax earnings, total non-housing financial wealth, and the total amount of household consumption; The d.f. represents the degree of freedom.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 1-6: Arellano-Bond Model results for urban older adults.

	Private Transfer-In				Private Transfer-Out			
	Incidence		Amount		Incidence		Amount	
	M(1)	M(2)	M(1)	M(2)	M(1)	M(2)	M(1)	M(2)
Incidence of current public transfer	-0.011	-0.008			4.283**	0.092		
	(0.041)	(0.040)			(1.847)	(0.056)		
Lagged incidence of public transfer	-0.119***	-0.137***			-0.183	0.006		
	(0.044)	(0.044)			(0.349)	(0.064)		
Amount of current public transfer			-0.157	-0.349			-0.364**	-0.385**
			(0.138)	(0.342)			(0.159)	(0.161)
Lagged amount of public transfer			-0.361*	-2.219*			-0.380*	-0.390*
			(0.213)	(1.252)			(0.226)	(0.207)
Current level of healthcare spending		0.004		-1432.299		0.068*		951.134
		(0.022)		(1343.786)		(0.038)		(853.547)
Lagged level of healthcare spending		-0.012		-3312.428*		0.127***		188.507
		(0.025)		(1810.258)		(0.037)		(612.308)
Lagged incidence of private transfer-in	-0.024	-0.016						
	(0.042)	(0.050)						
Lagged amount of private transfer-in			0.128	1.012***				
			(0.260)	(0.308)				
Lagged incidence of private transfer-out					-0.502***	-0.026		
					(0.164)	(0.062)		
Lagged amount of private transfer-out							-0.093	0.015
							(0.098)	(0.035)
Obs.	1629	1234	1614	1224	1589	1205	1582	1199
d.f.	3	6	3	6	3	6	3	6
Sargan Test Chi2	10.42	5.77	1.42	4.40	9.38	5.83	5.93	9.87
Sargan Prob>chi2	0.015	0.449	0.700	0.623	0.025	0.443	0.115	0.130
Hansen Test Chi2	10.80	6.41	4.06	3.51	10.17	4.27	5.66	12.56
Hansen Prob>chi2	0.013	0.379	0.255	0.743	0.017	0.640	0.129	0.051

Notes: Standard errors are in parenthesis; The M(1) model uses current and lagged public transfers as instruments. The M(2) model adds current and prior catastrophic health expenditure or hospital stays in the instrumental group. Besides the variables shown in the table, all models control for variables including age, educational attainment, marital status, self-reported health status, retired employment status, number of people living in the household, the total number of living parents, number of living children, number of co-resident children, number of children living nearby, informal child care provision, amount of after-tax earnings, total non-housing financial wealth, and the total amount of household consumption; The d.f. represents the degree of freedom.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 1-1: Dynamic relationships between public and private transfers.



Appendix 1-1: Summary of social assistance programs in contemporary China.

Name	Launch year	Coverage	Target
Cash subsidies			
Dibao	1999(urban)/ 2007(rural)	National	Provide basic safety nets for the low-income.
Sanwu	1950s	Urban	Provide essential livelihood support to older adults, children, and people with a physical disability or mental illness who have no ability to work, no income, and no family support.
Wubao[7]	1950s	Rural	Provide basic livelihood support to five groups of populations (including people who are old, vulnerable, orphaned, widowed, or disabled) and who have no ability to work and no support by family.
Medical Assistance	2003(rural)/ 2005(urban)	National	Provide support to pay for health insurance premiums, doctor visits, and inpatient services through reimbursement.
In-kind Programs			
Education Assistance	2004	National	Provide tuition and fee waiver and boarding subsidy for children in Dibao families in compulsory education.
Temporary Assistance	2007	National	Provide both cash and in-kind subsidies to people who have extreme disasters or severe acute diseases.
Category Assistance			
Pension	2009(rural)/ 2011(urban)	National	Provide a basic pension insurance system for non-working urban and rural residents who are aged 60 years old and above.
Disabilities Assistance	2015	National	Provide living subsidies, rehabilitation training, and assistive devices to people with disabilities and living hardships.

Resources: Gao, 2017; Yang, 2018; National Bureau of Statistics of China, multiple years

[7] Some Sanwu and Wubao beneficiaries received both cash benefits and in-kind assistance. After 2014, Sanwu and Wubao programs have been unified as Tekun program which has similar target but covers both rural and urban eligibilities.

PAPER II: Does participating in New Rural Cooperative Medical Insurance change catastrophic health expenditure? Evidence from the China Household Income Project

Abstract

One of the primary goals of the New Rural Cooperative Medical Insurance (NRCMI) is to provide financial protection and alleviate the financial burdens of rural residents in China. This study examined whether NRCMI participation affected the incidence of catastrophic health expenditure (CHE) among middle-aged and older adults (45 years old or older) using China Household Income Project 2007 rural data and an instrumental variable estimation method in Anhui and Sichuan provinces, where there was heterogeneity in the NRCMI implementation schedule. The results show that NRCMI participation was not associated with changes in CHE incidence among families. The finding is consistent with the prior literature using quasi-experimental study designs. This study provides empirical evidence to policy makers that the effect of NRCMI participation on financial protections is limited despite its broad population coverage. The limited effects are probably due to the low reimbursement rate and more utilization of expensive health care services.

Introduction

The growing cost of health care services has been a concern for many countries. For example, 62% of bankruptcies in the United States were partially linked to medical problems

(Himmelstein, Thorne, Warren, & Woolhandler, 2009). Fifty-eight percent of low-income Vietnamese who had severe illness would avoid or quit their treatment when needed due to unaffordable medical bills (Vuong, 2015). More than 40% of total health expenditures were paid out-of-pocket in many developing countries such as Mexico, Columbia, and Thailand (Ke Xu et al., 2003).

Medical expenditures accounted for as much as 65% of per capita income in some low-GDP counties in 2011 (T. Yang et al., 2016). Medical poverty could negatively affect people in many ways in the short and long term. In the short term, it could prevent individuals from seeking timely diagnoses or treatment (Mauch et al., 2011), increase households' interfamily labor substitution (Sauerborn, Adams, & Hien, 1996), and threaten their life by forcing them to sell assets or borrow money from loan sharks (Kruk, Goldmann, & Galea, 2009). In the long term, it could also trap those with limited financial resources facing medical bills in a vicious cycle between poorer health and more intense poverty (Daivadanam, 2012).

Chinese residents in urban and rural areas have had health coverage and received health care services for free or at very low prices since the founding of the People's Republic of China. This system finally collapsed due to the significant financial burden on the central government (Y. Sun, Gregersen, & Yuan, 2017). After the late 1970s, the majority of rural residents and about half of the urban residents lost health insurance coverage. In 1998, China formally launched a reformed national health insurance scheme, the Urban Employee Basic Medical Insurance, to provide comprehensive health insurance coverage for the majority of urban employees with the requirement of premium payments from both employers and employees. During 1998–2006, there was a substantial urban–rural health insurance coverage gap. In 2006, rural residents started receiving health insurance coverage when China formally launched the

New Rural Cooperative Medical Insurance (NRCMI) nationwide. The NRCMI was initiated in some villages in 2006 and gradually expanded to the rest of the villages in 2007 and 2008.

Like other health insurance, the primary goal of NRCMI is to provide financial protection to the insured. The NRCMI implementation was guided by the central government, and provincial governments decided which counties would implement it in which year. Once the NRCMI was implemented at the county level, leaders at both county and village levels would decide which village will participate in which year. It covers 740 million rural residents, the majority of whom are more economically vulnerable and had fragmented coverage of health insurance since the mid-1980s. By the end of 2006, the enrollment rate of NRCMI had reached 95%, and 54% of the national population obtained health insurance in only 3 years (National Bureau of Statistics of China, 2018).

Even though the NRCMI covers most rural residents in China, the reimbursement rates for both inpatient and outpatient services are considerably low compared to the Urban Employee Basic Medical Insurance program. NRCMI participants can get reimbursed at rates as low as 30% for outpatient services at top-tier hospitals in urban areas and 60% for inpatient services at village clinics. In contrast, the average reimbursement rate of the Urban Employee Basic Medical Insurance for inpatient services is 80%, and ratio ranges between 50% (in top-tier hospitals) and 80% (in community clinics) for outpatient services (National Healthcare Security Administration, 2019).

Given that NRCMI is a significant health policy breakthrough after China's economic reforms in the 1970s, and covers much of the rural population, its impacts on financial protection warrant rigorous evaluation. Using the gradual rollout schedule or NRCMI at the village level, which enabled the use of instrumental variable methodology, this study examined if participating in NRCMI changed the probability of experiencing CHE among middle-aged and older adults in rural China.

Literature Review

Effects of NRCMI on health outcomes and health utilization

A large body of literature has examined the effects of NRCMI on health outcomes, psychological well-being, doctor visits, and inpatient service utilization (Babiarz, Miller, Yi, Zhang, & Rozelle, 2012; Cheng et al., 2013; Huo & Chen, 2017; Liang, Guo, Jin, Peng, & Zhang, 2012; Yu et al., 2010). Overall, the findings of the effects of NRCMI participation on health outcomes and health utilizations are mixed.

Some studies found positive effects of the NRCMI, especially on inpatient service utilization (Babiarz et al., 2012; M. Li & Wang, 2017; Ma, Zang, & Gan, 2010). For example, using primary data collected in five provinces in 2005 and 2008 and the method of difference-in-differences, Babiarz et al. (2012) found that the NRCMI implementation improved the finances of township health centers and NRCMI participation significantly increased inpatient service utilization. Using China Health and Retirement Longitudinal Study 2011 data and multilevel regressions, Li and Wang (2017) found that NRCMI participation was associated with increased utilization of inpatient and outpatient health care services. Ma et al. (2010) used China Health and Nutrition Survey 2004 and 2006 data and the method of propensity score matching and difference-in-differences to explore the effect of NRCMI participation on food consumption. They found that NRCMI improved beneficiaries' intake of protein, carbohydrates, and fat. However, other studies found no effects of NRCMI on health outcomes, well-being, and service utilization. For instance, in contrast to the findings of Babiarz et al. (2012) and Li and Wang

(2017), Yu et al. (2010) used a primary dataset collected in Ningxia and Shandong provinces in 2006 and found NRCMI enrollment was not significantly associated with inpatient service utilization for middle- and low-income families. Using China Longitudinal Healthy Longevity Survey 2005 and 2008 data and a combined method of propensity score matching and difference-in-differences, Cheng et al. (2015) found that NRCMI did not improve enrollees' self-perceived health status nor mortality. Huo and Chen (2017) also found that participating in NRCMI did not affect the happiness of recipients using two datasets, the China Family Panel Study and China Health and Nutrition Survey.

The examination of NRCMI's effects on health outcomes and health service utilization often concerns the issue of self-selection-based endogeneity bias (Liang et al., 2012). To address these issues, Lei and Lin (2009) used longitudinal data from the China Health and Nutrition Survey and the county-level NRCMI implementation year as the instrumental variable. They found that participating in NRCMI at the individual level had no effect on formal health service utilization nor health conditions. The instrument was argued to be valid because individual participation was highly correlated with county-level implementation because individuals could only participate in NRCMI when the county implemented the NRCMI plan. Additionally, the county-level implementation of NRCMI was exogenous to individual's health use and health conditions, because the variation in the timing of implementing NRCMI was mainly following the guidance of central and provincial governments.

Effects of NRCMI on health expenditures and poverty

Another set of studies investigated the role of NRCMI implementation in alleviating poverty by relieving the health expenditure burdens of families. Xu, Li, and Wu (2011) compared the incidence rates of health payment-induced poverty before and after the implementation of NRCMI. They found that the incidence rates decreased in all five counties in Guangdong province. Similarly, Chen, Xu, and Wang (2005) found that the poverty gap narrowed by 25.79% among the trial counties of NRCMI in Hubei province in 2003. Sun, Sleigh, Carmichael, and Jackson (2010) used primary data collected in Shandong province in 2014. They reached a similar finding that NRCMI reimbursement reduced health payment-induced poverty by a percentage point.

Though informative, the results obtained from these descriptive studies may be biased. It is unclear whether the occurrence rates or intensity of poverty are comparable before and after NRCMI implementation. Moreover, the trial counties in the studies of Chen et al. (2005) and Sun et al. (2010) were not randomly selected. The participants and nonparticipants of NRCMI were different in many ways, including socioeconomic status, access to health care services, receipt of other local welfare programs, etc.

Similar to the work of Lei and Lin (2009) as mentioned, to address issues of self-selection bias and reverse causality, Cheung and Padieu (2015) used the combined methods of fixed effects and instrumental variable estimation. In contrast, Cheung and Padieu (2015) assessed the household enrollment rates of NRCMI in the communities to investigate the impact of NRCMI on household savings. The authors stated that the instrumental variable was exogenous because the participation rates of NRCMI in communities were correlated with the efforts led by the central and provincial governments but were not associated directly with household savings and consumption behaviors.

Large-scale surveys usually measure economic burdens of health care payments by using either the absolute amounts of expenses or relative burdens. CHE refers to the relative impact of health care payments on the basic standards of living of a household, which is defined as a ratio of medical costs to disposable income, varying from 5% to 40% across countries (Reddy, Ross-Degnan, Zaslavsky, Soumerai, & Wagner, 2013; Ke Xu et al., 2003). Neither of the outcomes measured in the two relevant studies previously described reflects the relative financial burdens of NRCMI.

Effects of NRCMI on CHE

Seven studies have examined the effects of NRCMI on CHE. Similar to findings regarding the impact of NRCMI on health service utilization and health outcomes, findings of the effects of NRCMI on the incidence or prevalence of CHE obtained in prior studies are mixed.

Five of the seven studies used either linear or logistic regressions to simply compare the incidence or intensity of CHE before and after the implementation of NRCMI. Two of the studies showed that the NRCMI was effective in reducing the prevalence and intensity of CHE. Gong, Yu, Meng, Yan, and Rachel (2019) found that the implementation of NRCMI significantly reduced the prevalence of CHE in 2006 and 2008 in Shandong and Ningxia provinces. Zhang, Cheng, Tolhurst, Tang, and Liu (2010) found that NRCMI reimbursement helped reduced the intensity of CHE, especially among lower-income people using inpatient services. Two of the studies, however, found that NRCMI was not effective. Jiang, Ma, Zhang, and Luo (2012) found that increasing reimbursement benefits of NRCMI did not reduce the incidence of CHE among families with chronic patients. Li et al. (2014) found that NRCMI participation was not significantly associated with lower CHE nationally in 2008. Sun, Jackson, Carmichael, and Sleigh (2009), however, found the NRCMI reimbursement did not reduce the prevalence of CHE but reduced the intensity of CHE in Shandong province in 2004. As mentioned, these five studies may involve endogeneity issues. Enrollees who chose to participate in NRCMI may be significantly different from nonenrollees. In addition, the likelihood of experiencing CHE and participation in NRCMI could affect each other bidirectionally.

The other two studies applied quasi-experimental designs and found no effect of NRCMI participation on reducing the incidence of CHE. Specifically, Wagstaff et al. (2009) used the combined method of propensity score matching and difference-in-differences and two primary datasets collected in 12 trial provinces between 2003 and 2005. They found that NRCMI participation did not significantly change the incidence of CHE, using 10%, 20%, and 40% as cutoffs, respectively. The other study used similar methodologies and primary data collected in 17 trial provinces in 2003 and 2005 (Health statistical information Center, 2007). It found that NRCMI participation had no effect on the incidence of CHE. However, none of the two quasi-experiment studies examined the effects of NRCMI in the later stage of its expansion, after 2006.

Other factors influencing health-related financial burdens

Prior studies also explored three clusters of leading factors of health payment-related impoverishment: socioeconomic status before health care, chronic or severe illnesses, and certain demographic and behavioral factors. Higher socioeconomic status (SES) groups in developing countries and countries in transition are more likely to obtain health care when needed, and the proportion of medical expenditures is much less than those with lower SES (Makinen et al., 2000). Health-induced poverty is also more likely to occur in families with members who have chronic diseases (Mwangi & Kulane, 2015), injuries or other health shocks (Verguet, Memirie, & Norheim, 2016), multiple morbidities (Schoenberg, Kim, Edwards, & Fleming, 2007), and serious illnesses (Moffatt, Noble, & White, 2012). Additionally, higher health payment-induced burden is associated with older age (Mohanty, Ladusingh, Kastor, Chauhan, & Bloom, 2016) and broader social networks that allow patients to get access to more health care services (Ayé, Champagne, & Contandriopoulos, 2002).

No existing study examined the effects of NRCMI on CHE using instrumental variable estimation, a rigorous quasi-experimental design that is suitable when policy rollout is gradual. Building on the existing literature, this study (1) captured the impact of NRCMI on the relative financial burden by using the ratio of health-induced expenditure to disposable income instead of an absolute poverty line in determining poverty status; (2) used instruments to address the concern of selection bias and reverse causality; and (3) examined the effects of NRCMI participation on enrollees' financial burdens in the later stage of its expansion.

Methods

Data

This paper used China Household Income Project (CHIP) 2007 data. CHIP data has been the only nationally representative data with information on both NRCMI implementation at the village level and NRCMI participation at the individual level in 2007. In addition, CHIP explicitly collected information on incomes and expenditures at both the individual and household level, which helps explicate the incidence of CHE more accurately.

CHIP features three questionnaires that cover three target populations: urban residents, rural residents, and the migrant population. This study used the rural dataset. A total of 8,000 households were randomly selected from 800 villages in nine provinces, which were also randomly chosen to represent the three regions: east, central, and west China. Among the 8,000 households, all family members aged 16 or older were interviewed face-to-face if they lived in the same households for more than 6 months in the prior year.

This study used individual-, household-, and village-level characteristics. Individual information was collected from each family member. Household-level data were obtained from the household head, such as information about social networks, family events or shocks, and welfare receipt as a household. Village-level information was also used in the analysis, and was collected from village leaders. As a result, each respondent had three levels of information in the analytic data. Given that the samples were not selected through probability-proportional-to-size sampling, multiple weights were adopted in the analysis in this study.

In the CHIP 2007 dataset, four of the nine provinces had all villages implement the NRCMI in 2007, and three other provinces had more than 98% of the villages implement NRCMI by 2007. Therefore, this study excluded these seven provinces and focused on the two remaining provinces, Anhui and Sichuan provinces, which had village implementation rates in 2007 of 72.5% and 91.8%, respectively. This study also excluded participants who did not report their health-related costs. The final analytic sample size was 3,583 individuals in 1,980 households in 197 villages. The unit of analysis in this study was the individual, which is consistent with the work of Lei and Lin (2009). Even though theoretically, enrollment in NRCMI occurs at the household level, some members may opt out from enrollment. The participation information collected in the CHIP survey also reflected that not all household members participated in NRCMI in 2007.

Measurement

The key dependent variable of CHE is defined as the occurrence (1 = yes and 0 = no) if the ratio of health-related costs to disposable income exceeded 40%. There is no uniformly accepted threshold for measuring CHE. The thresholds vary between 5% and 40% depending on denominators, numerators, and the study population (Berki, 1986; Wagstaff & Doorslaer, 2003;

Wagstaff et al., 2018; World Health Organization, 2005). Usually, higher thresholds (i.e., 40% or 30%) are usually adopted in developing countries or when the denominator is the ability to pay or disposable income (household income minus food and other needed expenses). Lower thresholds (i.e., 5%, 10%, or 20%) are typically adopted in developed countries or when the denominator is annual household income or consumption.

In this study, health-related costs (the numerator of CHE) included payments to health care services after reimbursement, medical assistance and health insurance premiums paid out-of-pocket, and other accommodation costs, i.e., transportation costs that were related to health care service receipt. Household income (the denominator of CHE) included salary income, net business income, intra- and interfamily transfers, and other government transfers. Also, given that China is a middle-income country in terms of real GDP per capita, following the work of Xu et al. (2007), I choose a higher threshold of CHE (40%) in the analysis. To test the robustness of the results, this study also used 20% and 10% as the thresholds of CHE (Wagstaff et al., 2007) in a sensitivity analysis.

As a comparison, this study also used the amount of medical expenses as the dependent variable to test the effect of NRCMI participation on the absolute amount of expenses in addition to the relative financial burden measured by CHE. The amount of medical spending was the total amount an individual paid out-of-pocket, excluding reimbursements and reduced amounts, for insurance premiums, medications, treatment, facilities, and other health-related services in 2007. The key independent variable was individuals' NRCMI enrollment status in the survey year, which was dummy coded as 1 if they enrolled in the survey year and 0 otherwise. There were two instrumental variables in the analysis. One was the year of NRCMI implementation at the village level (coded from 2002 to 2007 and as 9999 if not yet implemented). The other was the

NRCMI participation rates in the survey year at the village level (coded as a continuous variable and coded as 0 if not yet implemented). Both were reported in the village survey questionnaires by the leaders of the villages. To examine if the results persisted, this study also used the NRCMI participation rate and rollout time at the county level in the sensitivity analysis. More information regarding the implementation of NRCMI and the validity of these instrumental variables are explained in the empirical strategy section.

The control variables included individual demographic characteristics and health status. The demographic characteristics included age, marital status (coded as 1 if married or remarried, and 0 if cohabiting, divorced, widowed, or never married); educational attainment (coded as 1 if never been to school, 2 if completed elementary school, 3 if completed junior middle school, and 4 if completed high school or above); the quintile of annual income; and the province dummy variable. The control variables of health status included self-perceived health status (range = 1–5; a higher value indicates worse health status), disability status, and disease history in the last 3 months (coded as 1 if the respondent reported disability and disease history, and otherwise 0).

Empirical strategies

To address the issues of selection bias and reverse causality, this study used the method of the instrumental variable (Angrist, Pischke, & Pischke, 2013). This study used two instrumental variables—the time of NRCMI implementation in each village and the participation rates of NRCMI in the village. More specifically, it assessed individual NRCMI enrollment status using village-level NRCMI implementation and the percentage of enrolled households in the village. Both instrumental variables have been tested and shown to be valid both conceptually and statistically by multiple studies (Cheung & Padieu, 2015; Huo & Chen, 2017; Lei & Lin, 2009). To reduce the overidentification problem, this study used the two instrumental variables jointly in the first set of analyses and also applied each instrumental variable separately in other sets of analyses (Le & Nguyen, 2015).

As mentioned in the background section, the year of macro-level implementation of NRCMI, the first instrumental variable in the analysis, was decided by the central government and provincial governments. Once the NRCMI was implemented at the county level, leaders at both county and village levels would decide which village would participate in which year. Lei and Lin (2009) used county-level NRCMI implementation as the instrumental variable to examine the effects of NRCMI enrollment on health service utilization and health conditions. Based on the implementation procedure, I hold a similar assumption that the village-level implementation of NRCMI is exogenous to individuals' health expenditures.

Additionally, this study used a second instrumental variable—the participation rate of NRCMI in a village in the survey year. This operation follows the work of Cheung and Padieu (2015), which operationalized NRCMI enrollment using the percentage of enrolled households in the community to examine the effect of NRCMI on household savings. Despite the nature of voluntary enrollment at the household level, village-level participation rates are more determined by macro-level efforts and motivations. During the implementation of NRCMI, the central and provincial governments provided increased reimbursement rates and other benefits to encourage rural residents' participation. In addition, village leaders conducted home visits to transfer knowledge and emphasize the necessity of participating in NRCMI (Brown & Theoharides, 2009; Dong, 2009). Therefore, I hold a similar assumption as Cheung and Padieu (2015), that the NRCMI participation rate in the village is exogenous to individuals' health expenditures.

The validity of the two instrumental variables was also tested statistically using three tests—the Kleibergen-Paap rank Lagrange multiplier (LM) test as an underidentification test, the

Cragg-Donald Wald F statistics as a weak identification test, and the Sargan-Hansen test as an overidentification test. The underidentification test indicates if the excluded instruments were correlated with the endogenous regressors (Baum, Schaffer, & Stillman, 2010). A rejection of the null hypothesis with a chi-square p-value (< .05) in this test means the model was identified.

The weak identification test determines if the instruments were weakly correlated with the endogenous regressors. Both the Cragg-Donald Wald F statistic and Kleibergen-Paap Rank Wald F statistic are compared to the 10% maximal IV size generated by Stock-Yogo weak ID test critical values, which in this analysis was 19.93. Greater F statistics than the 10% maximal IV size indicate that the instruments were not correlated with the endogenous regressors, even weakly (Baum et al., 2010).

The last validity test in this analysis was the overidentification test of all instruments. The null hypothesis of this test is that all instruments are exogenous under the assumption that the valid instrument is no less than the endogenous regressors. A large chi-square p-value (> .05) indicates that the instruments were valid in that they were not correlated with the residuals and the instruments were excluded from the estimating model correctly (Baum et al., 2010).

Sensitivity analysis

In the last step, this study applied two sensitivity tests to check the robustness of the results obtained from the IV analyses. First, instead of using 40% as the threshold of CHE, the sensitivity test used 20% and 10% as the thresholds of CHE, meaning that if the respondent's health-related expenditures exceeded 20% or 10% of annual household income, this respondent would be categorized into the group that experienced CHE in the survey year.

The second sensitivity test used the NRCMI participation rate and rollout time at the county level as the instrumental variables. Specifically, following the work of Lei and Lin

(2009), I treated the counties in which any villages had NRCMI implemented in or before 2017 as having NRCMI implemented at the county level. The NRCMI participation rate at the county level was calculated from the average participation of all villages in a county with NRCMI implemented. Similar to the main IV analysis, results obtained using the two instruments jointly and separately are both reported.

Results

Descriptive analysis

The descriptive analysis results show the village, household, and individual characteristics by NRCMI implementation or participation status in 2007. At the village level, the NRCMI implementation numbers were 68 and 101 in Anhui and Sichuan, respectively. The average household participation rates in the implemented villages were 90.5% to 91.6%, respectively. In general, compared to the villages that had implemented NRCMI in 2007, those with no NRCMI implementation had a smaller population and household size and lower average household income. The time to county and time to the nearest clinic did not vary between the two types of villages in both Anhui and Sichuan.

The second section in Table 1 presents the household characteristics. The number of NRCMI participating households were 689 and 1,007 in Anhui and Sichuan, respectively. In 2007, 205 and 81 households did not participate in NRCMI in these two provinces. The participating and nonparticipating households had different characteristics: the nonparticipating households had fewer adult members aged 60 or older, lower total household income, more extensive social networks, and slightly fewer major household events in both Anhui and Sichuan.

In terms of the individual characteristics of the analytic sample, the prevalence of CHE was higher among individuals with no NRCMI than those with NRCMI in 2007 in both Anhui and Sichuan provinces. The nonparticipating sample had lower average annual income but better self-perceived health status than their participating peers in Anhui. These characteristics in the two groups did not vary in Sichuan. The attributes of average age, educational attainment, and marital status did not significantly differ between participating and nonparticipating individuals in both Anhui and Sichuan.

[Table 1 about here]

Instrumental variable estimation results

Overall, individual NRCMI participation was not significantly associated with the changes in the incidence of CHE. The results are consistent across the pooled sample (N = 3,424), the Anhui sample (n = 1,385), and the Sichuan sample (n = 2,039), as shown in the first columns in Table 2, Table 3, and Table 4, respectively. The last few rows of these tables indicate that the group instrumental variable, using the village-level participation rate and rollout time simultaneously, was valid, passing the over-, under-, and weak identification tests.

However, individual NRCMI participation was significantly associated with increased medical expenses in Anhui province. More specifically, compared to nonparticipants, participants spend 175.1 yuan more on medications, treatment, facilities, and other health-related services, on average, in 2007 (Table 3). The significant association was not observed in the sample in Sichuan province nor in the pooled sample, however (Table 4). These results are based on the condition that the two instruments used in the analyses passed the three validity tests.

Similar results were obtained using the village-level NRCMI participation rate and NRCMI rollout time, respectively, as the instrumental variable in the analyses. NRCMI participation had no significant impact on changes in CHE in both Anhui and Sichuan, but it increased the amount of medical expenses in Anhui. However, it should be noted that the instruments did not pass the overidentification test because the equations using the two instrumental variables, respectively, were exactly identified with p-values smaller than .05.

[Tables 2 to 4 about here]

Sensitivity analysis results

The first set of sensitivity test results, shown in Appendix Table 1, confirmed the robustness of the results. In the first sensitivity test, using 20% and 10% as the CHE thresholds, the analyses found that NRCMI enrollment could not predict any changes in the incidence of CHE among middle-aged and older adults in Anhui and Sichuan. The instruments passed all the validity tests in these analyses.

As shown in Appendix Table 2, using the county-level participation rate and rollout time as instruments, the sensitivity analysis obtained consistent results with the analyses using the village-level participation rate and rollout time as instruments, both for the incidence of CHE and the actual amount of medical expenses. NRCMI participation did not change the incidence of CHE significantly nor the amount of medical spending in the pooled sample.

Discussion and Conclusion

Using China Household Income Project 2007 rural data and the instrumental variable method, this paper examined the impact of participating in NRCMI on the incidence of CHE and the actual amount of medical expenses. The results show that NRCMI enrollment did not affect the likelihood of experiencing CHE among middle-aged and older adults in Anhui and Sichuan. However, NRCMI participation increased the actual amount of medical expenses in Anhui in

2007 but not in Sichuan. These results were confirmed by robustness tests using alternative CHE cutoffs and county-level instruments. These results suggest that NRCMI did not alleviate the health-related financial burdens of rural beneficiaries. Policy makers could consider implementing cash subsidies or other relative welfare programs to reduce out-of-pocket payments for health care services among those who are more likely to experience CHE.

Prior studies have concluded mixed findings regarding the effects of NRCMI on the value of health-related expenses and economic burden induced by health services and medicines. Although none of the prior studies used instruments and village-level fixed effects or accounted for the endogeneity issue to investigate the impact of NRCMI on relative financial burden among recipients, the results found in this study are generally aligned with the prior findings, especially those of quasi-experimental studies using propensity-score matching and difference-in-differences, that financial burdens are not significantly affected by participating NRCMI. This study took a further step and examined both the relative financial burden, measured by CHE, and the absolute financial burden, measured by the actual amount of medical expenses.

There are two potential explanations for these results. First, the reimbursement rates, even though varying across regions and provinces, are generally low, especially for outpatient services, which are more frequently used. The average reimbursement rate in 2008 was 26.6% for inpatient services (Tang, 2014). For outpatient facility and clinic doctor visits, the reimbursement rates were even lower (Wagstaff et al., 2009). Additionally, due to the complicated reimbursement criteria and guidelines, beneficiaries were less likely to know what would be reimbursed and how much reimbursement they were qualified to receive. Therefore, the NRCMI beneficiaries increased their utilization of health service and did not reduce the costs of health services.

The other potential explanation for these results could be related to the changing behavior of health service utilization. Urban insured residents in China were found to increase their use of more expensive treatment, services, and medicines after getting health insurance (Wagstaff & Lindelow, 2008). No study has tested whether this also applies to rural beneficiaries yet. But it is also likely that newly insured people in rural areas would try to seek health care from formal health care facilities, which are usually more expensive than treatment received from "barefoot" doctors in villages. Annual household income may not have significantly varied before and after NRCMI enrollment, but health care costs may have increased significantly due to the use of more expensive health care services and medicines. Therefore, the relative financial burden, in contrast to decreasing or staying at the same level, increased significantly among new NRCMI recipients.

This study made three contributions. First, it examined the effect of NRCMI on the relative financial burdens of beneficiaries, which had not been studied using an instrumental variable and village-level fixed effect. This helped account for endogeneity issues. Prior mixed findings are likely primarily due to different empirical strategies each study used to deal with selection bias, omitted variables, bidirectional causality, etc. Second, this study moved beyond the absolute measure of out-of-pocket health expenses in dollar values. It focused on CHE, measured as a ratio of health-related costs to total household disposable income, to examine the relative financial burden of NRCMI beneficiaries. Third, this study supplemented research on the later-stage effect of NRCMI implementation. Most of the prior studies that examined the impact of NRCMI used pilot counties or the few counties that implemented NRCMI at the very early stage as their analytic sample. In contrast, this study used counties that implemented NRCMI in the last 2 years before the implementation rates reached as high as 95%.

However, the results obtained from this study should be interpreted cautiously, given that there are a few limitations in this study. The first limitation is that the two analytic provinces were not randomly selected. However, they were the only two provinces that had significant variations in NRCMI implementation at the village level and NRCMI enrollment at the individual level. Therefore, the generalizability of the results of this study may be limited. Second, due to data limitations, this study could not investigate what type of health care facilities NRCMI beneficiaries used in the survey year. The prices of different facilities vary a lot. In addition, the frequency of using health care services was not recorded in CHIP surveys. This dataset can't be used to test if the increased health care costs were due to more expensive health care services being used or because health care services were more frequently used.

This study provides empirical evidence to policy makers that the effect of NRCMI participation on financial protections are limited, while bearing the limitations of the study in mind. Future policy efforts could involve applying more strategies to boost the effect of NRCMI in reducing health-related financial burdens. Future studies could examine the longer-term effects of NRCMI on financial burdens by observing more years of changes in enrollment status and CHE after the overall implementation rates reached 95% in 2008. Furthermore, studies should also be conducted to compare the impacts of universal health care programs and the means-test cash transfer programs in alleviating health payment-induced poverty in other countries. This could provide more evidence for the Chinese government to accelerate the implementation of certain types of welfare programs to achieve the goal of eradicating poverty by 2020 (The State Council Leading Group Office of Poverty Alleviation and Development, 2017).

Table 2-1: Descriptive results of the village-, household-, and individual-level factors by NRCMI implementation and participation.

	Anhui & Sichuan				**Anhui**				**Sichuan**			
	With NRCMI		Without NRCMI		With NRCMI		Without NRCMI		With NRCMI		Without NRCMI	
	Mean/%	S.D.	Mean/%	S.D.	Mean/%	S.D.	Mean/%	S.D.	Mean/%	S.D.	Mean/%	S.D.
County-level	n=11		n=3		n=7		n=2		n=4		n=1	
Participation rate	87.95	9.02	-	-	87.30	10.63	-	-	89.08	6.52	-	-
Village-level factors	n=169		n=28		n=68		n=20		n=101		n=8	
Participation rate	91.17	6.45	-	-	90.49	7.17	-	-	91.63	5.92	-	-
# of total population	2230.54	1264.40	2014.36	828.62	2602.50	1610.56	2169.70	854.36	1980.11	889.09	1626.00	652.55
# of total household	624.13	359.85	511.14	194.55	678.68	455.74	539.15	201.52	587.41	273.87	441.12	167.11
Category of income/capita	10.40	2.17	8.57	1.55	10.12	2.44	8.55	1.10	10.58	1.97	8.62	2.45
# of migrant-out	588.18	437.53	638.86	437.50	701.04	569.02	738.75	473.39	512.19	300.29	389.12	173.91
# of migrant-in	65.93	309.44	28.53	45.92	38.08	101.31	31.43	51.25	84.40	390.27	20.4	29
Reduced production	13.00	12.62	14.43	15.23	11.54	10.57	9.65	13.95	13.98	13.79	26.38	11.75
Time to county	2.30	0.78	2.25	1.00	2.28	0.59	2.20	0.89	2.32	0.88	2.38	1.30
Time to nearest clinic	1.29	0.50	1.39	0.50	1.35	0.48	1.35	0.49	1.25	0.52	1.50	0.53
Household-level	n=1694		n=286		n=689		n=205		n=1007		n=81	
# of household members	3.91	1.30	4.08	1.33	4.09	1.27	4.13	1.37	3.78	1.30	3.96	1.21
# of elder members	1.18	1.34	1.02	1.39	1.02	1.27	0.99	1.46	1.29	1.37	1.10	1.19
# of child members	0.87	0.82	1.00	0.92	0.97	0.84	1.1	0.94	0.80	0.79	0.75	0.83
Income/capita	3932.27	2201.77	3418.45	1816.15	4025.3	2405.6	3551.29	1910.28	3869.14	2049.35	3082.23	1511.78
Social network	5.65	8.38	6.96	7.98	5.06	7.42	6.22	7.26	6.05	8.95	8.91	9.41
Serious sickness	0.10	0.30	0.06	0.24	0.06	0.24	0.04	0.19	0.13	0.34	0.12	0.33
Individual-level	n=3123		n=460		n=1176		n=302		n=1947		n=158	
CHE incidence	0.05	0.22	0.07	0.25	0.04	0.20	0.06	0.23	0.06	0.23	0.08	0.28
Age	58.32	9.48	58.25	9.95	57.63	9.88	58.43	10.06	58.73	9.20	57.91	9.76
Edu attainment	2.23	0.87	2.28	0.93	0.90	0.30	2.29	1.04	2.27	0.81	2.26	0.67
Married	0.89	0.32	0.92	0.28	3.25	1.43	0.93	0.25	0.88	0.32	0.89	0.32
Income quantile	3.29	1.45	3.08	1.49	2.34	0.91	2.96	1.55	3.31	1.45	3.32	1.36
Health	2.51	0.87	2.21	0.97	0.06	0.23	2.00	0.91	2.61	0.83	2.62	0.96
Physical disability	0.07	0.26	0.10	0.29	0.12	0.32	0.08	0.28	0.09	0.28	0.12	0.33
Sick in last 3 mo	0.15	0.36	0.23	0.42	0.04	0.20	0.28	0.45	0.17	0.38	0.14	0.35

Notes: Time to county and time to the nearest clinic was measured as a categorical variable—from 1 to 5 (less than 0.5 hours, 0.5-1 hours, 1-2 hours, 2-4 hours, and more than 4 hours). The variable of serious illness captured the total times the household members had in the last year. The variable of the social network was calculated from the number of people they thought they would be able to borrow money when needed

Table 2-2: Instrumental variable estimations of effects of NRCMI participation on CHE incidence and medical expense amount among adults aged 45 and above in Anhui and Sichuan provinces using 40% as the threshold of CHE.

	IV (participation rate, village roll-out)		IV (participation rate)		IV (village roll-out)	
VARIABLES	CHE Incidence	Expense Amount	CHE Incidence	Expense Amount	CHE Incidence	Expense Amount
NRCMI	-0.009	17.867	-0.007	18.271	-0.009	17.871
	(0.012)	(103.782)	(0.012)	(105.444)	(0.012)	(103.788)
Observations	3,424	3,424	3,424	3,424	3,424	3,424
R-squared	0.149	0.129	0.149	0.129	0.149	0.129
F statistics	15.53	12.55	15.52	12.61	15.53	12.55
Overidentification test	0.841	0.001	0.000	0.000	0.000	0.000
p-value	0.359	0.977	-	-	-	-
Underidentification test	553.5	553.5	551.3	551.3	553.4	553.4
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Cragg-Donald Wald F statistic	12000	12000	18000	18000	25000	25000
Kleibergen-Paap rk Wald F stats	4426	4426	7996	7996	8769	8769
10% maximal IV size	19.93	19.93	16.38	16.38	16.38	16.38

Notes: Robust standard errors in parentheses; Control variables include age, gender, educational attainment, marital status, income level, health status, disability status, disease history in last three months, and province dummy variable; Overidentification test of all instruments uses Hansen J statistic; Under-identification test uses Kleibergen-Paap rank LM statistic; Both Cragg-Donald Wald F statistic and Kleibergen-Paap rank Wald F statistic are weak identification tests which should be larger than the critical value of 10% maximal IV size (19.93) produced by Stock-Yogo weak ID test.
*** p<0.001, ** p<0.01, * p<0.05

Table 2-3: Instrumental variable estimations of effects of NRCMI participation on CHE incidence and medical expense amount among adults aged 45 and above in Anhui province using 40% as the threshold of CHE.

	IV (participation rate, village roll-out)		IV (participation rate)		IV (village roll-out)	
VARIABLES	CHE Incidence	Expense Amount	CHE Incidence	Expense Amount	CHE Incidence	Expense Amount
NRCMI	0.014	175.087*	0.015	214.111**	0.014	176.436*
	(0.015)	(68.364)	(0.015)	(75.058)	(0.015)	(68.507)
Observations	1,385	1,385	1,385	1,385	1,385	1,385
R-squared	0.166	0.164	0.166	0.164	0.166	0.164
F statistics	6.384	5.156	6.385	5.164	6.384	5.156
overidentification test	0.707	3.783	0.000	0.000	0.000	0.000
p-value	0.400	0.052	-	-	-	-
underidentification test	390.6	390.6	387.8	387.8	390.5	390.5
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Cragg-Donald Wald F statistic	7622.421	7622.421	10000.000	10000.00	15000	15000.00
Kleibergen-Paap rk Wald F stats	11245	11245	18020	18020	22296	22296
10% maximal IV size	19.93	19.93	16.38	16.38	16.38	16.38

Notes: Robust standard errors in parentheses; Control variables include age, gender, educational attainment, marital status, income level, health status, disability status, disease history in last three months; Overidentification test of all instruments uses Hansen J statistic; Under-identification test uses Kleibergen-Paap rank LM statistic; Both Cragg-Donald Wald F statistic and Kleibergen-Paap rank Wald F statistic are weak identification tests, which should be larger than the critical value of 10% maximal IV size (19.93) produced by Stock-Yogo weak ID test.

*** p<0.001, ** p<0.01, * p<0.05

Table 2-4: Instrumental variable estimations of effects of NRCMI participation on CHE incidence and medical expense amount among adults aged 45 and above in Sichuan province using 40% as the threshold of CHE.

	IV (participation rate, village roll-out)		IV (participation rate)		IV (village roll-out)	
VARIABLES	CHE Incidence	Expense Amount	CHE Incidence	Expense Amount	CHE Incidence	Expense Amount
NRCMI	-0.033	-200.517	-0.029	-231.613	-0.033	-199.993
	(0.022)	(240.514)	(0.023)	(241.553)	(0.022)	(240.508)
Observations	2,039	2,039	2,039	2,039	2,039	2,039
R-squared	0.144	0.129	0.144	0.128	0.144	0.129
F statistics	11.43	13.47	11.42	13.53	11.43	13.47
overidentification test	0.950	3.095	0.000	0.000	0.000	0.000
p-value	0.330	0.079	-	-	-	-
underidentification test	167.9	167.9	167.9	167.9	167.7	167.7
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Cragg-Donald Wald F statistic	4491.039	167.877	6985.919	6985.919	8985.775	8985.775
Kleibergen-Paap rank Wald F stats	768.1	768.1	1455	1455	1535	1535
10% maximal IV size	19.93	19.93	16.38	16.38	16.38	16.38

Notes: Robust standard errors in parentheses; Control variables include age, gender, educational attainment, marital status, income level, health status, disability status, disease history in last three months; Overidentification test of all instruments uses Hansen J statistic; Under-identification test uses Kleibergen-me rank LM statistic; Both Cragg-Donald Wald F statistic and Kleibergen-Paap rank Wald F statistic are weak identification tests, which should be larger than the critical value of 10% maximal IV size (19.93) produced by Stock-Yogo weak ID test.

Appendix 2-1: Sensitivity analysis results of the effects of NRCMI participation on CHE incidence using different thresholds of CHE and instrumental variable estimations among adults aged 45 and above in Anhui and Sichuan provinces.

VARIABLES	40%	20%	10%
NRCMI	-0.009	-0.032	-0.016
	(0.012)	(0.017)	(0.021)
Observations	3,424	3,424	3,424
R-squared	0.149	0.202	0.214
F statistics	15.53	36.48	73.91
Overidentification test	0.841	0.000	0.316
p-value	0.359	0.987	0.574
Underidentification test	553.5	553.5	553.5
p-value	0.000	0.000	0.000
Cragg-Donald Wald F statistic	1.20E+04	1.20E+04	1.20E+04
Kleibergen-Paap rank Wald F statistic	4426	4426	4426
10% maximal IV size	19.93	19.93	19.93

Notes: Robust standard errors in parentheses; Control variables include age, gender, educational attainment, marital status, income level, health status, disability status, disease history in last three months, province dummy variable; Overidentification test of all instruments uses Hansen J statistic; Under-identification test uses Kleibergen-Paap rank LM statistic; Both Cragg-Donald Wald F statistic and Kleibergen-Paap rank Wald F statistic are weak identification test,s which should be larger than the critical value of 10% maximal IV size (19.93) produced by Stock-Yogo weak ID test.
*** p<0.001, ** p<0.01, * p<0.05

Appendix 2-2: Sensitivity analysis results of the effects of NRCMI participation on CHE incidence and medical expense amounts using county-level instrumental variables among adults aged 45 and above in Anhui and Sichuan provinces.

	IV (participation rate, county roll-out)		IV (participation rate)		IV (county roll-out)	
VARIABLES	CHE incidence	Expense Amount	CHE incidence	Expense Amount	CHE incidence	Expense Amount
NRCMI	-0.008	66.917	-0.042	-46.769	-0.008	67.051
	(0.014)	(107.030)	(0.202)	(978.410)	(0.014)	(107.030)
Observations	3,488	3,488	3,488	3,488	3,488	3,488
R-squared	0.153	0.129	0.151	0.129	0.153	0.129
F statistics	16.45	13.12	16.55	13.36	16.45	13.11
Overidentification test	0.030	0.014	0.000	0.000	0.000	0.000
p-value	0.865	0.907	-	-	-	-
Underidentification test	538.1	538.1	43.62	43.62	537.5	537.5
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Cragg-Donald Wald F statistic	4894.704	4894.704	8.36	8.36	9776.22	9776.22
Kleibergen-Paap rk Wald F stats	1190	1190	118.4	118.4	2289	2289
10% maximal IV size	19.93	19.93	16.38	16.38	16.38	16.38

Notes: Robust standard errors in parentheses; Control variables include age, gender, educational attainment, marital status, income level, health status, disability status, disease history in last three months; Overidentification test of all instruments uses Hansen J statistic; Underidentification test uses Kleibergen-Paap rank LM statistic; Both Cragg-Donald Wald F statistic and Kleibergen-Paap rank Wald F statistic are weak identification tests which should be larger than the critical value of 10% maximal IV size (19.93) produced by Stock-Yogo weak ID test.

*** p<0.001, ** p<0.01, * p<0.05

PAPER III: Does closing the donut hole under the Affordable Care Act reduce financial burdens of prescription medication expenses among Medicare Part D beneficiaries?

Abstract

The Medicare Part D donut hole has been gradually closed since 2010. But it is still unclear how it has affected the beneficiaries' relative financial burdens, especially in the later stage of the closing plan. The measurement of catastrophic health expenditure induced by prescription drugs (CHE-Rx) reflects the relative financial burden on beneficiaries' household income, which bears more information than the measure of dollar-value expenses or the absolute poverty line used in prior studies. This study used Medical Expenditure Panel Survey 2008-2017 longitudinal national representative data and the method of difference-in-differences to examine the effects of the donut hole closing policy in prescription drug use and relative financial burdens. Using pooled data, it found that the donut hole closing policy was associated with more usage of prescription drugs ($b = 2.84$, $p = .023$) and a higher likelihood of experiencing CHE-Rx ($b = 2.4\%$, $p = .011$) among those who fell in the donut hole. This paper, for the first time, extended the prior literature by including the most recent four years of data, between 2013 and 2017, during which the donut hole had closed by an additional 35%. The results confirmed that the donut hole closing policy, to some extent, reduced the barriers for the enrollees to access prescription drugs. This is in line with policy makers' intentions of implementing the policy. However, it should also be noted that the effect of closing the donut hole on reducing relative financial burdens was not observed in this study.

Introduction

More than half a century has passed since the War on Poverty was initially launched in 1964. From then to 2017, the overall poverty rate decreased from 22% to 12.3%, and the poverty rate among adults aged 65 or older dramatically dropped from 28.5% to 9.6% (Cubanski, Orgera, Damico, & Neuman, 2018). However, 39.7 million people, including 4.7 million older adults, are still in poverty, with limited financial resources and high economic insecurity (Fontenot, Semega, & Kollar, 2017).

The United States stands out among Organization for Economic Co-operation and Development (OECD) countries in terms of its high poverty rate. The most recent study showed that the U.S. poverty rate in 2017 was the second-highest among all 35 OECD countries, only 0.1% lower than the highest rate (Israel) and 12% higher than the lowest rate (Iceland) (OECD, 2019). The poverty rate among adults aged 66 or older in the United States was higher than in 27 OECD countries.[8]

Unlike many countries that provide universal health care to their citizens, the United States has many health care models designed for diverse target populations. The main components include Medicare, Medicaid, and employer-sponsored health insurance. The Medicare program is a federal health insurance program for people aged 65 or older, younger people with disabilities, or people with end-stage renal disease. The Medicaid program is financed by both the federal and state governments through tax payments and provides health coverage to people with low income or disabilities. The Affordable Care Act extended Medicaid coverage to low-income people and provided subsidies for people below 400% of the federal

[8] It should be noted that the poverty lines here represent half the median household income of the total population in each country.

poverty line to buy health insurance through federal and state marketplaces (The Henry J Kaiser Family Foundation, 2018). Most private health insurance in the United States is employer sponsored, which is jointly financed by employers and employees through payroll deductions. Yet 27.7 million people in 2017 were uninsured.

The complex U.S. health care system has been criticized for not being cost effective. The total spending on health as a percentage of GDP in the United States increased from 5% in 1960 to around 17% in 2017 (Catlin & Cowan, 2015; Martin, Hartman, Washington, & Catlin, 2019). This is substantially greater than the average share among OECD countries, which was 8.8% in 2017 (OECD, 2019). However, health outcomes in the United States, including life expectancy and the number of deaths of infants under 1 year of age, do not indicate that the United States is doing better than other OECD countries. On the contrary, both the average life expectancy and infant mortality rate in the United States ranked at a below-average level (OECD, 2011).

In addition to low cost effectiveness, the affordability and accessibility of the U.S. health care system have also been questioned. The Commonwealth International Survey found that 37% of patients did not receive recommended treatment, prescription medications, and doctor visits due to difficulty paying medical bills in 2013 (Davis, Stremikis, Squires, & Schoen, 2014). In 2017, 1 in 4 uninsured people postponed seeking care due to high medical costs. Such delayed health-seeking behavior also happened among 9% of Medicaid or other public insurance beneficiaries and 6% of employer-sponsored or other private insurance consumers aged between 18 and 64 in 2017 (The Henry J Kaiser Family Foundation, 2018). The high cost of medical services has increased people's risk of adopting risky strategies to minimize the impacts of the financial cost of illness on their household. One quarter of retired older adults returned to full- or part-time work after retirement in the United States. Undergoing adverse economic shocks due to health issues in their households is one of the primary reasons (Maestas, 2010). A study also found that hospital admissions were associated with 4% and 6% increases in bankruptcies for nonelderly insured and uninsured adults, respectively (Dobkin, Finkelstein, Kluender, & Notowidigdo, 2018). Expected or existing high out-of-pocket medical payments caused people with limited financial resources to delay or give up needed health services and prescription drugs (The Henry J Kaiser Family Foundation, 2018; Tolla et al., 2017; Wagstaff et al., 2018).

Background

Medicare Part D, also referred to as Medicare prescription drug benefits, is health insurance that seeks to reduce the cost of prescription drugs for Medicare beneficiaries, including older adults and people with disabilities in the United States. It was nationally implemented on June 1, 2006, and it has been extraordinarily important for those who have moderate income but high spending on prescription drugs. Unlike original Medicare (Part A and Part B), Part D is not directly provided by the federal government but administered by private insurance companies through contracts with Medicare. It is one component of the complicated U.S. health care policies. More than 1,000 plans are offered nationally, and beneficiaries in each county need to select from three to 30 plans with various monthly premiums, deductibles, coinsurance, coverage lists, etc.

The enrollment rate of Part D has steadily increased in the last 14 years. Medicare beneficiaries can either choose to enroll in the prescription drug plan when they sign up for Part A or Part B or obtain Part D benefits when they sign up for the Advantage plan (Part C). In 2006, 52% (22.5 million) of Medicare beneficiaries selected Part D plans[9] (Cubanski & Neuman, 2007; U.S. Department of Health and Human Services, 2008). This number steadily increased to 72% (43.4 million) in 2018 (Cubanski, Neuman, & Damico, 2018).

However, many enrollees may still struggle to afford prescription drugs. Before 2010, Part D enrollees needed to pay 100% out of pocket after spending a certain amount of money for covered drugs, as they fell into the so-called donut hole (also referred to as coverage gap). The donut hole involves a limit on what the Part D plans will cover for the enrollees, excluding those who have low-income subsidies. Below the initial limit of the donut hole, Part D enrollees only need to pay their deductibles and around 25% of the costs. Above the higher limit of the donut hole, the enrollees reach catastrophic coverage and the coinsurance rate dramatically reduces to 5%. The initial and higher limits of the donut hole vary across years. The initial limits increased from $2,250 in 2006 to $4,020 in 2020, and the higher limits increased from $3,600 in 2006 to $6,350 in 2020 (Q1Medicare, 2020). In 2007, about 26% of Part D enrollees who had any prescription fillings fell in the donut hole (Hoadley, Hargrave, Cubanski, & Neuman, 2008).

To further alleviate prescription drug costs for Medicare beneficiaries, later in 2010, the Affordable Care Act (ACA) started to gradually reduce the coinsurance rate of the donut hole from 100% in 2010 to 25% in 2020. Between 2013 and 2018, the donut hole closed by 35% for generic drugs and by 12.5% for brand-name drugs.

Over time, monthly premiums in Medicare Part D have stabilized as more people have enrolled. From 2006 to 2019, the average monthly premium was between $22 to $33 (Cubanski, Neuman, et al., 2018). For enrollees with income and assets below certain thresholds, a low-

[9] A total of 30.4 million Medicare beneficiaries have prescription drug coverage, including Part D (Cubanski, 2006).

income subsidy (also called Extra Help) is also available to reduce premiums, deductibles, and copayments in the coverage gap. In addition, studies consistently found that Part D increased medication adherence and decreased out-of-pocket spending (Ketcham & Simon, 2008; Lichtenberg & Sun, 2007; Yin et al., 2008). However, when decomposing the types of beneficiaries, scholars found that most decreased out-of-pocket spending occurred among those who were dually eligible and who received the low-income subsidy (Boxberger et al., 2009).

However, few empirical studies have investigated the effect of closing the Part D donut hole on reducing poverty rates. Theoretically, participants' prescription drug costs could decrease because they only pay proportionally for their covered prescription drugs. It also could increase due to medication adherence and more frequent use. In addition, older adults at different income levels could be affected differently by Medicare Part D. For example, those near poverty who have financial burdens due to prescription drugs but limited income resources are easily ignored by current antipoverty policies, because they are not entitled to either Medicaid or other cash subsidies. In contrast, others either have Medicaid as a safety net or have higher income resources to afford their drug costs.

This study used Medical Expenditure Panel Survey (MEPS) 2008-2017 longitudinal and nationally representative data to explore the trend and prevalence of catastrophic health expenditure induced by prescription drugs (CHE-Rx) and examine the antipoverty effects of the donut hole closing plan under the ACA. Specifically, this paper asks: Has the frequency of filling and refilling prescription drugs increased since the policy was implemented? Does participation in Part D reduce the likelihood of experiencing CHE-Rx among older adults over time? Does the effect of donut hole closing on CHE-Rx differ among different beneficiaries? The results will provide empirical evidence for future Medicare Part D implementation in the United States, especially in terms of the marginal benefits of decreasing the coinsurance rate of the donut hole. It will also shed light on the enactment of prescription drug policies in other countries.

Literature Review

Measurement of financial burdens

Extensive studies have adopted various strategies to define and measure absolute poverty, relative financial burdens, material hardships, etc. The primary arguments mostly focus on values and percentages used as thresholds in the measurement, including what should be included in necessary expenses, what earnings should be counted as income, what should be regarded as wealth, and how many people should be counted when calculating household income per capita.

One set of such studies used dollar values by family size as cutoff lines to measure poverty. For example, the U.S. Census Bureau has used the official poverty measure (OPM) since the 1960s. The threshold of OPM is derived from 3 times the cost of basic foods, which is updated for inflation with the Consumer Price Index and differs according to family size and the age of household members each year. After 2011, the Census Bureau started reporting the supplemental poverty measure (SPM), which expanded both resources and basic needs based on the OPM definitions, to provide additional economic statistics but not used for program eligibility (United States Census Bureau, 2019). Besides basic needs such as food, shelter, clothing, and utilities, and out-of-pocket medical expenses, including health insurance premiums and Social Security payroll taxes, are also deducted from the household when calculating the threshold. Later, Korenman and Remler (2013) proposed adopting the health-inclusive poverty measure (HIPM) to reflect health insurance coverage as a resource in addition to health-related payment in the measurement.

The second primary set of prior studies used the concept of inequalities, such as income-related inequality, to measure financial burdens. One example is the concentration index, which depicts the proportion of specific categories of expenditures in various population groups ranked by income (Carvalho, Petrie, Chen, Salomon, & Clarke, 2019). The area between the concentration index curve and the line of equality line (a 45-degree line) represents the intensity of inequalities. In addition, the position of the concentration index curve to the equality line demonstrates how the expenditures are concentrated. For instance, if the concentration index curve is below the equality line, it means that the expenses are concentrated in the lower-income population.

However, neither of these approaches are sufficient to answer the research question of this study. The measure using dollar values as cutoff lines does not capture those who had higher expenditures on health-related services but with income above the poverty cutoff point. Even though the measure of HIPM accounts for access to health insurance and the amount spent on health care, it does not reflect the proportion of health expenditures against the ability to pay. Although the concentration index curve, to some extent, could indicate health expenditures in terms of income rank, it could be primarily driven by the density of the occurrence of such inequalities. For instance, if much a higher proportion of health expenditures occurs among low-income or pro-low-income populations, those who have higher income and higher health expenditures would be mostly ignored by the study.

Another major set of prior studies used rates as thresholds to define material impoverishment or financial burdens. For example, conventional economic studies measured health-related expenditures based on people's ability to pay (Russell, 2001). This measurement approach assumes that people have the capabilities to rationally adjust their allocations on food, housing, health care, and other needs they are willing to pay for based on their budget constraints so that their utilities are maximized. Some scholars use CHE to compare the financial burdens induced by health-related expenses. CHE is defined as when household disposable income per capita spent on health-related consumptions exceeds a certain threshold (Ke Xu et al., 2003).

One of the primary goals of the Medicare Part D donut hole closing plan is to reduce the financial burdens of beneficiaries. Given that prior studies studied the impacts of Medicare Part D on either poverty prevalence using absolute poverty cutoffs or the actual amount of out-of-pocket spending, this paper aimed to evaluate the effects of the donut hole closing policy on the relative financial burdens of recipients, measured by CHE, in the last 10 years.

Factors associated with older adults' financial burdens

Existing studies investigated the roles of individual demographic characteristics in predicting the incidence or severity of material impoverishment among older adults (Chae & Heshmati, 2017; S. Lee & Shaw, 2008; Mohanty et al., 2016; Vandecasteele, 2011). They identified age, gender, educational attainment, and changes in marital status as significant factors for poverty in later life. Older age and lower educational attainment are associated with a higher probability of living in poverty (Chae & Heshmati, 2017; Srivastava & Mohanty, 2012). In countries such as Korea, older women are more likely to have lower socioeconomic status and mainly rely on their husbands' income. Therefore, marital status is a strong predictor as well, especially among women who are single or widowed, of poverty status (Chae & Heshmati, 2017; S. Lee & Shaw, 2008).

Besides individual traits, human capital characteristics have also been found to be significantly associated with older adults' higher financial burdens, including low pension income, certain types of occupation, few work years, and long gap years in employment (Chae & Heshmati, 2017; Saunders & Lujun, 2006; Srivastava & Mohanty, 2012). Among these factors, working status and income, such as a pension, have been investigated as strong predictors. Chae (2017) found that 1 more year of working was associated with a 3% decrease in experiencing poverty, and a 1-year increase in gaps between two jobs was associated with a 3% increase in likelihood of poverty.

Additionally, health-related factors such as poor health conditions and inadequate health insurance coverage could also predict higher financial burdens. A random trial study found that patients with full prescription coverage after myocardial infection had reduced drug costs and follow-up health care services by 74% on average compared to those who had usual prescription coverage (Choudhry et al., 2011). Even with health insurance, patients with specific diseases could experience high financial burdens. Sullivan et al. (2011) found that in the United States, insured cancer patients spent 20% more on treatment, drugs, and other indirect costs compared to noncancer patients. Another study found out-of-pocket health expenditures increased by 41%, 85%, and 100% when older adults in the United States had two, three, and four chronic conditions, respectively (Schoenberg et al., 2007).

Effects of Medicare Part D and donut hole closing policy

The implementation of Medicare Part D was found to be associated with decreased out-of-pocket drug expenses. Before Medicare Part D went into effect, Medicare beneficiaries paid out of pocket for their outpatient prescription drugs purchased at retail, mail order, home infusion, and long-term care pharmacies if they had no additional coverage plans (Center for

Medicare Advocacy, 2018). This resulted in financial burdens on those who had constant needs for prescription drugs and underuse of essential medications (Heisler, 2011; Levy & Weir, 2010).

Overall, many studies measured the effects of Medicare Part D on reducing out-of-pocket drug spending by conducting before-and-after comparisons of the implementation of Medicare Part D. Soumerai et al. (2006) discovered that 13% of older adults and 29% of people with disabilities among Medicare beneficiaries reported skipping or reducing prescription drugs due to cost 1 year before the implementation of Part D. After the implementation, Yin et al. (2008) found that enrollment in Part D significantly decreased average out-of-pocket drug expenditures by 8.8% and 13.1% during the penalty-free enrollment period (January to May 2006) and stable enrollment period (June 2006 to April 2007), respectively, compared to the pre-enrollment period (September 2004 to December 2015).

The effect of Part D was found to vary across income groups. Lower-income individuals (< 200% federal poverty level) were more likely to have more than $100 in out-of-pocket drug spending during 2003 and 2006 when they had no prescription drug coverage compared to higher-income people (> 200% federal poverty level). Therefore, it would be meaningful to evaluate the antipoverty effects of Medicare since 2006 by accounting for health-related expenditures (Safran et al., 2010).

Some studies have detected the effectiveness of Medicare Part D on other health care outcomes. Researchers found that Part D participation was correlated with a 6% to 13% increase in total medication use (Polinski, Kilabuk, Schneeweiss, Brennan, & Shrank, 2010), an increase in pharmacy service utilization (Yin et al., 2008), a decrease in hospitalization rates (Afendulis, He, Zaslavsky, & Chernew, 2011), and an increase in medication adherence (Y. Zhang, Lave, Newhouse, & Donohue, 2010). Studies also detected that essential medication use decreased by around 5% to 16% when enrolees reached the coverage gap (Fung et al., 2010; Polinski et al., 2010; Schneeweiss et al., 2009).

The impacts of the Medicare Part D donut hole closing policy under the ACA, however, were found to be mixed. Bonakdar Tehrani and Cunningham (2017) found that the amount spent on prescription drugs significantly dropped after the ACA, especially among those whose medication expenses fell in the donut hole. Another set of studies, however, showed that for certain populations, out-of-pocket spending on prescription drugs increased after the ACA, including those who took specialty pharmaceuticals (Paez, Zhao, & Hwang, 2009; Trish, Xu, & Joyce, 2016) or with multiple chronic diseases (Graetz, Anderson, & Kaplan, 2018). No study has investigated its antipoverty effects by accounting for affordability and financial well-being.

Research gaps and study aims

The current eligibility for these policies is calculated based on the OPM, which does not account for out-of-pocket health care payments and many other expenses related to basic needs. People below the poverty threshold are eligible for Medicaid benefits, and those who are near poor are eligible for the low-income subsidy. Theoretically, beneficiaries of Medicare Part D should either have sufficient income to cover their needed prescription medication and other basic needs such as food, clothing, shelter, and utilities or can purchase prescription medications with the assistance of Medicaid or the low-income subsidy. However, in reality, people whose income is just above the federal poverty line but who need prescription drugs are likely to suffer financial hardships, especially those who reach the coverage gap. They may also have problems with paying coinsurance due to the high expenses of other basic needs.

Prior studies examined the financial burdens of health care spending by summarizing the total amount of spending on health care services and premiums (Banthin, Cunningham, &

Bernard, 2008; Blumberg, Waidmann, Blavin, & Roth, 2014; Cunningham, 2010). Many of them stratified their study sample by income level to evaluate the different levels of the financial burden. However, none of these measurements reflects the influence of health care spending on relative financial burdens induced by prescription drug costs. In addition, middle- and high-income people also have options to choose advanced health care services, which could generate a considerable amount of spending. Therefore, those with higher health care spending are not necessarily those who bear higher financial burdens.

It is unclear how this donut hole closing policy might be associated with beneficiaries' relative financial burdens. It is also unclear to what extent the ACA reduced the financial burdens or hardships among beneficiaries with lower income and chronic diseases. In addition, the latest relevant work examining the effect of ACA on prescription drug costs looked at the changes that occurred before 2013. Subsequent impacts on reducing financial burdens are unknown, even though the donut hole closed by another 35% between 2013 and 2018.

Methods

Data

This study used Medical Expenditure Panel Survey Household Component (MEPS-HC) 2008-2017 data, collected and distributed by the Agency for Healthcare Research and Quality. It is a longitudinal and national representative dataset that includes a rich array of information at the personal level, such as demographic characteristics, employment status, income and poverty level, physical and mental conditions, health care service utilization, health-related expenses, and detailed insurance coverage. Each year, a new panel with more than 15,000 participants is recruited and followed for 2 years. Therefore, in every calendar year, the dataset contains two panels of participants for comparisons—one from the new panel and the other from the prior panel. Each survey participant is interviewed five times (rounds) in the 2 calendar years. To illustrate, I used different colors to show the panel design between 2008 and 2017 in Figure 2.

The study population of interest of this paper is Medicare Part D older enrollees and their peers who share similar characteristics except for not being enrolled in Medicare Part D. Generally, the eligible age for Medicare Part D is 65 years old. Therefore, this paper excluded those who were between 55 and 64 years old who did not have any private insurance plans covering prescription drugs and those who were younger than 54 years old. Certain groups of beneficiaries, including those who are dually eligible for Medicare and Medicaid, those who do not need to pay premiums for Medicare Part D, and those whose family income is below 150% of the poverty line, receive a low-income subsidy. The donut hole policy does not apply to them. Therefore, this study excluded these groups of beneficiaries. Additionally, this paper excluded participants who did not complete all five rounds of the panel. The total analytic sample after exclusions was 24,090 individuals, and the sample size for each panel ranged from 3,995 to 5,379.

Measurement

The study contained two sets of dependent variables. The first set captured the total counts of all filling and refilling of outpatient prescription drugs purchased in the calendar year. The second set of dependent variables featured two variables: one was CHE induced by the total amount of health expenses, and the other was CHE induced by the total amount of prescription drug costs, or CHE-Rx. The CHE variable was coded as 1 if the ratio of the sum of out-of-pocket payments for health services—including prescription drugs, home health services, office-based medical provider visits, outpatient facility services, emergency room services, hospital inpatient services, dental visits, and other medical expenses—to family income exceeded 10%[10] (including those who had negative family income), and coded as 0 if the ratio was under 10% (including those who did not have any health or prescription drug expenses). Family income was composed of wages, salaries, bonuses, tips, commissions, business and farm gains and losses, unemployment and workers' compensation, interest and dividends, public subsidies or assistance, private transfers, private pensions, and gains and losses from assets and investments. Similarly, the variable of CHE-Rx was coded as 1 if the ratio of out-of-pocket payments spent on prescription drugs to family income exceeded 10% and coded as 0 if the ratio was under 10%.

The independent variable in this study was Medicare Part D coverage. Each respondent was surveyed in each round about their type of health insurance coverage, such as Medicare, Medicaid, private insurance, or no coverage. Additionally, respondents were asked if they were covered by Medicare Part D and other private prescription drug plans. The independent variable of Medicare Part D coverage was coded as 1 if a respondent aged 65 or older was covered by Medicare and enrolled in Medicare Part D and was coded as 0 if a respondent aged 55 or older was covered by a third-party private prescription drug plan, including those who were covered Medicare but not enrolled in Medicare Part D and those who were not covered by Medicare but enrolled in private prescription drug plans.

The control variables covered individual characteristics and health status. Individual characteristics included age, gender, race, highest educational attainment, marital status, and

[10] There is no uniform threshold for measuring CHE. Usually, higher thresholds (i.e., 40% or 30%) are adopted in developing countries or when the denominator is ability to pay or disposable income (household income minus food and other needed expenses). Lower thresholds (i.e., 5%, 10%, or 20%) are typically adopted in developed countries or when the denominator is annual household income or annual household consumption (Hailemichael et al., 2019; Wagstaff & Doorslaer, 2003; Wagstaff et al., 2018; Ke Xu, 2005). Given that I calculated CHE as health expenses relative to annual family income, I chose to use 10% in this study and 20% in the sensitivity analysis.

poverty level. The variable of race was categorized into four groups: coded as 1 if respondents were White and reported no other race; 2 if respondents were Black and reported no other race; 3 if respondents were Asian, Native Hawaiian, or other Pacific Islander categories; and 4 if respondents reported other or multiple races. Highest educational attainment was grouped in six categories: coded as 1 if the respondent completed Grades 1–8 or below, 2 if they attended but did not complete high school, 3 if they graduated from high school, 4 if they attended but did not complete college, 5 if they graduated from college, and 6 if they completed a master's degree or beyond. Marital status was coded as five categories: 1 = married, 2 = widowed, 3 = divorced, 4 = separated, and 5 = never married. The poverty category was calculated by family income as a percentage of the poverty line (based on family size and composition) in each year and coded as 1 if low income (150%–199%), 2 if middle income (200%–399%), and 3 if high income (400% or above).

The second set of control variables reflect respondents' health conditions, including self-perceived physical health, self-perceived mental health, diagnosed cancer, and diagnosed chronic diseases.[11] Both self-perceived physical and mental health conditions used a 5-point Likert scale ranging from 1 (*excellent*) to 5 (*poor*). The diagnosed cancer variable was a continuous variable that reflected the total number of diagnosed cancers, such as cancers of the bladder, breast, cervix, colon, lung, and so on, if any. Similarly, the diagnosed chronic diseases variable was a continuous variable that reflected the total number of diagnosed chronic diseases, such as diabetes, arthritis, asthma, etc., if any. None of these health measures was highly correlated with another in our analytic sample.

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[11] The variable of diagnosed chronic diseases is from the MEPS-Household Component dataset.

Empirical strategies

This study adopted the method of difference-in-differences (DID) for multiple reasons. First, the DID method helps generate intuitive interpretations of the immediate effects of each change of reduced coinsurance rates when comparing before and after the change. Second, the DID method accounts for changes due to both observable and unobservable factors other than the treatment. In this study, a set of demographic factors and health conditions were controlled for in the analysis. This may have omitted factors such as respondents' attitudes toward prescription drug usage, which is not affected by treatment but could affect the likelihood of experiencing CHE and CHE-Rx. Third, the method of DID can take advantage of the nature of longitudinal data to obtain more rigorous estimations of policy effects, if assumptions met, than using ordinary least squares.

The survey design and policy implementation met the assumptions for using DID. The first assumption for using DID requires that the intervention is unrelated to the outcome at baseline. The Medicare Part D donut hole closing plan applies to all Part D enrollees. In addition, enrollment in Medicare Part D is more related to age eligibility and less to self-selection. Even though the Part D plan is a voluntary program, given that the high penalty for late enrollment and a few subsidy programs available to low-income and new poor Medicare beneficiaries, the participation rate of the Part D plan among all Medicare beneficiaries was about 75% as of 2019 (Kaiser Family Foundation, 2019). The majority of the remaining beneficiaries had prescription drug coverage through other plans. For example, 23% had private health insurance plans covering prescription drugs and 2.7% had employer plans with retiree drug subsidies in 2017 (Kaiser Family Foundation, 2017). Also, enrollment and premiums were not dependent on enrollees' health conditions and prior medical claims. Therefore, the treatment was unrelated to the health expenditure at baseline.

Another assumption for using DID requires that the treatment and comparison groups have parallel trends in outcomes in the absence of treatment. I conducted visual inspections and observed that the outcomes were generally parallel between comparison and treatment groups in each panel. Figure 3 shows that prescription drug use, percentages of CHE, and percentages of CHE-Rx for the comparison groups were generally flat between 2008 and 2017. But these outcomes for the treatment groups, including those who had Medicare Part D, those who reached the donut hole, those who reached donut hole but did not reach catastrophic coverage, and those who reached catastrophic coverage, fluctuated during this period. This graph provides visual evidence of the contrary trends between the treatment and comparison groups (Angrist et al., 2013).

[Figure 2 about here]

Given that the donut hole closing policy may be more beneficial for people whose health-related or prescription drug expenses fall into the donut hole, this study additionally examined the policy effects by restricting the analytic sample to those whose out-of-pocket payments for prescription medications in the prior year reached the lower boundary of the donut hole[12] (second scenario in Table 1). Considering the coinsurance rate dramatically reduced to 5% once the enrollees reached catastrophic coverage, this study further restricted the analytic sample to those whose medication costs fell in the donut hole, meaning their expenses were above the lower

[12] The lower boundaries of the donut hole were $2,510 in 2008, $2,700 in 2009, $2,830 in 2010, $2,840 in 2011, $2,930 in 2012, $2,970 in 2013, $2,850 in 2014, $2,960 in 2015, $3,310 in 2016, and $3,700 in 2017.

boundary of the donut hole but did not reach catastrophic coverages[13] (third scenario in Table 1). The design of the first three scenarios follows the strategies applied in Bonakdar Tehrani and Cunningham's (2017) work. Given that enrollees whose expenses on prescription drugs reached catastrophic coverage paid the entire donut hole cost, the effects of the donut hole closing policy on changes in the incidence of CHE would be more accurately reflected among this group of participants. Therefore, in addition to the first three scenarios studied by Bonakdar Tehrani and Cunningham (2017), this study additionally examined the effects of the donut hole closing policy among enrollees whose prescription drug costs in prior years reached catastrophic coverage[14] (fourth scenario in Table 1). The limits for donut hole and catastrophic coverage vary across the years. Appendix Table 1 lists the reduced coinsurance rates due to the donut hole closing policy and the changing limits for the donut hole and catastrophic coverage between 2008 and 2017.

[Table 1 about here]

All analyses were tested using DID in each panel and generated DID results by panel first to observe the immediate effects of the gradual reduction in coinsurance rates of the donut hole. The results indicate how sensitive the beneficiaries' relative financial burden was to each reduction. This study also used the pooled 2008–2017 data to generate an aggregated result first, which follows the operationalization of Bonakdar Teharni and Cunningham (2017). The model specification applied in this study is as follows:

$$Y = \beta_0 + \beta_1 * (time) + \beta_2 * (treat) + \beta_3 * (time * treat) + \beta_2 * X + \varepsilon$$

[13] The donut hole ranges were \$2,510–\$4,050 in 2008, \$2,700–\$4,350 in 2009, \$2,830–\$4,550 in 2010, \$2,840–\$4,550 in 2011, \$2,930–\$4,700 in 2012, \$2,970–\$4,750 in 2013, \$2,850–\$4,550 in 2014, \$2,960–\$4,700 in 2015, \$3,310–\$4,850 in 2016, and \$3,700–\$4,950 in 2017.

[14] The lower boundaries for catastrophic coverage were \$5,7265.25 in 2008, \$6,153.75 in 2009, \$6,440.00 in 2010, \$6,447.50 in 2011, \$6,657.50 in 2012, \$6,733.75 in 2013, \$6,455.00 in 2014, \$6,680.00 in 2015, \$7,062.50 in 2016, and \$7,425.00 in 2017.

wherein Y represents the outcomes, the frequency of filling prescription drugs, CHE, or CHE-Rx; is the panel variable in each panel analysis and the year variable in the pooled analysis; stands for the treatment (whether the respondent enrolled in the Medicare Part D plan); $time * treat$ is the interaction term between time and treatment variables; β_3 is the coefficient of interest, which represents the effect of the policy in the treatment group in the posttreatment year compared to the comparison group in the pretreatment year; and X represents the set of covariates. All analyses used the individual sampling weights in the MEPS-HC data.

Results

Descriptive results

The descriptive statistics obtained using MEPS-HC 2008-2017 data in this study are consistent with the administrative data and prior relative studies. The number of Medicare Part D beneficiaries in the sample increased from 2008 through 2017, with a slight decrease from 2009 to 2010, which is consistent with the enrollment summary report released by the Centers for Medicare & Medicaid Services (2020). Figure 1 shows that the average out-of-pocket spending on outpatient prescription drugs for the treatment and comparison groups decreased since 2011. The total health out-of-pocket payments toward facilities, services, and providers for both treatment and comparison groups do not show a clear downward pattern after closing the donut hole. Additionally, the average out-of-pocket payment on both health-related services and prescription drugs decreased among Medicare Part D beneficiaries who reached catastrophic coverage after closing the donut hole, which is consistent with the results of Cubanski et al. (2018).

[Figure 1 about here]

In terms of prescription drug use, relative financial burdens, demographic characteristics, and health conditions across panels, the descriptive analysis results generally also present a consistent pattern. The frequencies of drug filling and refilling, the likelihood of experiencing CHE (and CHE-Rx), and reaching donut hole or catastrophic coverage slightly fluctuated but overall were stable. As shown in Table 2, the average number of prescription filling and refilling stabilized at about 23% to 25% across the nine panels. A total of 5% to 7% of participants experienced CHE and 3% to 4% experienced CHE-Rx. For each demographic characteristic and health condition included in the analytic models, there was no striking difference or change for any specific panel during 2008 and 2017.

[Table 2 about here]

Panel DID results

In each panel, this paper investigated the immediate effects and marginal benefits of reducing coinsurance rates for the donut hole each year since 2011. The results show that closing the donut hole did not significantly change prescription drug usage, incidence of CHE, or incidence of CHE-Rx for all nine panels between 2008 and 2017.

[Table 3 about here]

Similar results were obtained when restricting the sample to those who spent more than the limits of the donut hole but did not reach catastrophic coverage. Prescription drug usage and the likelihood of experiencing CHE or CHE-Rx were not affected significantly by the donut hole closing policy under the ACA for any panel, with the exception that between 2014 and 2015, the incidence of CHE reduced by 7.5% on average.

[Table 4 about here]

When further restricting the analytic sample to those who reached the donut hole but not catastrophic coverage, drug usage and incidence of CHE-Rx, along with the probability of experiencing CHE, were not significantly affected by the donut hole closing policy, with the exception that between 2013 and 2014, the incidence of CHE-Rx increased by 7.3%.

[Table 5 about here]

When examining the effects of the donut hole closing policy among those whose drug expenses exceeded catastrophic coverage using the panel DID method, drug usage was no longer affected. The likelihood of experiencing CHE reduced by 11.7% between 2014 and 2015 due to the closing policy. Besides that, all other outcomes across all nine panels were not significantly affected by the donut hole closing policy under the ACA.

[Table 6 about here]

Aggregated DID results

As stated in the methodology section, this study also examined the effects of the Medicare Part D donut hole closing policy using pooled data. Different from the results obtained using the panel DID analysis, the results using the aggregated DID show that the donut hole closing policy significantly increased total prescription drug usage by 2.8 fillings on average and increased the likelihood of experiencing CHE-Rx by 2.4% for those whose medication expenses exceeded the limit of the donut hole but did not reach catastrophic coverage (Table 7). However, for those whose medication expenses reached catastrophic coverage, the total drug usage significantly decreased by 5.2 fillings among Medicare Part D enrollees, compared to their peers who had third-party prescription drug plans or Medicare beneficiaries who did not enroll in Medicare Part D. The effects of the Medicare Part D donut hole closing policy on drug usage and the likelihood of experiencing CHE and CHE-Rx were not statistically significant in the analytic sample and the restricted sample whose drug costs exceeded the limit of the donut hole.

[Table 7 about here]

Discussion and Conclusion

Using MEPS-HC 2008-2017 data and the DID method, this study examined the marginal and overall effects of closing the donut hole on reducing relative financial burdens. The results show that the coinsurance rate reductions of the donut hole were not associated with changes in prescription drug fillings, incidence of CHE, or incidence of CHE-Rx in the following year. However, using pooled data and aggregated DID analysis, this study found that closing the donut hole was associated with higher prescription drug usage and more incidence of CHE-Rx among participants whose expenses were between the limits of the donut hole and catastrophic coverage.

This study confirmed the effect of donut closing policy on increasing prescription drug use. The coefficient of aggregated DID results on total prescription drug usage was positive (b = 2.841) and significant among those who fell in the donut hole but did not reach catastrophic coverage. The direction and magnitude of the results are in line with the results obtained by Bonakdar Tehrani and Cunningham (2017), even though the effect on the total number of prescription drugs were not significant at the 95% statistical level in their work. This implies that the donut hole closing policy, to some extent, reduced barriers for enrollees to access prescription drugs, even though the policy was not associated with lower financial burden. The increased prescription drug usage demonstrated that enrollees benefited from an early investment in diagnosis, which is part of the intent of closing the donut hole.

This study repeated the analyses among three samples: those who fell in the donut hole but did not reach catastrophic coverage, those who reached the donut hole, and those who had Medicare Part D coverage. This study added another group that reached catastrophic coverage to reflect the effects of closing the donut hole among those who paid for the entire gap of the donut hole. The aggregated DID results show significant reductions in prescription drug usage, which contrasted with the results obtained for the other three study groups. The significant impacts no longer persisted when comparing the outcomes between two consecutive years.

There are two potential explanations for the different results obtained using aggregated and panel DID methods. First, the coinsurance rates reduced much slower in the following years (from 50% to 40% between 2012 and 2017). The rates decreased by 7% evenly each year for generic medicines from 2010. These changes between two consecutive years may not be large enough to boost the impact of the donut hole closing policy. Second, due to higher coverage in the Medicare Part D plan, enrollees may choose to use more expensive medications (Wagstaff et al., 2007). Higher expenses for more expensive medicines may offset the positive impacts of the donut hole closing policy on reduced drug costs.

To my knowledge, this is the first study to use a panel DID design to explore the immediate and additional effect of the roughly 10% reduction in coinsurance rate every year since 2011. This study made four contributions. First, beyond studying the effect of closing the donut hole on out-of-pocket dollar value payments or poverty status using absolute poverty lines, this study explored the impact on relative financial burden by introducing the concept of CHE and CHE-Rx in the analysis. Second, this study also included four additional years of change in the donut hole closing compared to the latest publications that investigated the effects of donut hole closing on the financial well-being of beneficiaries. Third, it added panel DID analyses in addition to the aggregated DID analyses, which reflected the immediate effects of each coinsurance rate reduction. Last, it classified Medicare Part D beneficiaries into four groups and obtained more accurate results by focusing on groups that have been affected by the donut hole closing policy more directly.

This study also has two limitations that should be noted when interpreting and generalizing the results. First, the premiums of Medicare Part D were not recorded in the MEPS data, and the amounts vary by states and plans. Therefore, the premium amounts were not counted in the calculation of CHE and CHE-Rx in the analysis. The actual prevalence of CHE and CHE-Rx could be slightly higher than the results reflect. However, the impact should be limited because the amounts were not substantially high—the average monthly premiums increased \$27.93 and \$42.17 from 2008 to 2017 (The Official U.S. Government Site for Medicare, 2020). Second, given the survey design of MEPS, in which each participant was followed for up to 2 years, the long-term effects of the closing donut hole could not be observed. Therefore, the results of this study should be interpreted cautiously—the nonsignificant impact of the policy implementation does not mean that closing the donut hole was not effective in the long run, but the immediate effects could not be reflected by reducing coinsurance rates by several percentage points.

In June 2020, the Trump Administration asked the U.S. Supreme Court to abolish the ACA, including the Medicare Part D donut hole closing plan. The results of this study show that the donut hole closing plan has increased prescription drug usage significantly among enrollees. If the lawsuit succeeds and the ACA is determined unlawful, the donut hole will reopen and this research suggests we would see a decline in prescriptions being filled when older adults fall into the donut hole and are exposed to high cost-sharing. Because prescriptions are often used to treat diagnosed conditions, this would diminish the efficacy of the health care provided and make the costs of such care less worthwhile.

Future studies could further this research by extending the study period to 2019, when the donut hole was closed. Scholars could also consider applying other relative income-related inequality measures, such as the concentration index, to evaluate the effects of closing the donut hole. Furthermore, future studies could also specify expenditures on generic and brand-name drugs to investigate if the impact of donut hole closing policies on utilization and financial outcomes differ based on type of drug.

Table 3-1: The design of treatment and comparison groups for the four scenarios.

	Treatment Group	Comparison Group
1st scenario: All analytical sample	Respondents aged 65 and above with Medicare Part D	Respondents aged 55 and above without Medicare or Medicaid but with private health insurance which has drug coverages AND respondents aged 65 and above with Medicare but without Part D coverage
2nd scenario: Over donut hole	Respondents aged 65 and above with Medicare Part D and reached the donut hole	Respondents aged 55 and above without Medicare or Medicaid but with private health insurance which has drug coverages and reached donut hole amount AND respondents aged 65 and above with Medicare but without Part D coverage whose drug spending reached donut hole amount
3rd scenario: Between donut hole and catastrophic coverage	Respondents aged 65 and above with Medicare Part D and reached donut hole but did not reach catastrophic coverage	Respondents aged 55 and above without Medicare or Medicaid but with private health insurance which has drug coverages and reached donut hole amount but did not reach catastrophic coverage AND respondents aged 65 and above with Medicare but without Part D coverage whose drug spending reached the amount between the donut hole and the catastrophic coverage
4th scenario: Over catastrophic coverage	Respondents aged 65 and above with Medicare Part D and reached catastrophic coverage	Respondents aged 55 and above without Medicare or Medicaid but with private health insurance which has drug coverages and reached catastrophic coverage AND respondents aged 65 and above with Medicare but without Part D coverage whose drug spending reached catastrophic coverage amount.

Table 3-2: Descriptive statistics of prescription drug utilization, CHE, CHE-Rx, demographic characteristics, and health conditions.

	08-09 Mean/SD	09-10 Mean/SD	10-11 Mean/SD	11-12 Mean/SD	12-13 Mean/SD	13-14 Mean/SD	14-15 Mean/SD	15-16 Mean/SD	16-17 Mean/SD
Medicare Part D	0.36	0.36	0.38	0.39	0.40	0.40	0.41	0.42	0.43
	(0.48)	(0.48)	(0.48)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.50)
Donut hole	0.43	0.48	0.48	0.46	0.52	0.55	0.54	0.55	0.58
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
Catastrophic coverage	0.44	0.46	0.48	0.47	0.49	0.57	0.55	0.60	0.60
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.49)
Rx refilling	24.75	25.44	23.61	23.59	23.15	22.97	24.11	22.86	22.61
	(28.51)	(30.23)	(27.18)	(29.34)	(28.24)	(28.28)	(29.55)	(28.19)	(27.42)
CHE	0.06	0.07	0.07	0.06	0.05	0.06	0.07	0.05	0.07
	(0.24)	(0.26)	(0.25)	(0.25)	(0.22)	(0.24)	(0.25)	(0.23)	(0.25)
CHE-Rx	0.03	0.04	0.04	0.04	0.03	0.03	0.04	0.03	0.04
	(0.18)	(0.20)	(0.19)	(0.19)	(0.16)	(0.18)	(0.18)	(0.16)	(0.18)
Age	66.43	66.84	67.20	66.91	66.98	66.81	67.09	67.30	67.57
	(8.91)	(9.15)	(9.01)	(8.89)	(8.91)	(8.78)	(9.02)	(8.96)	(8.95)
Poverty category	3.91	3.88	3.85	3.79	3.87	3.81	3.81	3.84	3.83
	(1.28)	(1.28)	(1.31)	(1.33)	(1.32)	(1.32)	(1.34)	(1.33)	(1.34)
Gender	1.56	1.56	1.54	1.55	1.57	1.56	1.57	1.55	1.55
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Race	1.39	1.35	1.39	1.38	1.45	1.41	1.45	1.41	1.40
	(0.71)	(0.67)	(0.72)	(0.68)	(0.74)	(0.73)	(0.75)	(0.74)	(0.72)
Edu attainment	3.51	3.58	3.60	3.58	3.61	3.51	3.52	3.54	3.63
	(1.48)	(1.46)	(1.44)	(1.41)	(1.55)	(1.53)	(1.55)	(1.52)	(1.46)
Physical health	2.62	2.61	2.58	2.60	2.57	2.56	2.60	2.57	2.60
	(1.13)	(1.10)	(1.10)	(1.08)	(1.09)	(1.10)	(1.11)	(1.11)	(1.08)
Mental health	2.14	2.13	2.12	2.14	2.15	2.12	2.20	2.17	2.16
	(1.02)	(1.03)	(1.01)	(1.01)	(1.01)	(1.01)	(1.03)	(1.04)	(1.03)
Cancer	0.39	0.39	0.39	0.42	0.37	0.39	0.42	0.41	0.41
	(0.80)	(0.81)	(0.80)	(0.83)	(0.79)	(0.82)	(0.84)	(0.83)	(0.84)
Chronic disease	2.58	2.59	2.55	2.54	2.52	2.60	2.58	2.54	2.49
	(1.89)	(1.89)	(1.85)	(1.85)	(1.84)	(1.90)	(1.87)	(1.86)	(1.81)
N	4700	4755	4146	5519	4901	5037	4898	5561	5231

Table 3-3: Effects of donut hole closing policy on prescription drug utilization, CHE, and CHE-Rx using the panel DID methods among all the analytical samples.

Panel	08-09	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17
Rx Use DID	2.491	0.008	-0.255	0.493	2.615	0.929	-1.774	1.388	0.626
	(1.411)	(1.565)	(1.460)	(1.433)	(1.360)	(1.323)	(1.444)	(1.267)	(1.265)
R-squared	0.347	0.313	0.357	0.268	0.303	0.323	0.333	0.322	0.321
CHE DID	0.009	0.005	-0.008	-0.007	-0.019	0.001	-0.021	-0.021	0.002
	(0.014)	(0.015)	(0.015)	(0.012)	(0.013)	(0.013)	(0.013)	(0.011)	(0.012)
R-squared	0.154	0.181	0.170	0.160	0.148	0.147	0.169	0.125	0.139
CHE-Rx DID	0.006	0.008	-0.003	0.011	-0.007	0.006	-0.011	-0.006	0.008
	(0.009)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)	(0.008)
R-squared	0.115	0.174	0.151	0.162	0.131	0.121	0.123	0.100	0.113
N (C t0)	1477	1485	1259	1681	1437	1427	1396	1563	1442
N (T t0)	766	824	720	991	862	985	934	1118	1102
N (C t1)	1452	1485	1272	1627	1426	1495	1434	1574	1444
N (T t1)	829	801	744	1024	968	982	1002	1124	1046
N (Total)	4,524	4,595	3,995	5,323	4,693	4,889	4,766	5,379	5,034

Notes: Standard errors in parentheses; Control variables in each model include age, gender, race, highest educational attainment, marital status, poverty level, self-perceived physical and mental health, and numbers of diagnosed cancer and chronic diseases. The notion of Diff means difference, N stands for the number of observations, Rx stands for prescription drugs, C stands for the comparison group, T stands for the treatment group, t(0) stands for the results in the baseline, and t(1) stands for the post-treatment results. Rx Use is a categorical variable coded as 0 if no prescription drug used, 1 if 1-9 filling/refilling of prescription drugs, 2 if 10-49 filling/refilling, and 3 if 50 and above filling/refilling. CHE and CHE-Rx are both dummy variables coded as 0 if health/prescription drug costs did not exceed 10% of household annual income and 1 if the ratio exceeded 10%.

*** p<0.001, ** p<0.01, * p<0.0

Table 3-4: Effects of donut hole closing policy on prescription drug utilization, CHE, and CHE-Rx using the panel DID methods among those whose prescription drug costs reached the donut holes.

Panel	08-09	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17
Rx Use DID	4.234	-3.878	1.687	-2.928	-4.083	3.104	-3.879	0.354	-4.663
	(3.453)	(4.271)	(3.836)	(4.600)	(4.116)	(3.963)	(3.961)	(3.519)	(3.890)
R-squared	0.324	0.211	0.276	0.172	0.236	0.306	0.280	0.276	0.247
CHE DID	0.067	0.032	0.021	-0.055	-0.025	0.020	-0.075*	-0.062	0.005
	(0.035)	(0.038)	(0.042)	(0.038)	(0.039)	(0.034)	(0.035)	(0.032)	(0.036)
R-squared	0.176	0.182	0.234	0.165	0.146	0.146	0.155	0.149	0.085
CHE-Rx DID	0.037	0.036	0.005	-0.020	0.031	0.042	-0.044	0.000	0.013
	(0.028)	(0.031)	(0.034)	(0.028)	(0.028)	(0.028)	(0.027)	(0.023)	(0.026)
R-squared	0.179	0.203	0.211	0.183	0.180	0.124	0.111	0.111	0.070
N (C t0)	321	254	213	271	202	199	208	259	208
N (T t0)	321	341	267	320	304	371	383	437	402
N (C t1)	287	269	229	275	234	229	251	251	190
N (T t1)	329	336	288	335	382	428	418	439	369
N (Total)	1,258	1,200	997	1,201	1,122	1,227	1,260	1,386	1,169

Notes: Standard errors in parentheses; Control variables in each model include age, gender, race, highest educational attainment, marital status, poverty level, self-perceived physical and mental health, and numbers of diagnosed cancer and chronic diseases. The notion of Diff means difference, N stands for the number of observations, Rx stands for prescription drugs, C stands for the comparison group, T stands for the treatment group, t(0) stands for the results in the baseline, and t(1) stands for the post-treatment results. Rx Use is a categorical variable coded as 0 if no prescription drug used, 1 if 1-9 filling/refilling of prescription drugs, 2 if 10-49 filling/refilling, and 3 if 50 and above filling/refilling. CHE and CHE-Rx are both dummy variables coded as 0 if health/prescription drug costs did not exceed 10% of household annual income and 1 if the ratio exceeded 10%.
*** p<0.001, ** p<0.01, * p<0.0

Table 3-5: Effects of donut hole closing policy on prescription drug utilization, CHE, and CHE-Rx using the panel DID methods among those whose prescription drug costs were between donut holes and catastrophic coverages.

Panel	08-09	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17
Rx Use DID	7.935**	-3.020	6.474	1.178	-5.542	5.857	3.234	4.641	0.709
	(3.013)	(3.443)	(3.859)	(3.396)	(4.470)	(3.759)	(3.933)	(3.566)	(4.511)
R-squared	0.276	0.258	0.237	0.231	0.222	0.263	0.287	0.221	0.176
CHE DID	0.029	0.037	0.083	-0.076	-0.028	0.041	-0.034	-0.020	0.037
	(0.037)	(0.039)	(0.046)	(0.042)	(0.043)	(0.039)	(0.041)	(0.036)	(0.042)
R-squared	0.255	0.173	0.257	0.178	0.157	0.215	0.195	0.184	0.107
CHE-Rx DID	0.009	0.045	0.069	0.002	0.020	0.073*	-0.021	0.008	0.022
	(0.028)	(0.029)	(0.035)	(0.027)	(0.029)	(0.031)	(0.027)	(0.026)	(0.026)
R-squared	0.237	0.199	0.244	0.199	0.173	0.200	0.121	0.146	0.096
N (C t0)	222	181	149	184	134	128	122	169	122
N (T t0)	207	227	176	202	191	208	210	212	195
N (C t1)	204	180	154	175	150	137	145	150	99
N (T t1)	197	209	180	202	2240	210	208	213	172
N (Total)	830	797	659	763	715	683	685	744	588

Notes: Standard errors in parentheses; Control variables in each model include age, gender, race, highest educational attainment, marital status, poverty level, self-perceived physical and mental health, and numbers of diagnosed cancer and chronic diseases. The notion of Diff means difference, N stands for the number of observations, Rx stands for prescription drugs, C stands for the comparison group, T stands for the treatment group, t(0) stands for the results in the baseline, and t(1) stands for the post-treatment results. Rx Use is a categorical variable coded as 0 if no prescription drug used, 1 if 1-9 filling/refilling of prescription drugs, 2 if 10-49 filling/refilling, and 3 if 50 and above filling/refilling. CHE and CHE-Rx are both dummy variables coded as 0 if health/prescription drug costs did not exceed 10% of household annual income and 1 if the ratio exceeded 10%.
*** p<0.001, ** p<0.01, * p<0.05

Table 3-6: Effects of donut hole closing policy on prescription drug utilization, CHE, and CHE-Rx using the panel DID methods among those whose prescription drug costs reached the catastrophic coverages.

Panel	08-09	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17
Rx Use DID	-9.354	-4.515	-6.087	-7.960	-0.059	5.647	-11.240	-1.485	-10.612
	(7.005)	(9.945)	(7.506)	(10.219)	(7.682)	(7.252)	(6.636)	(6.124)	(5.837)
R-squared	0.365	0.194	0.348	0.176	0.289	0.317	0.308	0.290	0.323
CHE DID	0.121	0.027	-0.047	-0.016	-0.008	0.020	-0.117*	-0.103	-0.023
	(0.073)	(0.081)	(0.084)	(0.072)	(0.076)	(0.061)	(0.059)	(0.057)	(0.059)
R-squared	0.137	0.211	0.229	0.201	0.164	0.106	0.143	0.145	0.079
CHE-Rx DID	0.061	0.030	-0.085	-0.052	0.059	0.014	-0.059	-0.012	0.003
	(0.060)	(0.071)	(0.075)	(0.061)	(0.058)	(0.052)	(0.049)	(0.041)	(0.047)
R-squared	0.178	0.233	0.205	0.210	0.226	0.092	0.119	0.107	0.070
N (C t0)	99	73	64	87	68	71	86	90	86
N (T t0)	114	114	91	118	113	163	173	225	207
N (C t1)	83	89	75	100	84	92	106	101	91
N (T t1)	132	127	108	133	142	218	210	226	197
N (Total)	428	403	338	438	407	544	575	642	581

Notes: Standard errors in parentheses; Control variables in each model include age, gender, race, highest educational attainment, marital status, poverty level, self-perceived physical and mental health, and numbers of diagnosed cancer and chronic diseases. The notion of Diff means difference, N stands for the number of observations, Rx stands for prescription drugs, C stands for the comparison group, T stands for the treatment group, t(0) stands for the results in the baseline, and t(1) stands for the post-treatment results. Rx Use is a categorical variable coded as 0 if no prescription drug used, 1 if 1-9 filling/refilling of prescription drugs, 2 if 10-49 filling/refilling, and 3 if 50 and above filling/refilling. CHE and CHE-Rx are both dummy variables coded as 0 if health/prescription drug costs did not exceed 10% of household annual income and 1 if the ratio exceeded 10%.

*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 3-7: Effects of donut hole closing policy on prescription drug utilization, CHE, and CHE-Rx using the aggregated DID results among four study groups.

	All analytical sample			Over donut hole			Between donut hole and catastrophic coverage			Over catastrophic coverage		
VARIABLES	Rx Use	CHE	CHE-Rx	Rx Use	CHE	CHE-Rx	Rx Use	CHE	CHE-Rx	Rx Use	CHE	CHE-Rx
Diff-in-diff	0.827	-0.007	0.001	-0.995	-0.009	0.008	2.841*	0.011	0.024*	-5.187*	-0.028	-0.010
	(0.463)	(0.004)	(0.003)	(1.314)	(0.012)	(0.009)	(1.245)	(0.013)	(0.010)	(2.468)	(0.022)	(0.018)
Observations	43,198	43,198	43,198	10,820	10,820	10,820	6,464	6,464	6,464	4,356	4,356	4,356
R-squared	0.316	0.151	0.128	0.242	0.144	0.138	0.215	0.172	0.165	0.253	0.119	0.123
N (C t0)	13167	13167	13167	2135	2135	2135	1411	1411	1411	724	724	724
N (T t0)	8302	8302	8302	3146	3146	3146	1828	1828	1828	1318	1318	1318
N (C t1)	13209	13209	13209	2215	2215	2215	1394	1394	1394	821	821	821
N (T t1)	8520	8520	8520	3324	3324	3324	1831	1831	1831	1493	1493	1493
Mean control t(0)	-9.765	0.212	0.224	25.90	0.169	0.261	24.77	0.206	0.275	25.24	0.120	0.247
Mean treated t(0)	-6.464	0.189	0.212	36.79	0.133	0.230	30.86	0.152	0.240	41.43	0.103	0.215
Diff t(0)	3.301	-0.0228	-0.0116	10.89	-0.0361	-0.0314	6.094	-0.0541	-0.0352	16.19	-0.0170	-0.0321
Mean control t(1)	-9.540	0.213	0.225	27.56	0.166	0.258	25.29	0.205	0.273	25.67	0.107	0.235
Mean treated t(1)	-5.412	0.183	0.215	37.45	0.121	0.235	34.23	0.161	0.262	36.68	0.0612	0.194
Diff t(1)	4.128	-0.0299	-0.0105	9.896	-0.0450	-0.0235	8.935	-0.0435	-0.0108	11.01	-0.0454	-0.0416

Notes: Standard errors in parentheses; Control variables in each model include age, gender, race, highest educational attainment, marital status, poverty level, self-perceived physical and mental health, and numbers of diagnosed cancer and chronic diseases. The notion of Diff means difference, N stands for the number of observations, Rx stands for prescription drugs, C stands for the comparison group, T stands for the treatment group, t(0) stands for the results in the baseline, and t(1) stands for the post-treatment results. Rx Use is a categorical variable coded as 0 if no prescription drug used, 1 if 1-9 filling/refilling of prescription drugs, 2 if 10-49 filling/refilling, and 3 if 50 and above filling/refilling. CHE and CHE-Rx are both dummy variables coded as 0 if health/prescription drug costs did not exceed 10% of household annual income and 1 if the ratio exceeded 10%.
*** p<0.001, ** p<0.01, * p<0.05

Figure 3-1: Descriptive connected graph for average out-of-pocket payment on prescription drugs and health care by the treatment between 2009 and 2016.

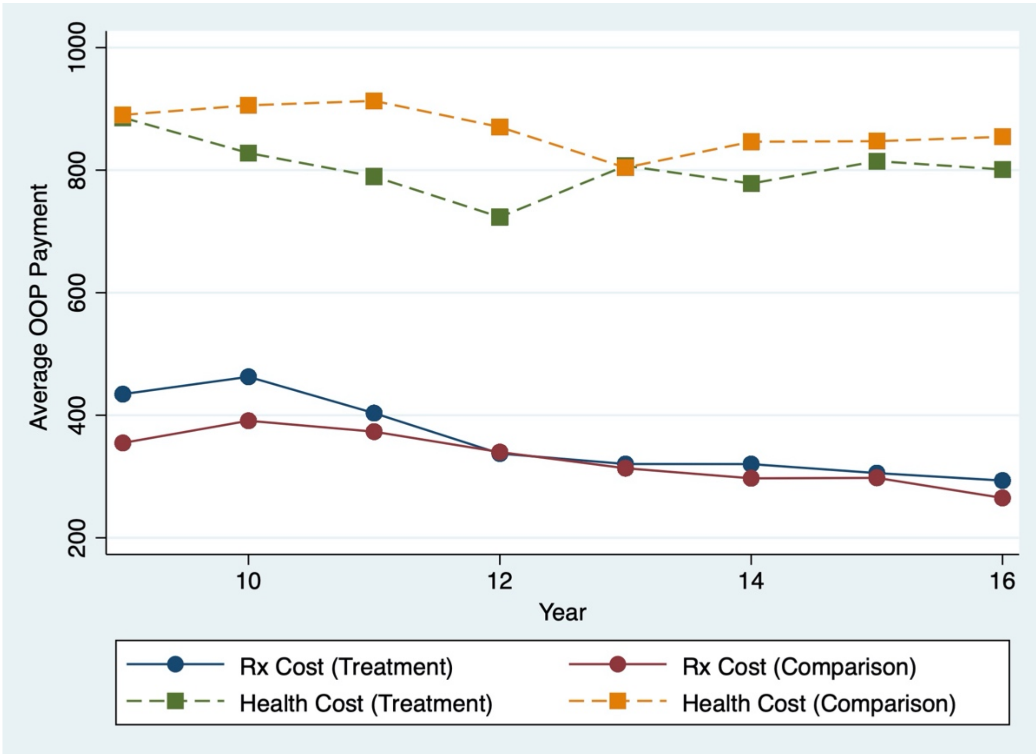
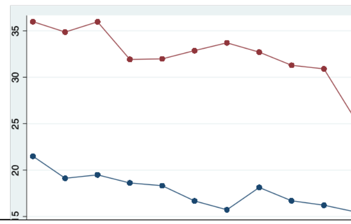
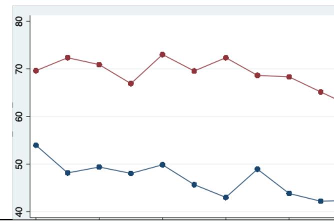
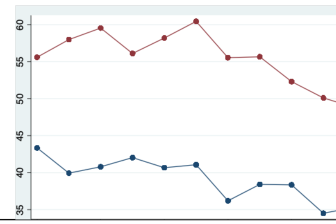
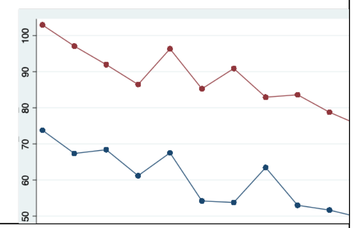
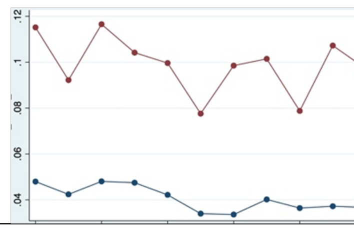
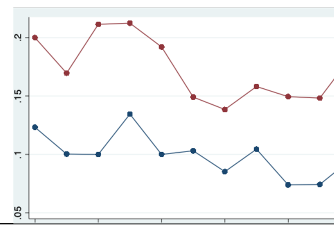
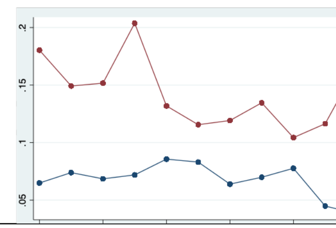
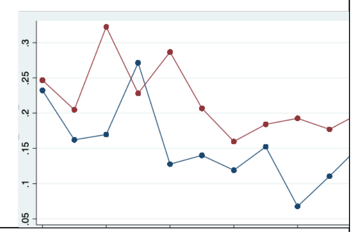
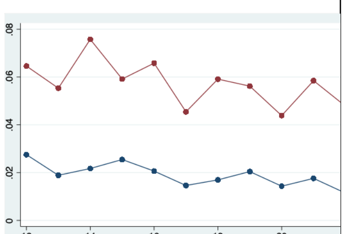
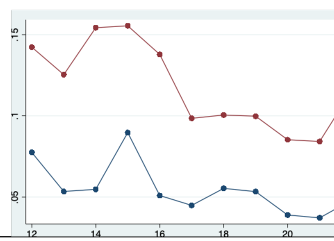
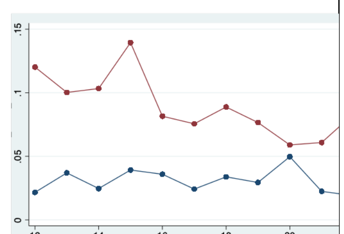
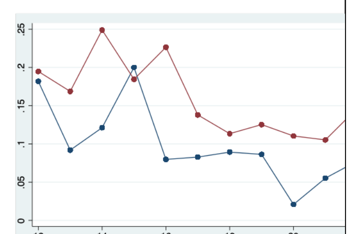


Figure 3-2 Trends of prescription use, CHE, CHE-Rx among Medicare Part D enrollees, those who reached donut hole, and those who reached catastrophic coverage from 2008 to 2017.

	All analytical sample	Over donut hole	Between donut hole and catastrophic coverage	Over catastrophic coverage
Rx use				
CHE				
CHE-Rx				

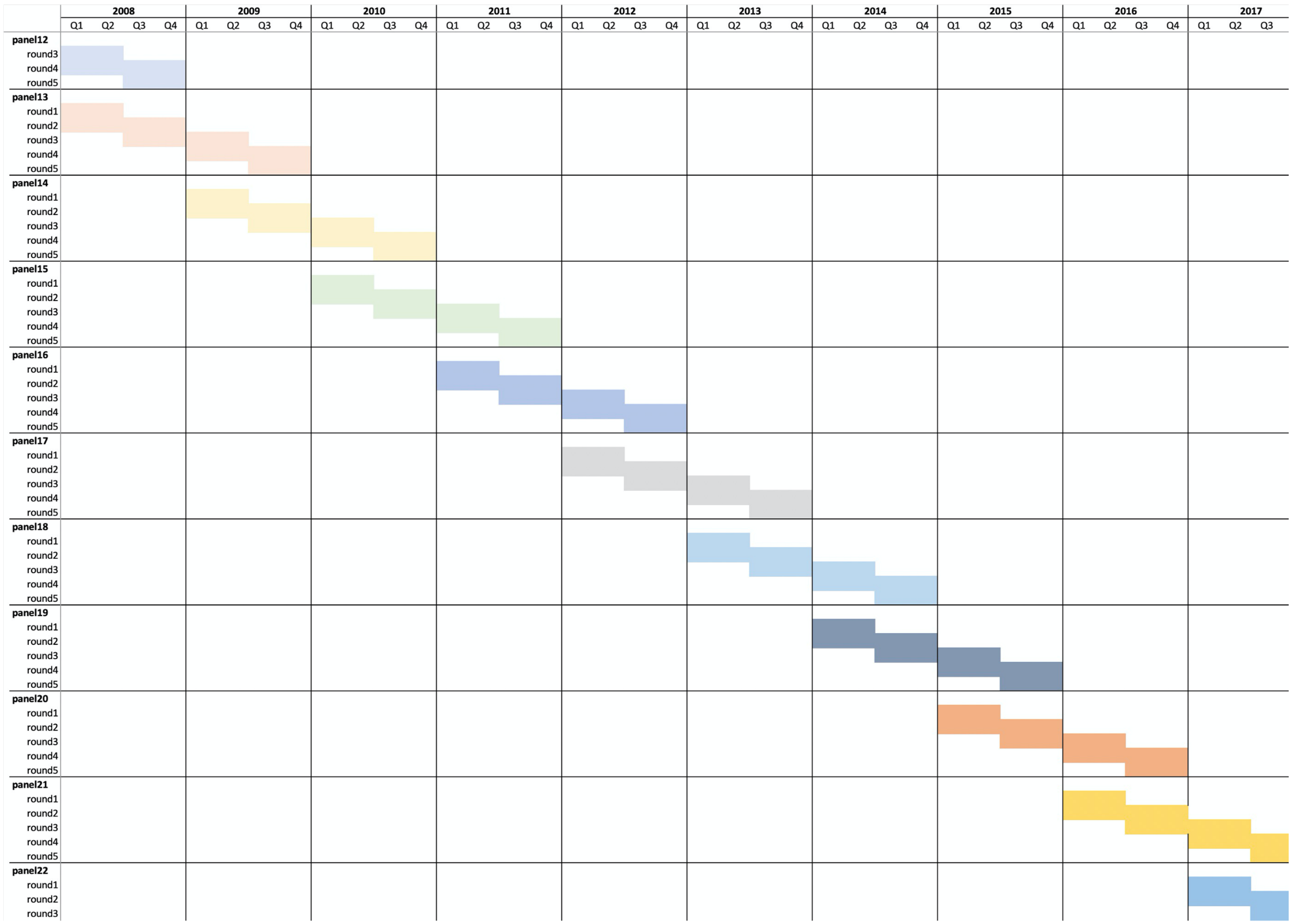
Notes: The red dots represent the treatment groups, and the blue dots represent the comparison groups

Appendix 3-1: The coinsurance rates and thresholds of donut holes and catastrophic coverages for Medicare Part D between 2008 and 2017.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Initial coverage limit: Donut Hole begins at this point ($)	2,510.00	2,700.00	2,830.00	2,840.00	2,930.00	2,970.00	2,850.00	2,960.00	3,310.00	3,700.00
Total covered Part D drug out-of-pocket spending including the coverage gap: Catastrophic Coverage starts after this point ($)	5,726.25	6,153.75	6,440.00	6,447.50	6,657.50	6,733.75	6,455.00	6,680.00	7,062.50	7,425.00
Coinsurance rate for brand-name drugs in Donut Hole (%)	100	100	100	50	50	47.5	47.5	45	45	40
Coinsurance rate for generic drugs in Donut Hole (%)	100	100	100	93	86	79	72	65	58	51

Resources: Cited and retrieved from https://q1medicare.com/PartD-The-MedicarePartDOutlookAllYears.php。

Appendix 3-1: The survey design graph of Medical Expenditure Panel Survey 2008-2017.



Conclusion

Conclusion

Health-induced poverty is prevalent and risky among older adults in both China and the United States. Using three nationally representative datasets and rigorous study designs, this dissertation investigated the consequences of health-induced poverty on private transfers and effects of national health insurance programs, including the New Rural Cooperative Medical Insurance in China and the Medicare Part D donut hole closing policy under the Affordable Care Act in the United States, on reducing health-induced poverty. Overall, the results show that health-induced poverty intensified the crowding-out effect of public transfers on private transfers among older adults in urban China, and the two health insurance programs did not help mitigate health-induced poverty among older adults in China and the United States.

More specifically, this dissertation found that health-induced poverty diminished the total benefits recipients could receive from public transfers among urban older adults in China. In addition to the negative consequences of health-induced poverty found in prior studies, such as selling living stocks, delaying treatment, and skipping medications, this study added empirical evidence about another negative consequence: A higher level of health care spending could worsen the crowding-out effect of public welfare transfers on interfamily transfers among urban older adults.

In addition to the effects on health care service or medication utilization and dollar amount spending as examine in prior studies, this dissertation extended the current literature by testing the impact of health insurance policies on relative financial burden. It found limited effects of the two insurance policies in China and the United States on reducing catastrophic health expenditures. The donut hole closing policy under the Affordable Care Act in the United States significantly increased prescription drug usage and the incidence of catastrophic health expenditure induced by prescription drug costs among those whose prescription drugs costs reached the initial limits of the donut hole. Participating in the New Rural Cooperative Medical Insurance in China was not significantly associated with changes in the likelihood of experiencing catastrophic health expenditures among middle-aged and older adults.

Implications for Social Policy, Practice, and Research

Findings from this dissertation have several implications for social policy, social work practice, and research. First, future social policy reforms should note the failure of the current health insurance programs in reducing health-induced poverty and the cost-related barriers to accessing health care services and medications by providing extra subsidies, shortening the time dedicated to closing the coverage gap, or increasing reimbursement rates. Expenses on health-related services are a critical human capital investment for older adults but could be easily skipped when faced with financial strains to meet other daily needs such as food, clothing, and housing. Prior studies have found that people reported forgoing care including skipped prescribed medications, missed or delayed follow-up treatment, and reduced dosages due to high costs of such treatment, even though they had invested in receiving health care services to diagnose their health issues (Kalousova & Burgard, 2013; X. Li, Chen, Wang, & Si, 2018).

In this dissertation, the results show that the Medicare Part D donut hole closing policy in the United States was associated with a significant increase in prescription drug usage. This implies that the policy helped reduced barriers to accessing prescription drugs. However, the dissertation also found that the donut hole closing policy did not reduce the relative financial burden as intended. Policy makers could consider efforts to reduce the proportion of household income spent on prescription drugs, such as providing tiered subsidies to different income groups. For the New Rural Cooperative Medical Insurance in China, future policy implementation could involve increasing the reimbursement rates, especially for outpatient services, to alleviate the enrollees' out-of-pocket payments.

Second, policy makers should also take actions to reduce nonfinancial barriers, such as increasing the number of health facilities that are close to older adult communities to boost access to health care services and medications. A prior study found that 1 in 5 patients who had unmet needs for health care services faced nonfinancial barriers including inaccessibility, unavailability, and unacceptability (Kullgren, McLaughlin, Mitra, & Armstrong, 2012). Both cost-related and nonfinancial barriers to accessing prescriptions and follow-up treatment stopped low-income enrollees from benefiting from early investment in diagnosis. More importantly, the cost-related barriers and forgone care could pull low-income enrollees into the vicious cycle between illness and poverty.

Third, policy makers should pay attention to the existence of a negative spillover effect and make further adjustments, such as providing in-kind benefits including free care for certain diseases and populations, to reduce the likelihood of crowding out interfamily private transfers. The negative spillover effect of the intensified crowding-out effect on interfamily private transfers contradicts the intentions of the policy makers, who designed public transfer programs to complement beneficiaries' incomes and improve their well-being. Neither did it necessarily boost the financial independence of older adults from their adult children, given no studies have investigated whether crowded-out private transfers were given to older adults in other ways, such as paying for their medical bills.

Concerning the implications for social work practice, this dissertation suggests the necessity of offering more social services to low-income older adults to prevent or reduce the likelihood of experiencing health-induced poverty. Such social services could include transitional care coaching, which helps discharged patients navigate follow-up doctor visits, treatment, and prescription medications to reduce the probability of returning to the hospital for the same health reason. Additionally, transitional care coaches could also connect eligible clients with other social services, such as free nonemergency medical transportation and nutritious meal delivery, to reduce their indirect health-related expenses.

In terms of the implications for future research, this dissertation demonstrated the benefits of using a relative poverty measure, catastrophic health expenditure, to evaluate the antipoverty effect of health policies. For example, lower-income enrollees may find it hard to pay for health care services even though their actual amount of spending is small. Conversely, for higher-income enrollees, their capabilities to pay are higher even though the actual amounts of spending are high. Examining the effects of health insurance programs on reducing the actual amount of expenditures may exaggerate the adverse effects on higher-income enrollees but ignore the impacts on lower-income ones. Additionally, using absolute poverty cutoffs or dollar values may result in overestimations among those who have higher health care needs and spending, such as older adults.

Future studies could build on this dissertation to further explore the long-term effect of social policies in reducing health-induced poverty. Future studies could also compare the measurement of catastrophic health expenditure with other poverty measures in examining health-induced poverty in the global context. Finally, comparative studies could be conducted to evaluate similar social policies in reducing health-induced poverty in developing countries.

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