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Three Essays on Social Insurance

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Abstract

This dissertation consists of three chapters on the economics of social insurance. Each chapter explores an aspect of the evaluation and design of social insurance in terms of nutrition, healthcare and unemployment.

The first chapter, Kim, Fleisher and Sun (2016) report evidence of long-term adverse health impacts of fetal malnutrition exposure of middle-aged survivors of the 1959-1961 China Famine using data from the China Health and Retirement Longitudinal Study. We find that fetal exposure to malnutrition has large and long-lasting impacts on both physical health and cognitive abilities, including the risks of suffering a stroke, physical disabilities in speech, walking and vision, and measures of mental acuity even half a century after a tragic event. Our findings imply that policies and programs that improve the nutritional status of pregnant women yield benefits on the health of a fetus that extend through the life cycle in the form of reduced physical and mental impairment.

In Chapter 2, I evaluate the welfare benefits of the New Cooperative Medical Scheme (NCMS), the main public health insurance plan for the rural population in China. I find that the value of the NCMS to recipients is slightly higher than the government's costs of implementation. Household benefits from the insurance through its value in transfer and insurance function. The estimated moral hazard costs are small

compared to the total benefits. The findings suggest that behavioral changes due to health insurance (i.e. increase of medical service utilization) are in large welfare improving among low-income households.

In Chapter 3, I examine the effect of a two-tiered unemployment insurance system, combining both the UISA and the current unemployment insurance. Unemployment insurance savings account (UISA) is a mandatory individual savings accounts that can be used only during unemployment or retirement. Different from unemployment insurance, UISA does not lead to moral hazard problem but also provide no public insurance to workers. Workers are mandated to save when employed and can withdraw from the account when unemployed. Once the account is exhausted, the unemployed worker receives the usual unemployment benefits. The two-tiered unemployment insurance works more efficiently than an unemployment insurance system since it provides government benefits only to individuals who are not capable of consumption smoothing themselves. Fitting the model to the US economy, I find that, relative to the existing unemployment insurance system, the proposed two-tiered unemployment insurance leads to a welfare gain of 1% and reduce unemployment duration for younger workers.

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Dedication

This thesis is dedicated to my parents Suzhen Zhang and Jinghai Sun, and my grandma Guiqiu Shi.

Contents

Chapter 1

The Long-term Health Effects of Fetal Malnutrition: Evidence from the 1949-1961 China Great Leap Forward Famine

(Joint with Seonghoon Kim and Belton Fleisher)

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1.1 Introduction

Malnutrition among pregnant women and children has been a long-standing problem in developing countries. For example, China, although achieving impressive economic development, still has more than 120 million individuals suffering from malnutrition and 7.2 million children with stunted growth (Chen, 2013). The 'Fetal Origins Hypothesis' of Barker (1990) and much subsequent work argue that fetal malnutrition 'programs' the fetus with metabolic characteristics that can lead to future diseases. In the absence of human-subject randomized con-trolled experiments that might establish a causal link between fetal malnutrition and later life health outcomes, historical events such as the Dutch Famine of 1944 (Roseboom et al., 2001; Scholte et al., 2015) have provided researchers with data permitting the study of the long-term effects of fetal malnutrition. The 1959–1961 China Great Leap Forward Famine (hereafter China Famine), being the worst famine in human history, caused about 30 million excess deaths (Li and Yang, 2005). The dramatic differences in famine intensity across cohorts and regions make the China Famine a particularly well-suited quasi-natural experiment to identify the causal influences of fetal exposure to malnutrition on subsequent physical and mental health outcomes.

We contribute to the literature by examining the long-term health effects of fetal malnutrition in a recently avail-able and large sample of China Famine survivors who were in their 50s by the time of the survey. Studies have shown that infants who experienced malnutrition during the fetal period may be born with normal birth weight and birth size but appear to suffer from various diseases, such as cardiovascular diseases, diabetes, and breast cancer in a later stage of life, because the initial adaptations of DNA to help the survival of a fetus can trigger health problems in later adulthood (Scholte et al., 2015; Lumey et al., 2011; Schulz, 2010). For example, the Dutch

Famine studies suggest that the adverse influences of in utero exposure to malnutrition on cognitive abilities be-came obvious when survivors turned into their

50s, even though no significant effects were seen during their 20s (Stein et al., 1972; Scholte et al., 2015). The delayed effects of prenatal influences are likely to have prevented earlier studies of the China Famine from identifying the full negative consequences of fetal malnutrition, because the age range of famine victims in earlier studies was largely younger than 40 years of age.

Half a century after the event, we are now able to examine the long-term impacts of in utero malnutrition on health outcomes of the survivors in their middle age with nationwide panel data on the Chinese elderly, called the China Health and Retirement Longitudinal Study (CHARLS). CHARLS is a biannual panel survey that began in 2011 and collects rich information on a wide array of detailed objective and subjective health measures of a representative national sample of individuals who were aged 45 and over in China. CHARLS has much richer information on various health measures than the China Population Census data and has a much larger sample than the China Health and Nutrition Study (CHNS) data.

There are several studies on the health effects of the China Famine, but they use relatively simple measures such as height and weight observed at early adulthood (Gorgens et al., 2007; Chen and Zhou, 2007; Meng and Qian, 2009; Fung and Ha, 2010), or they look at other health measures using a limited sample (e.g., data obtained from a local hospital) (Clair et al., 2005; Xu et al., 2009). There has been little, if any, comprehensive evaluation of the occurrence and magnitude of long-term health consequences of the China Famine, and the newly available CHARLS data allow us to evaluate these outcomes.

We identify the long-term health effects of fetal malnutrition using province-specific and year-specific death rates weighted by birth month as a proxy for the famine severity. We find that fetal exposure to the China Famine of individuals born during 1959–1961 has led to a 23.3% greater likelihood of developing a speech im-pediment, a 16% greater likelihood of suffering difficulty in walking, and a 5.1% greater chance of developing vision impairment later in life compared with individuals who were born before or after the China Famine. We also find that survivors who experienced the famine in utero have a higher probability of having suffered from a stroke compared with non-famine cohorts.

Consistent with the findings of the Dutch Famine studies, our results show that the survivors of the China Famine have a higher probability of low cognitive function. Survivors who experienced the famine in utero tend to perform much worse on simple arithmetic calculations and date recall tests. Because pregnancy is the critical period of time when the nervous system is developing and the human body of the pregnant women prioritizes the survival of a fetus over its brain development, malnutrition experience during the gestation can cause defects in the formation of famine survivors' neural system (Schulz, 2010).[1]

The remainder of the paper is structured as follows. In Section 1.2, we briefly discuss the background of the 1959 – 1961 China Famine and review the related literature. In Section 1.3, we describe the data and report sample statistics. Section 1.4 lays out our empirical strategy for estimating the long-term effects of fetal malnutrition on physical and cognitive outcomes. Section 1.5 presents and discusses the estimation results. Section 6 concludes the paper.

1.2 Brief Background and Related Literature on the 1959-1961 Great Leap Forward Famine

1.2.1. Brief background

In 1958, the Chinese Communist Party implemented a set of nationwide policies, known as the Great Leap Forward Movement, aiming to quickly catch up to the level of industrialization of the Soviet Union and the USA (Li and Yang, 2005). Available resources were diverted from the agriculture sector to the manufacturing sector, and the central government sharply increased grain procurement from the rural population for urbanization and export (Lin and Yang, 2000). The excess procurement of grain from rural areas, exacerbated by a series1 of severe weather conditions, led to a huge decrease in caloric intake of rural residents and thus reduced their physical capacity to engage in farm work (Li and Yang, 2005). As a result, grain production

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[1] Animal studies are also in line with our finding. For example, previous lab experiments on rodents show that decedents of undernourished mother rats tend to have fewer brain cells than decedents of normally nourished mother rats (Strauss, 1997)

dropped substa-tially, leading to a vicious cycle of malnutrition, lowered labor productivity, and further reductions in output of agricultural products worsened by reduced production incentives (Li and Yang, 2005; Meng and Qian, 2009).

Compared with the pre-famine production level, national grain output dropped by almost 30% in 1960 (Li and Yang, 2005). Exacerbating the impact of lower agricultural production, the Chinese central government's delayed response to the food shortage, severe limitations on interregional transfer of grain and other foods, transfer of food to the industrial sector's workers, and ignorance of local conditions (due in part to politically motivated over-reporting of grain output) all contributed to turning the overall reduction in food availability into probably the worst famine in human history as measured by excess deaths. Scholars estimate that the China Famine resulted in approximately 23–30 million deaths above what might have been expected under normal grain production and distribution and 30 million lost births (Chen and Zhou, 2007). Although the China Famine was a national phenomenon, the famine intensity varied significantly across provinces (Chen and Zhou, 2007). For example, central provinces such as Henan, Anhui, and Sichuan were severely affected by the famine, but the northeastern provinces were less severely impacted (Almond et al., 2010). Figure 1.1 shows the annual death rates during the famine period and its geographical variation.

The Chinese central government eventually recognized the severity of the famine and moderated its policies, reducing the transfer of grain from rural areas to urban areas and sending millions of people back to the countryside to boost agricultural production, raising the rural labor force by more than 50 million (Li and Yang, 2005). By 1961, death rates began to come back to the pre-1959 level in over half of the provinces, and birth rates started to rebound as shown in Figure 1.2.

1.2.2. Related literature

Most existing studies of the lasting impacts of the China Famine have focused on economic outcomes such as labor supply, income, or education attainment (Meng and Qian, 2009; Chen and Zhou, 2007; Shi, 2011; Almond et al., 2010; Kim et al., 2014). Using the 2000 China Population Census Data, Almond et al. (2010) show that individuals who experienced the famine in utero are more likely to be illiterate, less likely to work, and less likely to get married. Existing research has also found that the famine's impacts are not limited to the first generation. Children who were born to famine survivors tend to have fewer years of schooling, higher BMI, and stunted heights (Fung and Ha, 2010; Kim et al., 2014; Tan et al., 2014).

Studies regarding the China Famine's impacts on health outcomes are relatively limited because of the avail-ability of the data. Only simple health measures such as height, weight, and BMI were examined at relatively young ages (20s to 30s) (Chen and Zhou, 2007; Meng and Qian, 2009; Fung and Ha, 2010). It was shown that fetal exposure to malnutrition is associated with significant reduction of height and body weight (Chen and Zhou, 2007; Meng and Qian, 2009). Although height and weight are indicators of famine survivors' health conditions, they provide very rough indicators of the famine's influences on detailed health outcomes such as hypertension, cognitive abilities, mental functions, and other specific health conditions. Our study of the China Famine is an effort to fill the gap by examining a rich set of health outcomes and providing evidence of fetal malnutrition's long-lasting impacts in famine survivors' middle age.

Particularly for mental health, previous studies of the China Famine have focused mainly on fetal malnutrition's impacts on the probability of developing schizophrenia (Clair et al., 2005; Xu et al., 2009). Consistent with the Dutch Famine studies, exposure to malnutrition in utero is associated with higher risk of schizophrenia in survivors' early adulthood. However, the data for these studies tend to be restricted to narrow geographical areas. For example, Clair et al. (2005) and Xu et al. (2009) use local hospital records from Anhui and Guangxi autonomous region and thus cannot control for region-specific heterogeneity.

Our paper closely follows Almond et al. (2010) and Kim et al. (2014) in terms of the measurement of famine intensity and the identification strategy to estimate the long-term effect of fetal malnutrition experience. Both Almond et al. (2010) and Kim et al. (2014) use data from the 2000 China Population Census microdata, which provide limited information regarding individuals' health. Therefore, these two papers studied outcomes other than health indicators. Almond et al. (2010) mainly focus on the socioeconomic outcomes of the famine survivors, and Kim et al. (2014) look at the education outcomes of children of the famine survivors. Using the 2013 wave of

CHARLS, our paper contributes to the literature by examining the impacts of the China Famine on survivors' health outcomes in middle age.

1.3 Data

The CHARLS is a biannual longitudinal survey that collects rich information on economic, health, and social conditions for a representative sample of individuals in China who were 45 and over in 2011. CHARLS covers 150 counties in 28 provinces, and the sample size of the baseline survey is 17,692 individuals (8471 men and women) in 10,257 households.[2] The first baseline survey was conducted in 2011–2012 and the second one in 2013. In our study, we only use the second wave collected in 2013.

The advantages of using data from CHARLS for our research are that (i) it provides a wide array of measures of health and other individual and family characteristics; (ii) it focuses on the middle-age and older population, thus providing an adequate sample to study long-term health effects; and (iii) it contains the individuals' province of birth information. By comparison, the China Population Census would be the best available data in terms of sample size, but the Census asks for very little information on health (a single question on self-reported health status). The China Health and Nutrition Survey contains comparable information, but its

[2] Tibet is excluded from sampling.

effective sample size for our research is significantly smaller than that of CHARLS, because it surveys only nine provinces and covers all age ranges.[3]

We construct our sample using the following criteria. First, to include substantial time variation in our measure of in utero nutrition, we select those who were born from 1954 to 1966, 5 years before and after the China Famine. Second, we restrict the sample to those born in rural areas because the famine took place mostly in the rural areas. We drop individuals from the provinces where provincial death data are not available.[4]

Figure 1.3 shows that the size of the cohorts between 1959 and 1961 is much smaller than before or after this period, reflecting the increased death rate and the lowered birth rate resulting from the famine severity. We observe a continuing drop in the number of sample individuals starting in 1958 and then a sharp rebound after 1961. This pattern closely mirrors the distributions in birth and death rates in China from 1954 to 1966.

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[3] In addition, CHNS does not track survey participants who migrate out of the province of the initial interview, so it can potentially create a sample selection bias due to the different likelihood of migration by ability and health.

[4] Chongqing was previously a part of Sichuan but became a direct-controlled municipality in 1997. Therefore, there are no separate provincial death data for Chongqing. In the Supporting Information, we report the regression results including those who report Chongqing as their birth province by considering their birth province as Sichuan. Our results remain robust.

The specific definition of the health and cognitive ability variables we use are provided as follows:

1. ‘Speech impediment’ is a binary indicator of self-reported disability in speaking. CHARLS asks whether a respondent has any speech impediment. Answering ‘yes’ to the question would be recorded as 1 (i.e., having a speech impediment) or 0 otherwise.

2.‘Difficulty in walking’ is a binary indicator of self-reported physical disability in walking. CHARLS asks whether a respondent has any difficulty in walking 100 m. Answering ‘yes’ to the question would be recorded as 1 (i.e., having difficulty in walking) or 0 otherwise.

3.‘Vision disability’ is a binary indicator of self-reported disability in vision. CHARLS asks the individuals to report whether they have any disabilities in vision. Responding yes to the question would be coded as 1 (i.e., having vision disability) or 0 otherwise.

4.We also use a binary indicator of whether a respondent previously had a stroke diagnosed by a doctor. If the respondent answers yes, it is coded as 1 (i.e., had a stroke before) or 0 otherwise.

5. ‘Calculation error’ is a binary indicator of a respondent’s cognitive ability. CHARLS asks respondents to perform a simple arithmetic calculation task (subtracting 7 from 100 consecutively for five times). If a respondent makes an error, calculation error would be coded as 1 (and 0 otherwise).

6.‘Recall error’ is a binary indicator of a respondent’s ability to recall the date. CHARLS asks respondents to recall the date of yesterday (month and day). If a respondent answers either day or month of yesterday wrong, recall error would be coded as 1 (and 0 otherwise).

Sample statistics are reported in Table 1.1. The final sample size after imposing the aforementioned selection criteria is 7439; 53% of the sample is female, and 94% of the sample is married. The education level of the sample individuals is much higher than that of their parents: More than 65% of the sample completed primary school, while only 50% of their fathers and 18% of their mothers reached this level. The surveyed households on average have 3.45 family members.

We define total annual working hours as the sum of hours spent on farm work, household agricultural work, non-farm employed and self-employed work and unpaid family business, and other side jobs in the past year. There is wide dispersion in the distribution of annual income and working hours. The mean of annual income is 8183 yuan with a standard deviation of 21,561. The mean of the annual working hours is 363 with a standard deviation of 367. There are in total 1740 individuals reporting zero annual working hours, accounting for 23.4% of the total sample. The details of how we construct total annual working hours are described in the Supporting Information.

The mean of the weighted death rate (WDR) is 12.22 per 1000 persons with a standard deviation of 5.48. One standard deviation of the WDR is slightly smaller than the difference of average WDR between famine years (1959–1961) and non-famine years, which is 6.14. For physical disability measures, (i) 0.73% of the sample has a speech impediment; (ii) 5.91% of the respondents report vision disability; and (iii) 5.01% experienced difficulty in walking. Of the sample, 1.31% reports that they ever had a stroke. The size of the sample with cognitive problems is much larger: 42.9% of the sample made mistakes in carrying out simple arithmetic tasks, and 57.8% of the respondents recall the date incorrectly.

1.4 Econometric Specification and Empirical Strategy

Our econometric model is represented by the following equation:

$$Y_{iptk} = bWDR_{ptk} + gX_i + m_p + d_t + f_k + e_{iptk}$$

where the subscript i represents an individual, p a birth province, t a birth year, and k a birth month. We use the province-year level death rate weighted by months in utero during birth year t and year t − 1 as a measure of fetal exposure to malnutrition, following Almond et al. (2010) and Kim et al. (2014).[5] For example, an individual born in January 1960 in Shandong would be assigned 1/9th of Shandong's 1960s average death rate (ADR) and 8/9th of Shandong's 1959s ADR; for individuals born in September to December, the WDR is the same as the birth year's ADR, because

[5] Alternatively, one can use a county-specific measure of famine intensity (Meng and Qian, 2009), but CHALRS does not allow researchers to have access to the county information.

conception occurred in the year of birth. It follows that for those born in the months January through August, that is, k = 1,…, 8,

$$WDR_{ptk} = \frac{k}{9} \times ADR_{pt} + \frac{9-k}{9} \times ADR_{p,t-1}$$

where ADR is the province-specific and year-specific measure of famine intensity, equivalent to the number of deaths per 1000 individuals in year t and province p. X, a vector of controls, includes other characteristics that might affect current health outcomes such as gender and parents' education. In the regression, we control for permanent unobserved province-specific heterogeneity, μ_p, year-specific unobserved heterogeneity invariant across provinces, δ_t, and month-specific unobserved heterogeneity, ϕ_k. In the absence of confounding factors, can be interpreted as the estimated causal effect of fetal exposure to the China Famine on health outcomes.[6] The

[6] Young children could also have been affected by the famine. For example, our sample individuals born before the famine experienced mal-nutrition during the infancy period, but our measure of in utero famine intensity does not capture such early childhood experience. To the extent early infancy famine experience also negatively affects the health of adults, our comparison group may lead us to underestimate the magnitude of in utero effects compared with a population totally unaffected by in utero or early-childhood malnutrition. We do not jointly estimate the in utero famine experience and the early infancy famine experience because those two measures are correlated that the resulting multicollinearity reduces the statistical power available to test the Barker hypothesis. Because our primary goal is to precisely estimate the fetal impacts, we decided to focus on in utero exposure to malnutrition.

following discussion deals with potential confounding factors that would lead to biased estimation of β. [7]

1.4.1 Selective mortality

The most severely impacted individuals are more likely to have died during or shortly after the famine. Also, because the China Famine took place over half a century ago, those severely impacted individuals who man-aged to survive birth and early life are less likely to have survived into middle age. As a result, the famine survivors in our sample would be, in general, healthier than the famine victims who are missing because of selective deaths. We do not have any information about those who are missing because of the famine-caused deaths, so we cannot correct for this bias. However, because selective mortality makes our estimates biased toward zero, our estimates of the long-run health impacts of the fetal experience to the China Famine can be interpreted as the lower bounds of the true effects.

1.4.2 Selective fertility

Because of the extreme adverse environmental and nutritional conditions during the China Famine, marriages and childbearing were postponed or foregone

[7] The discussion of econometric issues in estimating the long-run health impacts of early-life malnutrition is largely taken from Almond et al. (2010) and Kim et al. (2014).

through choice and reduced chance of conceiving (Almond et al., 2010; Chen and Zhou, 2007). Shi (2011) reports that there were about 15 million lost births because of the China Famine. Therefore, children born during the famine would have come from families with better socio-economic and nutritional conditions. Similar to the bias caused by selective mortality, selective fertility during the famine period biases against rejecting the null of no impact of fetal exposure to the China Famine.

Moreover, parents whose childbearing were delayed by the famine appear to have offset the birth-rate dip after the famine ended. Figure 1.2 reveals a sharp increase in birth rates in 1962, the year after the famine ended. To the extent that the post-famine surge in birth rates is attributable to women whose health was impaired by the famine, it is likely that children born right after the famine inherited characteristics attributable to the famine. Thus, the two fertility selections (positive selection toward less-impacted parents during the famine and negative selection right after the famine) would bias our estimates against rejecting the null of no in utero impacts of the China Famine on long-run health outcomes.

1.4.3 Selective migration

The intensity of the China Famine varied greatly across provinces. Central provinces were the worst hit, while northeastern provinces were relatively spared (Almond et al., 2010). Migration from severely impacted areas to less-impacted regions was virtually prohibited before 1978. According to Chen and Zhou (2007), interprovincial migration accounted for only 0.3–0.7% of the population at risk between 1959 and 1963.

1.4.4 Measurement error

We acknowledge that WDR is not a perfect measure of fetal malnutrition. A pregnant woman's caloric intake would be a much better measure, but such information is not available. Thus, we argue that WDR is the best available source of information on fetal malnutrition shock during the China Famine. Assuming that fetal mal-nutrition is a stochastic function of WDR, we use WDR as a proxy for the degree of fetal malnutrition.

Formally, we can write that

$$WDR_{ptk} = dCal_{ptk} + w_{ptk}$$

would depend on the nature of such differential policy responses, if any. We are not aware of systematically different post-famine policy changes across provinces (Meng and Qian, 2009).

1.4.5 Other omitted variables

One might be concerned that our estimates of the fetal malnutrition impacts are confounded by the 1966–1976 Cultural Revolution's adverse influences. However, the Cultural Revolution was mainly an urban phenomenon, while the China Famine was mainly confined to rural areas. Thus, we believe that we can ignore its impacts in this study.

We control for the local institutional quality differences in policies that contributed to health through a province-fixed effect to the extent that such institutional differences are time invariant. Differences across provinces in policies adopted after the China Famine could lead to biased estimation, and the direction of the bias would depend on the nature of such differential policy responses, if any. We are not aware of systematically different post-famine policy changes across provinces (Meng and Qian, 2009).

1.5 Results

Table 1.2 presents our estimation results. Standard errors are clustered at the province level and reported in parentheses. Note that all specifications include the father's and mother's education and fixed effects for birth year, birth month, and birth province. We also include a female dummy variable to account for potential gender differences.[8] As discussed in the previous section, we interpret the estimated coefficient of WDR as a lower bound of the magnitude of the negative long-term health effects of fetal malnutrition. The coefficients reported in Table 1.2 represent the marginal effect of a unit change in WDR * 1000 on the probability of a corresponding dependent

[8] In the Supporting Information, we report the regression results of the subsample analysis separately by men and women.

variable of interest evaluated at the mean of WDR.[9] In order to show economic significance of the famine impact, we also report the effect of one standard deviation of WDR on the probability of a corresponding dependent variable in square brackets.

1.5.1 Regression results

As hypothesized, in utero exposure to the China Famine has had large and long-lasting impacts on survivors' physical health and cognitive abilities. Column (1) of Table 1.2 shows that a one standard deviation increases in famine intensity resulted in a 0.17 percentage-point increase in the probability of a speech impediment, which is a 23.3% increase in the likelihood of suffering from this disability compared with the average individual.

Column (2) reports the famine impact on respondents' evaluations of whether they have any trouble walking farther than 100 m. A one standard deviation increase in famine intensity is associated with a 0.8 percentage-point increase in the probability of difficulty of walking, or about 16% increase in the likelihood of experiencing this disability compared with the average.

[9]Sample size varies across different outcome variables because of the missing values in the corresponding outcome variables. However, our results are robust even if we use the identical sample across different outcome variables (i.e., the sample without missing values for all outcome variables).

Column (3) further confirms the causal relationship between fetal exposure to famine and physical disability: a one standard deviation increase in famine intensity increases the probability of developing vision disabilities by a 0.3 percentage-point increase, a 5.1% increase in the likelihood compared with the average individual. Disabilities in speech, vision, and difficulty in walking cannot only be viewed as direct health consequences of prenatal exposure to malnutrition but also as complications of other health problems such as stroke. There-fore, we could interpret the results of columns (1) to (3) as reflections of adverse impacts of fetal exposure to malnutrition on survivors' general physical health.

It has been reported that prenatal exposure to malnutrition negatively impacts survivors' cognitive abilities (Barker, 1990). Thus, we examine the relationship between fetal malnutrition and cognition outcomes. In CHARLS, respondents were asked to perform a series of simple arithmetic calculation tests and a date check test. Defining a failure to satisfy either of these tasks as an error, we show in column (4) that a one standard deviation increase in famine intensity resulted in a 1.6 percentage-point increase in the probability of calculation error, which is a 3.7% increase in the likelihood of error in the calculation test; in column (5), we see that a standard deviation increase in WDR leads to a 1.3 percentage-point increase in the probability of not knowing the correct survey date, which is a 2.2% increase in the likelihood of recall error. Interestingly, coefficient estimates on the female dummy are significant for both measures indicating a potential gender difference in impacts from fetal exposure to famine on cognitive functions.

Column (6) reports estimation results for the impact of in utero famine exposure on the probability of having suffered from a stroke. We see that a one standard deviation increase in famine intensity would lead to a 0.3 percentage-point increase in the probability of having had stroke, which amounts to a 22.9% increment of risk compared with the mean. This finding shows significant influences of adverse prenatal environment on survivors' cerebrovascular health.

Our results confirm many findings of the previous literature regarding the damaging effects of in utero exposure to malnutrition. However, we do not find substantial impact of famine on health measures commonly used in the China Famine literature such as height and weight as reported by Chen and Zhou (2007) as well as Meng and Qian (2009).[10] Neither do we find any statistically significant results for other ailments such as heart attack although many coefficients have the expected signs.

[10] We conjecture that the following reasons can explain the difference between our results and the findings of Chen and Zhou (2007) as well as Meng and Qian (2009) regarding height and weight. First, we use CHARLS, a nationally representative survey of individuals over age 45, while the other two studies use CHNS, which surveys only nine provinces and does not keep track of respondents who move out of the survey provinces. Therefore, our sample is much bigger in size and more representative. Second, the eligible sample size of CHNS as opposed to CHARLS is much smaller. Third, we use the survey conducted in 2013, while Chen and Zhou (2007) and Meng and Qian (2009) use the CHNS survey conducted in 1991 and 1989, respectively. Therefore, the famine effect on height and weight in relatively young ages could have become smaller because of age-related factors such as height shrinkage at old age as documented in Huang et al. (2013).

Because our sample individuals have only reached their middle ages, we might expect to observe more precisely estimated impacts on the health problems as they grow older.

1.5.2 Additional analysis

Fetal exposure to malnutrition could have impacted survivors through various pathways. For example, other than directly influencing survivors' health through fetal exposure to malnutrition, famine could also impact the later-life outcomes through education. To examine whether education is a potential pathway to the observed health impacts of the famine, we include the sample individual's own education attainment as an additional control in the baseline specification. The regression results are reported in Table 1.3. We acknowledge that education attainment can be partially determined by the famine exposure, and thus, it might not be an ideal control variable (the so-called Bad Control problem discussed in Angrist and Pischke (2009)). Thus, we interpret the findings in this analysis as suggestive only at this point.

After controlling for education attainment, we find that the coefficient estimates of WDR become somewhat smaller, suggesting that the negative long-term famine impacts can be partially explained by the education channel. The coefficient estimates on the education dummies also show that education and health are positively correlated, which is consistent with the existing literature.

To further examine the role of education on the health impacts of the famine, we check whether the famine exposure leads to lower education attainment by regressing different measures of education outcomes on WDR. The probit regression results on binary indicators of whether a respondent has graduated from a primary school, middle school, and high school, respectively, and the ordinary least squares regression result on the years of completed schooling are reported in Table 1.4. In general, our findings show that fetal malnutrition exposure has negative impacts on an individual's education attainment (except for the middle school graduation) al-though the coefficient estimates are not precise.[11] Thus, we argue that it is highly probable that the famine exposure has an indirect impact on health via the education channel.

In addition, we conduct various robustness checks. First, we estimate the linear model using the ordinary least squares method because our baseline specification is a non-linear probit model. Second, we estimate the baseline specification with the ADR, instead of the WDR. Third, we run the same set of regression on the urban-born population. Fourth, to explore the gender differences in the China Famine's impacts on survivors' health outcomes, we divide the sample into male and female subsamples and run the baseline probit regression on each subsample. Last, we construct two additional measures of recall error: whether a respondent can correctly recall the current season (Spring, Summer, Autumn, and Winter) at the time of interview and whether self-evaluated memory is bad or not. We then run the same baseline regression on these two

[11] Female respondents have significantly lower levels of education compared with male respondents. This finding is not surprising when considering China's son preference, especially in rural areas.

variables. We report and discuss the regression results of each of the aforementioned robustness checks in the Supporting Information.[12]

1.6 Conclusion

We report evidence of long-term adverse health impacts of fetal malnutrition based on survivors in their 50s who were born during the 1959–1961 China Famine. Our results support the Fetal Origins Hypothesis (Barker, 1990) that in utero shocks can alter the activities of the epigenome[13] in favor of survival, but only at the cost of a higher probability of developing certain diseases in later life stages. We find that fetal exposure to malnutrition has large and long-lasting impacts on both physical health and cognitive abilities, including the risks of suffering from a stroke, physical disabilities in speech, walking and vision, and measures of mental acuity. Our findings on the health impacts of fetal malnutrition on middle-age survivors suggest that it should be

[12] The regression results using ordinary least squares are in general similar to the baseline results except that the coefficient estimate of the probability of stroke becomes less statistically significant. However, the magnitude is comparable with the baseline probit result. Regression results using the ADR are robust to the modification of the measure of malnutrition exposure. We also run the same set of regression on urban-born population and find the results opposite of prediction. Because the sample size is much smaller, the estimated results may suffer from reduced power and measurement errors.

[13] Epigenome can be viewed 'a series of switches that cause various parts of the genome to be expressed or not' (Almond and Currie, 2011).

desirable to trace the changes of health status of the famine survivors as they age into later life stages.

Our study provides evidence supporting policies and programs to improve the nutritional status of pregnant women. As implied by one of the United Nations' Millennium Development Goals, maternal health has received increasing attention in recent years. For example, Improving Nutrition and Food Safety for China's Most Vulnerable Women and Children, a joint program by the United Nations and the Chinese central and local governments, has focused on food-related issues of 1.2 million children, women of childbearing age, and other at risk populations. It aims to reduce mortality and other adverse impacts of malnutrition by providing nutritional packages to children and pregnant women (Chen, 2013). Our findings imply that the payoffs to such interventions play out much further into the future than evaluation of their immediate benefits might suggest.

1.7 Tables

Table 1.1 Summary statistics

Variable	Observations	Mean	Statistics (SD)
Proportion married	7439	0.94	(0.23)
Annual working hours	7376	363	(367)
Proportion of individuals reporting zero annual working hours	7439	0.234	(0.423)
Proportion of the sample individual's father completed primary school	7439	0.50	(0.50)
Proportion of the sample individual's mother completed primary school	7439	0.18	(39)
Proportion of women	7439	0.53	(0.50)
Proportion of the sample individual completed primary school	7439	0.65	(0.48)
Family size	7439	3.45	(1.60)
Annual income (in 2013 CNY)	7376	8,183	(21,561)
Weighted death rate (WDR)	7439	12.22	(5.48)
Health outcome variables			
Speech impediment	7392	0.0073	(0.085)
Difficulty in walking	7272	0.0501	(0.22)
Vision disability	7391	0.0591	(0.24)
Ever had stroke	7087	0.0131	(0.11)
Calculation error	7393	0.429	(0.50)
Recall error	7393	0.578	(0.49)

Table 1.2 Probit regression results

	(1)	(2)	(3)	(4)	(5)	(6)
	Speech impediment	Difficulty in walking	Vision disability	Calculation error	Recall error	Had stroke
WDR * 1000	0.208**	1.20**	0.438**	2.99***	2.34**	0.419*
	(0.084)	(0.507)	(0.196)	(1.28)	(1.08)	(0.229)
	[0.0017]	[0.008]	[0.003]	[0.016]	[0.013]	[0.003]
Female	_0.0014	0.029***	0.004	0.015***	0.024*	0.0003
	(0.0013)	(0.005)	(0.005)	(0.014)	(0.013)	(0.003)
Pseudo-R^2	0.065	0.050	0.072	0.040	0.016	0.061
Observations	6878	7089	7227	7228	7228	6852

We estimate the probit model, and the estimated coefficients represent the marginal effects of the independent variables evaluated at the mean on the outcome variables. The effects of one standard deviation increase in weighted death rate (WDR) on the probability of outcome variables are reported in square brackets.
Standard errors clustered at provincial level are reported in parentheses. All regression results include fixed effects for birth year, birth month, birth province, and father's and mother's education.***p < 0.01; **p < 0.05; *p < 0.1.

Table 1.3 Robustness analysis: inclusion of the respondents' own education as a control

	(1)	(2)	(3)	(4)	(5)	(6)
	Speech impediment	Difficulty in walking	Vision disability	Calculation error	Recall error	Had stroke
WDR *1000	0.141**	1.16**	0.381*	2.73*	1.93*	0.398*
	(0.056)	(0.526)	(0.200)	(1.64)	(1.01)	(0.213)
Primary school	0.0045***	0.0219***	0.0892	0.300***	0.251***	0.002
	(0.001)	(0.004)	(0.007)	(0.024)	(0.016)	(0.002)
Middle school	0.0067***	0.0212***	0.021***	0.428***	0.331***	0.007***
	(0.001)	(0.005)	(0.005)	(0.0202)	(0.133)	(0.003)
Above middle school	0.0045***	0.0277***	0.035***	0.521***	0.342***	0.0015
	(0.0007)	(0.005)	(0.005)	(0.018)	(0.012)	(0.003)

Female	0.003**	0.022***	0.004	0.057***	0.057***	0.0005
	(0.001)	(0.005)	(0.005)	(0.014)	(0.011)	(0.003)
Pseudo-R2	0.133	0.06	0.081	0.12	0.069	0.067
Observations	6878	7089	7227	7228	7228	6852

We estimate the probit model, and the estimated coefficients represent the marginal effects of the independent variables evaluated at the mean on the outcome variables.
Standard errors clustered at provincial level are reported in parentheses. All regression results include fixed effects for birth year, birth month, birth province, and father's and mother's education.
***p < 0.01; **p < 0.05; *p < 0.1.

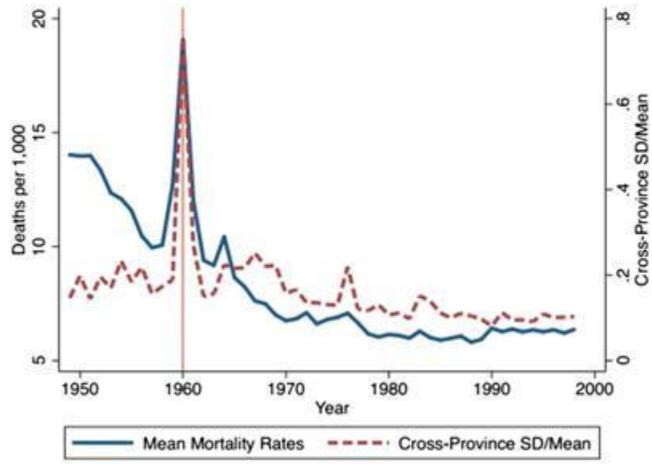
Table 1.4 Robustness analysis: impacts of WDR on education attainment

	(1)	(2)	(3)	(4)
	Graduated from primary school	Graduated from middle school	Graduated from high school	Years of completed education
WDR * 1000	_0.232	0.582	_0.366	_0.443
	(1.15)	(1.40)	(0.855)	(14.3)
Female	0.026	_0.120***	_0.103***	_2.87***
	(0.022)	(0.013)	(0.008)	(0.162)
(Pseudo-) R2	0.041	0.060	0.107	0.212
Observations	7272	7272	7272	7272

We estimate the probit model in columns (1) to (3) and the ordinary least squares model in column (4). The estimated coefficients represent the marginal effects of the independent variables evaluated at the mean on the outcome variables.
Standard errors clustered at provincial level are reported in parentheses. All regression results include fixed effects for birth year, birth month, birth province, and father's and mother's education.
***p < 0.01; **p < 0.05; *p < 0.1.

1.8 Figures

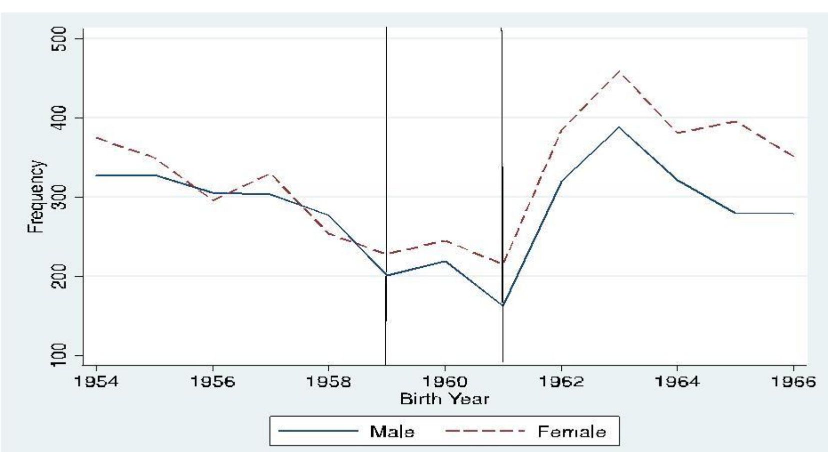
Figure 1.1 Severity and geographical variation of annual death rates in China.



Source: Meng, Qian and Yared (2014)

Source: Meng et al. (2014)

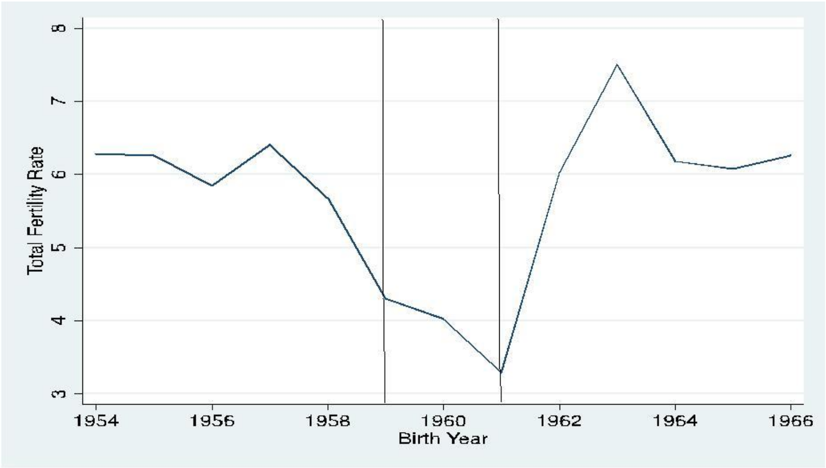
Figure 1.2 China's total fertility rate, 1954–1966.



Source: Authors' calculation

Source: China National Bureau of Statistic

Figure 1.3 Frequency of sample birth cohorts.



Source: China National Bureau of Statistics

Source: Authors' calculation

Chapter 2

Welfare Consequences of Access to Health Insurance: Evidence from New Cooperative Medical Scheme in Rural China

2.1 Introduction

Improving access to healthcare and financial protection through health insurance program among low-and middle-income households is a key concern for policymakers. One of the classic empirical results in public health insurance is that demand for healthcare increases due to the lowering of the out-of-pocket price. This finding has traditionally been interpreted as evidence of moral hazard: public health insurance distorts the relative price of consumption and health, increasing the cost of providing insurance. At the same time, health insurance coverage enables individuals to seek medical treatments that are previously not affordable, particularly among low-income households where the cost of treatment is high relative to income.

The goal of this paper is to understand the welfare consequences of access to health insurance and question whether the link between health insurance and medical spending is purely due to moral hazard among low- and middle-income households. The analysis is motivated by evidence that many uninsured households in developing countries have limited liquidity and adopt costly measures in consumption smoothing (Chetty and Looney, 2006,2007; Chetty, 2006; Liu, 2016). Indeed, nearly forty-percent of individuals residing in rural areas in China and Health Nutritional Survey (CHNS) report not to seek formal medical treatment when fell sick, suggesting that many individuals may avoid treatment due to expensive costs.

In this paper, I evaluate the welfare benefits of access to health insurance by exploiting a policy reform associated with the introduction of a large-scale health insurance program in rural China. The New Cooperative Medical Scheme (NCMS) is the main public health insurance plan for the rural population in China. Since its inception in 2003, access to health insurance for rural residents expanded dramatically given the fact that almost none were enrolled in health insurance in rural China (see Figure 1) in the 1990s. By the end of 2011, more than 97% of the rural population (800 million people) had been enrolled in the scheme (Hou et al. 2013).

Different from the traditional approach of structurally estimating a model's primitives and then numerically simulated the effects of policy changes, I adopt two approaches from Finkelstein et al. (2016): “complete-information” approach and “optimization” approach that are in the spirit of the “sufficient statistics” to analyze the welfare value. Particularly, I decompose the welfare effect in terms of transfer and insurance value, which would provide implications on the sources of welfare as well as the size of associated moral hazard costs. Compare to the structural method and reduced-form method, the advantages of using the two approaches are: (i) they are easier to implement; (ii) they are more empirically credible since program effects are estimated using quasi-experimental variations.

I implement these methods empirically by exploiting variation in the timing of introduction of the NCMS across counties to identify the impacts of the NCMS on required objects. The NCMS was implemented over a six-year period from 2003 to 2009 in different counties at different times in rural China. As a result, some areas received coverage earlier than others did, and the households in those areas were then subject to exogenous changes in health insurance status at different points in time. Since participation in the NCMS is voluntary, I use the proportion of households enrolled in NCMS at the residential community as an instrumental variable (IV) to account for potential adverse selection. Two additional features of the NCMS make the identification strategy more appealing. First, because of the household registration system, household mobility in China is restricted. Therefore, it is unlikely for households to select into the insurance through mobility. Second, the NCMS program was introduced at county level. Combining with the restricted mobility, the potential spillover effects will likely to be small.

The analysis is conducted using panel data from the China Health and Nutritional Survey (CHNS). The key findings are as the following. The baseline estimates indicate that the value of the NCMS to recipients is higher than the government's costs of provision. I estimate that welfare benefit to recipients per (gross) RMB of government spending is approximately 1.4. If (counter-factually) the NCMS recipients had to pay the government's average cost of the NCMS, they would much likely to accept the offer. Contrary to the findings from developed countries, I do not find a large proportion of transfers from the NCMS to external parties (i.e. individuals who are not enrolled in the program). This is largely because the uninsured in rural China typically pay all their medical expenses with little covered by hospitals or any other third parties.

An important question is whether the value of the NCMS to recipients exceeds the associated moral hazard costs. By decomposing the welfare estimates, I find that welfare value from NCMS's transfer function constitutes 50% to 70% of the total benefits. Compare with the net costs of providing the NCMS, I estimate the welfare benefits to recipients per *net* RMB of spending ranges from 1.39 to 1.44. A consistent estimate above 1 suggests that the moral hazard costs do not exceed the insurance value NCMS provides by moving resources across states of the world.

In addition to evaluating the welfare value of the NCMS, this paper contributes to the literature by providing welfare interpretation of the previously evaluated behavioral impacts of the NCMS. Some studies have found that participating in the NCMS has no significant effects on reducing out-of-pocket spending (Lei and Lin, 2009; Liu and Tsegai, 2011; Hou et al., 2013) or improving health status (Lei and Lin, 2009; Chen and Jin, 2012; Donato and Rokicki, 2016). In the meanwhile, compare to the uninsured, the NCMS enrollees are more likely to seek proper medical advice for minor symptoms at early stage (Liu and Tsegai, 2011), decrease the usage of folk doctor and increase the utilization of preventive care (Lei and Lin, 2009). Few have attempted to offer interpretation in terms of welfare. Among those that do, few papers have provided quantitative measurements.

This paper also contributes to our understanding of welfare effects of access to health insurance in developing countries, where formal insurance and credit markets are less developed. Closely related to the current paper is a set of papers analyzing the role of public insurance in mitigating the adverse outcomes associated with shocks in developing countries (e.g. Chetty and Looney, 2006; Wagstaff and Lindelow, 2008; Wagstaff et al., 2009; Liu, 2016). This paper adds on to the previous studies by quantifying the welfare value of access to public insurance and analyzing the sources of welfare benefits. The findings of this paper are consistent with previous literature: low- and middle-income households benefit from public insurances through more efficient consumption smoothing instruments compare to the ones (i.e. labour supply) used in self-insurance.

This paper provides important implications for policymakers. Some studies have found that the NCMS have limited or adverse effects in financial protection (i.e. no effect in reducing out-of-pocket spending (Lei and Lin, 2009; Wagstaff et al., 2009; Liu and Tsegai, 2011). The results of this study confirm the previous findings by showing that the magnitude of the welfare gains generated from the NCMS's insurance function. Though the total welfare benefits are higher than the implementation costs, the NCMS's ability in risk protection is limited. High percentage of recipient's value of the program come from its insurance function, reflecting the high demand of actuarially fair insurances and lack of access to complete credit market among households in rural China. To achieve higher welfare benefits, especially for the low-income households, the results suggest the need for a more generous NCMS program.

Naturally, the estimation results are sensitive to the modeling choices. I explored the sensitivity of the results to a variety of alternative assumptions. The evaluation of the welfare value associated with insurance function is more sensitive to modeling assumptions while the transfer values are relatively robust. The welfare value estimates are particularly sensitive to the imposed consumption floor. Households with better consumption smoothing abilities would place lower values on the insurance program. A 300 RMB increase of the imposed consumption floor lowers the benefit-cost ratio by 40%.

The rest of the paper proceeds as the following. Section 2 discusses the institutional background of the health insurance reform. Section 3 presents the welfare analysis framework. Section 4 discusses the empirical strategy. Section 5 describes data, sample construction and variables used in the estimation. Section 6 discusses the welfare estimation results, interpretation and sensitivity analysis. Section 7 concludes.

2.2 Institutional Background

Since its establishment in 1949, the People's Republic of China has undertaken a series of policy measures in providing health care to the public. From 1950 to 1984, under the central-planned economy, the Chinese government created state-run health care system similar to other communist countries and provided universal health care. Agricultural workers were covered by the Commune-based Cooperative Medical Scheme (CMS). Workers from state-owned enterprises (SOE) were covered under Labor Insurance Scheme (LIS) and civil servants were reimbursed through the Government Insurance Scheme (GIS). The CMS covered almost 90% of the rural residents in its peak in 1978 (Lei and Lin, 2009).

However, the Chinese government greatly reduced its role in providing health care services with free-market reforms starting from 1984. This radical policy change not only led to the dismissal of people's communes but also the collapse of the CMS. As a result, majority of the rural residents remain uninsured through 1985 to 2003 (Hou et al., 2014; Lei and Lin, 2009). Figure 2.1 shows the health insurance coverage for rural and urban population by income in 1993, 1998 and 2003, respectively. Compared to the urban counterparts, even the highest income quantile of the rural residents has much lower insurance coverage, indicating wide inequalities in health insurance accessibility.

To establish universal coverage and improve the affordability of medical services, the Chinese government announced the New Cooperative Medical Scheme (NCMS) in 2003, a highly subsidized public health insurance program for rural residents. The NCMS was rolled out gradually at the county level. Provincial governments have the autonomy in program adoption time and designs[14] following the guidelines from the central government. In 2003, pilot counties were selected at each province based on three criteria: the willingness to participate among the rural residents, fiscal soundness, and a solid foundation for management (Liu, 2016). The central government required provincial governments to expand the program to include at least 40% of all counties by 2006 and 60% by 2007 (Department of Health, 2006). By the end of 2013, 2,489 out of 2,862 counties had adopted the NCMS, accounting for 87% of all rural counties in China (Lei and Lin, 2009; China Statistical Yearbook, 2013). Thus, over almost a decade, rural households across counties in China had experienced different access to public health insurance. The access to coverage was determined by

[14] The 2002 State Council Policy Document No.13, Decisions of the State Council on Strengthening Rural Healthcare (State Council, 2002).

the county in which the household was registered. Due to the strict household registration system (*hukou*), mobility of households across counties is limited.

Enrollment in the NCMS is voluntary but it requires the participation of all household members. The NCMS is financed by both individual contributions and government subsidies: about 20% covered by central government, 50% by local government, and remaining 30% by the household's premium payments (Liu, 2016). Though the annual premium is kept low by the heavy subsidization from the government, it increases over the years: the typical annual premium was 20 RMB per person in 2008 but rose up to 150 RMB per person in 2016 (Department of Health, 2008; Ministry of Finance, 2016) .The total subsidies from central and local government steadily increased over time: from 80 RMB per person in 2008 to 420 RMB per person in 2016.

Table 2.1 reports the expansion of the NCMS program in the sample used in the analysis[15]. Column II and III describe the percentage of households had access to the NCMS program and enrolled from 1993 to 2011. Column IV shows the percentage of counties that have introduced the NCMS in each survey year. Before the first year of the implementation of the NCMS, the insurance coverage had been lower than 15%.

[15] Details of sample construction are discussed in Section 2.5.

Starting from 2004, the proportion of rural sample having insurance increased steadily from 15.2% to 98.1% in 2011, reflecting the rapid expansion of the NCMS.

2.3 Welfare Analysis Framework

Following Finkelstein et al. (2016), individual utility is derived from two components: non-medical goods consumption, c, and from health, h, following the utility function:

$$u = u(c, h) \quad (1).$$

Health is produced according to

$$h = \tilde{h}(m; \pi) \quad (2),$$

where m is the medical spending and π represents the existence of health shocks. In general, I assume that an individual's health is affected by a health shock and medical expenditures.

The presence of the NCMS is represented by the variable q, with q = 1 indicating that the individual is fully covered by the NCMS and q = 0 denoting no coverage. Consumption, medical expenditure and health are determined by NCMS status and the underlying state of the world.

The value of the NCMS, $\gamma(q)$, is defined as the implicit solution to:

$$E[u(c(0;\pi), h(0,\pi)] = E[u\big(c(q;\pi) - \gamma(q)\big), h(q,\pi)], \quad (3)$$

where expectations are taken over the probability distribution of the underlying states of the world, π. $\gamma(q)$ could be interpreted as the amount of consumption that would leave individuals indifferent in terms of expected utility between the world with the NCMS and the world without. The focus of the paper is to empirically estimate the value of $\gamma(q)$.

2.3.1 Complete Information Approach

The complete-information approach follows the spirit of structural estimation, specifying the normative utility function over all its arguments. I assume that the utility function follows: I assume that the utility function follows:

$$u(c,h) = \frac{c^{1-\sigma}}{1-\sigma} + \tilde{\phi}h \qquad (4),$$

where σ is the coefficient of relative risk aversion, $\phi = \tilde{\phi}/E[c^{-\sigma}]$ is the marginal value of health in units of consumption.

The utility function has two additive components: a standard CRRA function in consumption c with a coefficient of relative risk aversion of σ, and a linear term in h. Under this assumption, equation (3) could be written as:

$$E\left[\frac{c(0,\pi)^{1-\sigma}}{1-\sigma} + \tilde{\phi}h(0,\pi)\right] = E\left[\frac{(c(q,\pi)-\gamma(q))^{1-\sigma}}{1-\sigma} + \tilde{\phi}h(q,\pi)\right]. \qquad (5)$$

I use equation (5) to solve for the value of the NCMS $\gamma(q)$. The estimation requires observing the distributions of consumption and expected health status that would occur if the individual were on the NCMS and if he were not. One of them is a counter-factual of the other and therefore requires estimating the distributions of "potential outcomes" under treatment and control status.

The choice of the utility function naturally influences the estimation procedures and results. The additivity of utility function from consumption and health makes estimating the marginal consumption and marginal health distributions under each insurance status easier. Imposing complementarity between consumption and health is empirically feasible but more cumbersome to implement since it requires estimating the program influences on joint distributions. The linearity assumption in health, h restricts the estimation to average treatment effects. To capture the risk adverse nature of the individuals, I allow curvature in utility over consumption, which requires estimation of the distribution of consumption under each insurance status.

To reflect the sources of benefits from the NCMS program, I decompose $\gamma(q)$ into two components: (i) the transfer component, which reflects the average increases in available resources to the recipients; and (ii) the pure-insurance component, which captures the value from better allocation of resources across states of the world.

The transfer term, denoted by T, is given as the solution to the following equation:

$$\left[\frac{c(0,\pi)^{1-\sigma}}{1-\sigma} + \tilde{\phi}E[\tilde{h}(E(m(0,\pi),\pi)]\right] = E\left[\frac{(c(q,\pi)-T)^{1-\sigma}}{1-\sigma} + \tilde{\phi}\tilde{h}(E(m(q,\pi),\pi)\right]. \quad (6)$$

The health improvement is approximated as $E\left[\frac{d\tilde{h}}{dm}\right]E[m(q,\pi)-m(0,\pi)]$, where $E\left[\frac{d\tilde{h}}{dm}\right]$ is the slope of the health production function between $m(q,\pi)$ and $m(0,\pi)$, averaged over all states of the world. Details in estimation of $\frac{d\tilde{h}}{dm}$ are described in Appendix A.2. The transfer component represents the changes in utility from consumption and health if everyone has received the average increase in medical spending.

The pure-insurance term, denoted by *I*, is given by:

$$I = \gamma(q) - T. \qquad (7)$$

The pure-insurance term measures the value of the NCMS that results from the reallocation resources (i.e, relaxing the individual budget constraint) from lower-marginal utility states to higher ones.

2.3.2 Optimization Approach

To reduce the implementation requirements, I assume two additional economic assumptions under the optimization approach which allows me to estimate the value of the program without full specification of the utility function.

Assumption 1. *(Program structure) I model the NCMS program q as affecting the participants solely through its impact on the out-of-pocket expenditure p(q).*

Assumption 2. *Individuals choose m and c optimally, subject to their budget constraint. Individuals solve:*

$$max_{c.m}u(c,h) \text{ subjective to } c = y - x(q,m) \quad \forall m,q$$

where y denotes the household income.

Both assumptions are nontrivial under the context of health insurance especially since decisions are often made jointly by both enrollees and health providers (e.g., doctors). Providing health insurance may influence the provider behavior (e.g., providers are more likely to proscribe expensive treatments to patients with insurance).

For implementation purposes, I assume that the out-of-pocket spending on medical care follows:

$$x(q,m) = p(q)m \quad (8).$$

Defining out-of-pocket price $p(q)$ as $p(q) = qp(1) + (1-q)p(q)$, the out-of-pocket spending could be represented as:

$$x(q,m) = qp(1)m + (1-q)p(q)m \quad (9).$$

Under Assumption 2 and 3, the marginal welfare impact of insurance on recipients $\frac{d\gamma}{dq}$ follows after applying envelope theorem to equation (3):

$$\frac{d\gamma}{dq} = E\left[\frac{u_c}{E[u_c]}\left(-\frac{\partial x}{\partial q}\right)\right] \quad (10)$$

where u_c represents the partial derivative of utility with respect to consumption. Details of derivation are provided in Online Appendix A.1. Equation (10) uses the marginal utility of consumption to place a value on the relaxation of the budget constraint for each state of the world. A marginal increase in the NCMS's benefit has more value if it moves resources into the state of the world with higher marginal utility of consumption. Compared to the complete-information approach, the optimization approach only requires a partial specification of the utility function with regard to consumption since under assumption 2, individuals are indifferent between allocating the marginal increase of the NCMS benefits for consumption or for health. The non-marginal estimate of the total welfare value of the NCMS, $\gamma(q)$ is obtained by integrating with respect to q: $\gamma(q) = \int_0^1 \frac{d\gamma(q)}{dq} dq$.

To implement the optimization approach, I assume the utility function takes the following form:

$$u(c,h) = \frac{c^{1-\sigma}}{1-\sigma} + v(h) \quad (11)$$

where σ represents the coefficient of relative risk aversion and $v(.)$ is the sub-utility function for health, which is left unspecified. Combining with equation (9), equation (7) could be written as:

$$\frac{d\gamma}{dq} = E\left[\frac{c(q)^{1-\sigma}}{E[c(q)^{1-\sigma}]}\left(\frac{1}{q}\big(p(0) - p(q)\big)m(q)\right)\right] \text{ (12).}$$

I decompose the marginal value of the NCMS to the recipients into a transfer term (T) and a pure-insurance term (*I*). The decomposition is:

$$\frac{d\gamma}{dq} = E\left[\left(\frac{1}{q}\big(p(0) - p(q)\big)m(q)\right)\right] + Cov[\frac{c(q)^{1-\sigma}}{E[c(q)^{1-\sigma}]}, \left(\frac{1}{q}\big(p(0) - p(q)\big)m(q)\right)].$$

Since I do not observe all $q \in [0,1]$ and the intermediate values, the calculation of the non-marginal estimate of the total welfare value of the NCMS requires additional assumption. For the baseline estimation of the optimization approach, I make the following statistical assumption.

Assumption 3. (*Linear Approximation) The integral expression for $\gamma(q)$ is approximated by:*

$$\gamma(q) = \frac{q}{2}\left[\frac{d\gamma(0)}{dq} + \frac{d\gamma(q)}{dq}\right].$$

2.3.3 The costs of the NCMS

I benchmark the welfare estimates, $\gamma(q)$, against the government's costs of implementation. For this paper, I consider only the medical expenditures when estimating the program costs. This abstracts from any potential administrative costs associated with the NCMS. Under this assumption, the average cost to the government per recipient, which I donate as *G*, is

$$G = E[m(q) - x(q)] \quad (15).$$

This gross cost per enrolled family, *G*, is higher than the net cost to society. The net cost of the NCMS, which is denoted by *C*, is:

$$C = E[m(q) - m(0)] + E[x(0) - x(q)] \quad (16).$$

Net cost per recipient consists of the average increase in medical spending induced by the NCMS, plus the average decrease in out-of-pocket expenditure due to the NCMS.

2.4 Empirical Strategy

To identify the effects of enrolling in the NCMS on the outcome variables, I adopt the instrumental variable (IV) estimation strategy. It is modeled as follows:

$$y_{ijt} = \alpha_0 + \alpha_1 NCMS_{ijt} + \lambda_t + \lambda_j + \beta X_{ijt} + \epsilon_{ijt} \quad (17)$$

where y_{ijt} is the outcome of interest for household *i* residing in county *j* at year *t*. X_{ijt} includes a set of demographic variables, including log household size, share of children in the household, share of working-age adults in the household, age and age-squared of the household head, indicators for the education level of the household head, and whether the household head is single. X_{ijt} controls for the effects of household demographics on the outcome of interest. λ_j and λ_t are county and year fixed effects, respectively. The county fixed effects λ_j allow the fact that variation in the timing of the reform across counties may not have been exogeneous. The year fixed effects λ_t control the unobserved household characters over time that may be completely unrelated to the reform. λ_j are county fixed effects, which control for the average change in outcomes across all households or the change in aggregate resources within a county. $NCMS_{ijt}$ is a dummy variable indicating whether the household *i* enrolled in the NCMS in year *t* at county *j*. To capture any common influences to the outcome variable across households within the county and over time, standard errors are clustered at county level.

The coefficient of interest is α_1, the impacts of participating in the NCMS on the outcome variable. One major concern with equation (17) is that enrolment in the insurance could be endogenous since participating in the NCMS is voluntary. Households with existing health concerns may be more likely to participate than the ones without. To account for endogeneity of participation in the scheme, I adopt an instrumental variable strategy using the same set of control variables in equation (17). Recent studies suggest that an individual's peers and social interactions play a key role in adopting health products and taking up of social programs (Kremer and Miguel, 2007; Oster and Thornton, 2011; Dahl et al, 2015). The information transmission about costs and benefits among peers increases the likelihood of program participation. Following Cheung and Padieu (2015), I use the percentage of recipients in the community, excluding the observed household, as the instrument variable. The underlying assumption is that the higher the coverage in the community, the more credible and attractive the insurance is to households. The participation rate in the community influences the household's decision in enrolling in the NCMS but has no direct effects on the outcome variables.

The roll-out structure of the NCMS makes the identification strategy more appealing. The program was implemented over a six-year period from 2003 and 2009 in different counties at different times in rural China. Some areas received coverage earlier than others did, and the households residing in those areas were subject to exogenous changes in health insurance offering status at different times. In addition, the household registration (*hukou*) system in China restricts household mobility and makes selective mobility very unlikely. Therefore, households residing in a community could only enroll in the program if the NCMS was offered in the residential county. Together with the restricted mobility, the potential spillover effects are likely to be small.

Previous studies identifying the local average treatment effect (LATE) of the NCMS have adopted two other instrumental variables: county offer status (Lei and Lin, 2009), duration of community-level NCMS availability (Donato and Rokicki, 2016). All three IVs captures the relationship between the availability of the insurance and household participation. Using county NCMS offer status suffers from the critique that the IV may influence the outcome variable directly if the county implementation decision is correlated with the local economy level. Duration of community-level NCMS fails to capture the unobserved program intensity and credibility along time, leading to a potentially weak correlation with the household participation decision. Results using the other two IVs are available in Appendix A.3.

2.3 Data

I use data from the China Health and Nutritional Survey (CHNS). The CHNS began in 1989 and has eight subsequent waves in 1991, 1993, 1997, 2000, 2004, 2006 and 2011. It is based on a multistage, random cluster process that results in a sample of approximately 4,400 households with 19,000 individuals over the survey periods. It covers nine provinces (Guangxi, Heilongjiang, Guizhou, Henan, Hubei, Hunan, Jiangsu, Liaoning, and Shandong) that vary considerably in terms of geography, economic development and public resources.

In this study, I use data from 1993 to 2011, covering the entire duration of the health insurance reform. Since enrolment in the NCMS is at the household level, the unit of observation under analysis is the household. I use the following criteria for sample selection. First, I restrict the sample to be rural households, whose household head lives in a rural county and has a rural *hukou*[16]. Second, I exclude observations with missing information on key variables such as insurance enrollment status, county-level NCMS offer status, and education status of the household head.

Following Lei and Lin (2009), the year of the county level implementation is determined by community survey data from the CHNS. Government officials from each community were surveyed on whether the CMS had been implemented in their community, and if so, the starting date. Since the NCMS started from 2003, counties with CMS status before 2003 were implementing the old CMS. CMS plans that implemented after 2003 are defined as the NCMS. Since the NCMS operates at the

[16] Hukou is a residential registration system in China. Only individuals with rural hukou could participate in the NCMS.

county level, if any community within a county was known to have adopted the NCMS, the county as a whole was defined as having implemented the NCMS.

Table 2.2 Panel A presents descriptive statistics for the households used in the empirical analysis. The first column reports results for the whole population. Column 2 and 3 describe results for households without and with enrolment in the NCMS. Compared to the household with the NCMS, the head of the households without the NCMS tends to be younger, more likely to be a single, and less likely to achieve at least nine years of education. Households with the NCMS are smaller in size, have lower share of children and have a much higher total annual household income compared to those without.

In the rest of the section, I will first focus on outcome variables that are relatively easy to measure: medical spending (m), out-of-pocket spending (x), and out-of-pocket price (p). Then I will describe the estimation of monetized value of health (h) and consumption (c). The measure of consumption available from the CHNS is food consumption. However, the monetary value of the food consumption is not directly available from the data. Therefore, estimation of health and consumption requires additional assumptions. Table 2.2 Panel B presents summary statistics on key outcome variables in this study.

Medical spending m. The CHNS surveys respondents regarding their medical services utilization. The medical spending includes the costs of treating the same illness used to define the health shock at up to two clinics or hospitals, as well as the cost of informal treatment if the individual chooses to use informal care (i.e. did not go to a clinic). [17]

The household level medical spending is measured as the sum of all medical spending incurred by the household members. On average, monthly medical spending is about 308 RMB for households with NCMS and 112.9 RMB for households without.

Out-of-pocket spending *x.* The household out-of-pocket spending is derived from the same set of questions as the medical spending. The CHNS surveys respondents about the proportion of the cost paid by the insurance. The household out-of-pocket spending is measured as the sum of all out-of-pocket spending incurred by the household members. The average monthly out-of-pocket medical expenditure for households with the NCMS is 293.6 RMB and 484.6 RMB for those without.

Out-of-pocket prices p. The optimization approach requires the definition of the out-of-pocket price of medical care with the NCMS, p(q), and without, p(0). I measure the price of medical care p(q) as the ratio of mean out-of-pocket spending to mean total

[17] The first question asks what did the respondents do if the respondent reported being sick in the past four weeks. If the respondent reports self-care or visit local health worker, the second question asks the amount of total costs incurred. If the respondent reports seeing a doctor, the third question records the amount of total spending in hospital, which includes registration fees, medicines, treatment fees etc. If the respondent reports seeking a second health facility regarding the same illness, the total amount of medical spending is also recorded. The fifth question asks the amount of additional costs incurred in treating the same diseases. The four questions are available in all waves of the survey for every respondent aged 18 years or older.

spending: $p(q) = \frac{E[x(q,m)]}{E[m(q)]}$. I estimate p(0) = 0.99 and p(q) = 0.75. In other words, the uninsured pay almost the whole amount of their medical spending while the insured only pay 0.75 on 1 RMB for their medical spending.

2.3.1 Measuring requisite health (*h*) inputs

The complete-information approach requires estimation of the impact of the NCMS on health. There are several measures of health in the CHNS data. For the baseline analysis, I adopt the specification in Liu (2016). The household health status is derived from two questions in the survey. The first question asks whether the individual, during the past four weeks, had suffered from any illness; if yes, the second question records the number of days that the person had been unable to carry out daily activities due to the illness in the same period[18]. Both questions are available in all waves of the survey for every respondent aged 18 years or older[19].

The household-level health status is measured as the proportion of time in the past four weeks (in percentage points) that the household suffers from a severe illness:

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[18] The survey questions are: "During the past four weeks, have you been sick or injured? Have you suffered from a chronic or acute disease?" and "For how many days during the past four weeks were you unable to carry out normal activities due to this illness?"

[19] Self-assessed health status question is available in the CHNS but only from wave 1997 to wave 2006. Another potential measure is the self-reported ability to perform daily activities. However, the CHNS only collects data on physical limitations for individuals aged 55 and above, and the collection of these data ends with the 2006 wave.

$$h_{ijt} = \frac{\sum_{m=1}^{M} d_{ijt}^{m}}{28} \times 100 \quad (18),$$

where d_{ijt}^{m} measures the number of days in the past four weeks household members reported severe illness. The household health status is defined as a normalization over the length of the recall period (28 days). On average, households with the NCMS experience 0.884 days of sickness in the past four weeks while households without the NCMS experience 0.721 days.

Measuring health as the capacity to perform daily activities among all household members for rural households in China captures not only the benefits from improved health condition but also partially the benefits of avoiding inefficient insurance mechanisms. Recent literature has shown that household labor supply is an important insurance mechanism against health shocks among low-income households (Chetty and Looney, 2006; Chetty, 2006). Absent of health insurance, during a negative health shock, households tend to reduce investment in children's education and increase the use of child employment (Liu,2016). Evaluating health as the number of days that adult household members are unable to work indirectly captures the insurance's effects on labor supply.

A key challenge for welfare analysis is how to value changes in a given measure of health. With the health measure as the number of days unable to work, the standard approach is to evaluate using the hourly wage rate. Majority of the rural households in China do not engage in formal employment and many work on family business (e.g.

agriculture work, raising livestock). The CHNS provides annual household income and thus I measure the value of a labor day as $\phi = \frac{y_{ijt}}{260}$, where y_{ijt} is the annual household income of household *i* residing in county *j* at wave *t*.

2.3.2 Measuring requisite consumption (c) inputs

Both complete-information approach and optimization approach require measurement of consumption. The complete-information approach requires to estimate the impact of the NCMS on the distribution of consumption. And the optimization approach requires estimation of the joint distribution of consumption and out-of-pocket spending.

As a survey designed to track the nutritional intake of the respondents, the CHNS records food consumption as the amount of calorie intakes. Monetary value of the food consumption is, however, not directly available from the data. In this study, I proxy for non-medical household consumption c as the difference between total household income and out-of-pocket medical expenditure:

$$c = y - x \quad (19).$$

The consumption proxy assumes that each household member is entitled to same amount of consumption, i.e., the impact of a given amount of out-of-pocket expenditure on non-medical consumption is shared equally within household. This assumption is reasonable under the context of rural China given the joint nature in household consumption and labor supply. In the sensitivity analysis, I also report results in which I assume the other extreme: the out-of-pocket spending shock is borne entirely by each individual.

Since there is unavoidable measurement error in this approach to estimating *c*, and because welfare estimates are naturally sensitive to *c* at low values, I follow the standard procedure for ruling out implausibly low values of *c* (e.g. Brown and Finkelstein, 2008; Hoynes and Luttmer, 2011) by imposing an annual consumption floor. The baseline analysis imposes a consumption floor of 2,400 RMB per year, which corresponds to the 5th percentile of non-medical consumption for the whole sample. The value of the consumption floor is selected according to the 2010 China Statistical Year Book, where the total living expenditure for the low-income households is 2535.35 RMB. In the sensitivity analysis below, I explore sensitivity to the assumed value of the consumption floor.

2.4 Welfare Results

2.4.1 Empirical estimation results

This section examines the impacts of the NCMS on the following outcomes in sequence: health, household consumption, and health expenditure using the empirical strategy specified in Section 4. Table 2.5 reports the first stage estimation, regressing the household NCMS enrolment status against the proportion of households enrolled in the community excluding the observed household. The result indicates that the household's decision in participating in the NCMS is highly correlated with the proportion of enrolled households in the community, suggesting strong peer effects.

Table 2.3 Column 1 presents the coefficient estimate on the health measurement, the fraction of the past 28 days in which members of the household suffered from severe illness limiting daily activities. Enrollment in the NCMS increases the number of days household members unable to perform daily activities: on average, participating in the NCMS leads to an increase of 7.03 days, though statistically not significant.

I construct alternative health measurements to identify the effect of the NCMS on working-age adult household members. The health measurement is defined as the following:

$$h_{ijt} = \frac{\sum_{m=1}^{M} d_{ijt}^{m} 1(18 \leq age_m \leq 65)}{28} \times 100,$$

where $\sum_{m=1}^{M} d_{ijt}^{m} 1(18 \leq age_m \leq 65)$ is the total number of days in the past four-weeks household members age between 18 and 65 years old unable to perform daily activities. Table 2.3 Column 2 reports the estimation result. On average, participating in the NCMS leads to an increase of 2.04 days on number of days working-age household members unable to perform daily activities. Though statistically not significant, the estimated results show that the NCMS influences household labor supply decisions mainly through the non-working-age members.

Table 2.3 Column 3 and 4 present the coefficient estimates on household monthly non-medical consumption. On average, enrollment in the NCMS increases the household monthly consumption by 7.45 RMB or equivalently 2% of the total household non-medical consumption.

Table 2.4 presents the mean effect estimating the NCMS's impacts on health expenditures. Column 1 and 2 report the impacts of the NCMS on monthly medical expenditure. Participating in the NCMS increases the monthly medical expenditure of the enrolled households: on average, joining the NCMS leads to 19.04 RMB increase of medical spending, or 2% more compared to the households without the NCMS. Column 3 and 4 report the impacts of the NCMS on monthly out-of-pocket spending. Enrollment in the NCMS leads to an average 1.516 RMB increase or equivalently 0.03% more in monthly out-pf-pocket expenditure compared to the households without. None of the regression results are statistically significant.

The estimated effects of the NCMS on health, consumption and health expenditures are consistent with the findings of the previous studies. Joining the NCMS has modest impact on improving health status, reducing the total medical service usage and out-of-pocket spending (Lei and Lin, 2009; Wagstaff et al., 2009; Hou et al, 2014; Liu, 2016). Bai et al. (2013) also find that enrolment in the program increases non-medical consumption by approximately 5%, similar in scale with findings in this paper.

2.4.2 Welfare estimation results

Panel A of Table 2.5 reports the welfare results from the baseline analysis.

Complete-information approach

I estimate equation (5) for $\gamma(q)$. This requires me to estimate the mean health outcomes and the distribution of consumption for control compliers and treatment compliers. Table 2.3 column (1) shows the estimate of the average health differences of control compliers and treatment compliers. To estimate the distribution of consumption for the treatment and control compliers, I follow a parametric IV technique specified in Imbens and Rubin (1997). Details of implementation are described in Appendix A.1. The complete-information approach requires that an estimation of values in changed health, ϕ. As discussed above, the baseline analysis assumes ϕ = 73 RMB, the value of a labor day. I also assume in the baseline analysis that $\sigma = 1.5$.

The first column of Table 2.5 shows the resultant estimate: $\gamma(q) = 109.7$ RMB. In other words, the estimated result shows that an NCMS recipient would be indifferent between giving up the NCMS and giving up 109.7 RMB in monthly consumption. If we assume the same effects across the months, the annual welfare benefits of the NCMS per household is 1316.4 RMB. I decompose the welfare value of the NCMS to the recipients $\gamma(q)$ into transfer term of 71.4 RMB (see equation 6) and "pure-insurance" term of 38.3 RMB (see equation 7). The result suggests that approximately 65% of the value of the NCMS comes from the transfer component, and about 35% comes from the NCMS's ability to move resources across different states of the world.

Since the complete-information approach involves summing up over all the impacts of the NCMS on each argument of the utility function, it is natural to decompose the welfare value into components operating through health and component operating through consumption. I define the welfare value of the NCMS to recipients operating through consumption, γ_C as:

$$E\left[\frac{c(0,\pi)^{1-\sigma}}{1-\sigma}\right] = E\left[\frac{(c(q,\pi)-\gamma_C)^{1-\sigma}}{1-\sigma}\right],$$

and estimate $\gamma_C = 68.7$ RMB. Therefore, the value of the NCMS operates through health is $\gamma_M = 41$ RMB. Appendix A.2 provides implementation details. The estimation result suggests that recipients' value the NCMS both through its impact on consumption as well as on health.

Optimization approach

I estimate the transfer component and pure-insurance component separately, and then combine them for the overall welfare estimation under the optimization approach. The estimation of the transfer component is relatively straightforward. The estimation of the pure-insurance component requires an assumption about the coefficient of risk aversion. I use the same assumption as in the complete-information approach: $\sigma = 1.5$.

Without any assumption on utility function, the optimization approach estimates the value of the transfer component using only the estimates of the medical costs, *m*, and price, *p*. Using linear approximation, the transfer term is 50.6 RMB. The estimation of the pure-insurance term requires an estimate of the covariance between consumption distribution and medical spending, which can be obtained directly from data. Following the linear approximation assumption, the total pure-insurance component is 55.7 RMB.

The overall welfare benefits of the NCMS measured using the optimization approach is 106.3 RMB per recipient per month. The proportion of welfare benefits come from transfer component is slightly smaller compared to the results under the complete-information approach. Transfer component represents 48% of the total welfare value while pure-insurance term approximately 52%. The welfare value measured by the optimization approach is slightly lower than under the complete-information approach. I interpret the values from the two approaches as the upper and lower bounds of the potential range of the two welfare components.

2.4.3 Interpretation

I benchmark the welfare estimates against the costs of the NCMS. Government costs, G, are the difference between total medical spending and out-of-pocket spending for treatment compliers. The estimated government cost for the NCMS is approximately 77.5 RMB per recipient per month. The net cost of the NCMS, C, is 76.4 RMB per recipient per month. The estimates of the costs are in general consistent with external estimates of annual per-household spending in the NCMS program.

Define the monetary transfer from the NCMS to external party as the difference between the gross costs and net costs: $N = G - C$. The estimates of the gross costs and net costs of the NCMS leave a small margin for transfer to external parties: only 1.1

RMB per recipient per month. Since N measures the difference between the total medical bills and the amount the uninsured paid, it gives a value of implicit insurance for the uninsured. The result is not surprising under the context of rural China since the uninsured typically all their medical expenses out-of-pocket with little covered by hospital or any other third parties. Uninsured individuals may receive supports from family members or relatives but since the measurement unit is household in the analysis, the magnitude of those transfers is small.

To better understand the meanings of these estimates, I conduct several comparisons between the costs and the welfare evaluation. The results are summarized in Panel B of Table 2.6. Comparing the value of the welfare benefits and the government's gross costs of providing the insurance provides insights into the existing rural insurance market in China. If rural residents have access to a well-functioning private insurance market or other actuarially-fair risk protection products, the welfare value of the NCMS, $\gamma(q)$, may be less than the government's costs of provision, G. However, if self-insurance is the major mean of risk hedging among rural residents in China, the welfare benefits may be well-above the government's costs.

For both methods, I consistently estimate that the welfare benefit of the NCMS, $\gamma(q)$, is more than G. A benefit-cost ratio of 1.4 indicates that individual would prefer to obtain the NCMS at the cost of G in consumption than the *status quo*. Comparing the welfare value and the government's net costs of providing the insurance paints a similar picture. Excluding the potential transfer to external parties from the NCMS (N), the net costs reflect the "true cost" of the NCMS to the public sector. Depending on the approach, the ratio between the welfare value and the net costs varies from 1.39 to 1.44.

Across the baseline estimation, I consistently estimate that $\gamma(q)$ is more than *G*. Depending on the approach used, I estimate a ratio of welfare benefits and government gross costs is approximately 1.4. This implies that the recipients value the NCMS approximately equal or higher than the government's costs of providing the insurance. That is to say, an uninsured household would prefer to obtain the NCMS at the cost of *G* in consumption than the status quo. However, $\gamma(q)$ > G does not answer the question of whether an uninsured household would prefer receiving the NCMS than to receiving G in additional consumption or, equivalently, whether an insured household would be willing to give up the NCMS in exchange for a consumption increase of G.

Comparing the value of the welfare benefits and the government's net costs of providing the insurance provides consistent interpretation. Excluding the potential transfer to external parties from the NCMS (*N*), the net costs reflect the "true cost" of the NCMS to the public sector. Depending on the approach, the ratio between the welfare value and the net costs varies from 1.39 RMB to 1.44 RMB. The fact that $\gamma(q)$ is consistently above *C* implies that the insurance value of the NCMS to the recipients, *I*, exceeds the associated moral hazard costs. The results imply that formal medical care are "luxury" goods to rural households in China. Even with access to health insurance, rural households would prefer to seek formal medical services only when necessary.

The findings suggest that the NCMS is highly valuable to the rural households in China and government could increase the generosity of the insurance for higher welfare benefits. The high value of the welfare estimation of the NCMS is also because the uninsured in rural China pay all their medical spending with few incidences of receiving unpaid care. Therefore, the monetary transfer from the NCMS to external party is almost non-existent, leaving majority of the cost of the NCMS as net costs.

2.4.4 Sensitivity Analysis

Risk aversion and consumption floor

Table 2.7 column II to V explore alternative choices for risk aversion (coefficient of relative risk aversion of 1.2 and 3, compared to our baseline of 1.5) and the consumption floor (of 100 RMB or 500 RMB per month, compared to the baseline assumption of 200 RMB). Since the coefficient of relative risk aversion models individuals' attitude towards risk, the higher the σ, the more risk averse of the individuals and thus have a higher preference for consumption smoothing. The estimated results confirmed the hypothesis. Compare to the baseline results, the welfare benefits of the recipient exceed the government costs under higher risk aversion value (σ = 3) for both approaches. That is, if the households at rural China were more risk aversion compared to the baseline, they would value the NCMS much higher than the government's costs of providing it. Lowering the risk aversion value (σ = 1.2) results in a lower evaluation of the welfare value of the NCMS, which is as expected. Table

2.7 column IV and V report the results using different consumption floor. A higher consumption floor leads to lower welfare benefits, suggesting that if households have access to other consumption smoothing channels (i.e. higher household income), they would value the NCMS lower.

Alternative assumption about within-family smoothing.

The baseline consumption proxy assumed that out-of-pocket medical spending reduced consumption of each family member by the same amount. Health is measured at the unit of a household, assuming that the influence of the health shock will impact all household members equally. Under the context of rural China, within-family risk smoothing is common, given majority of the consumption is joint (e.g. food, housing) and many of the works are done as a family unit (e.g. farming). However, the extreme of the full smoothing within the family (i.e. the effect on an individual's consumption is the same regardless of whether the individual incurred the out-of-pocket spending) may not be guaranteed. In Table 2.8 Column II, I examine the sensitivity of the results to individual health measurement. Using individual health measurement, the welfare value is slightly lower than the baseline evaluation for the complete-information approach. The change has not impact on the results of the optimization approach. In Table 2.8 Column III, I examine the sensitivity of the results to an alternative assumption: that the out-of-pocket spending affects consumption only for the individual who incurred expenses. This slightly raises the estimates of the value of the

NCMS relative to the gross costs under complete-information approach. The results using the optimization approach have little changes.

2.5 Conclusion

This paper studies the welfare benefits of offering universal health insurance to low-income households. One of the major concerns for providing public health insurance is the associated moral hazard costs. Individuals consume more medical care because of lower out-of-pocket price. Traditionally, the moral hazard effect has been interpreted as welfare-decreasing. In recent studies, access to health insurance is shown to also contain a welfare-enhancing income effect, allowing individuals to seek medical treatments that are previously unaffordable. Whether this tradeoff results in positive welfare gain remains unclear especially among low-income households.

I empirically examine this issue through exploiting a health insurance reform, the New Cooperative Medical Scheme in rural China. The welfare value of the NCMS is evaluated from its function as resource transfer and from its role of consumption smoothing. I find robust evidence that the welfare gains individuals enjoy from the NCMS program are above its costs. A benefit-cost ratio of 1.4 confirms that enrolled individuals would much likely to take up the insurance given the government's costs. A positive welfare gain suggests that income effect plays a major role in individual's increased medical care consumption. Moral hazard costs, though exist, are smaller than the welfare benefits generated. Contrary to findings in the U.S., less than 1% of the gross costs is due to transfers to third party, suggesting that the NCMS enrollees are the main beneficiary of the program.

The welfare benefits come from both NCMS's ability in transferring resources to the recipients as well as its insurance function. One-third to half of the welfare benefits are from the NCMS's insurance function. The estimation results suggest that benefits of the public insurance program could come from offering efficient consumption smoothing mechanisms among low- and middle-income households. The existing literature have shown the public insurance programs in developing countries could lead to net welfare gains by reducing the use of costly self-insurance mechanisms. The findings in this paper support the same argument.

While the study focuses on China, the results have broader implications for many developing countries whose population have little access to formal insurances. The average annual consumption among rural households in 2010 is 4,381 RMB, similar to the consumption level at several low-, middle income countries. The insurance enrollment rate and average medical spending per person among rural China households prior to the offering of the NCMS are also comparable to many developing nations.

2.6 Tables

Table 2.1 Implementation of the Reform

	Household		County
Year	% access to NCMS	% Insured	% Treated
1993	0	4.53	0
1997	0	14.3	0
2000	0	8.07	0
2004	29.89	15.2	8.3
2006	68.16	52.2	61.1
2009	100	96.4	100
2011	100	98.1	100

Note: Each round of the survey contains households sampled from 36 counties (four counties per province). Four counties from Liaoning province dropped out in 1997 wave but were added back from wave 2000 onwards.

Table 2.2 Summary Statistics

Variable	All	Without NCMS	With NCMS
Panel A. Household Demographics			
Age of the head	46.900	45.445	48.951
	(10.260)	(10.386)	(9.718)
Head being single	0.091	0.094	0.086
	(0.288)	(0.292)	(0.281)
Head with at least 9 years of education	0.441	0.388	0.516
	(0.497)	(0.487)	(0.500)
Household size	3.089	3.465	2.558
	(1.471)	(1.507)	(1.238)
Share of children (aged 7 – 18)	0.183	0.223	0.125
in the household	(0.209)	(0.215)	(0.186)
Total annual household income	20,139	14,377	28,425
	(19,423)	(13,659)	(23,132)
Panel B. Outcome Variables			
Share of days with severe illness (all working members)	2.378	2.084	2.793
	(12.160)	(11.289)	(13.282)
Share of days with severe illness(all family members)	2.817	2.575	3.158
	(13.334)	(12.796)	(14.053)
Monthly out-of-pocket spending	160.9	111.4	230.7
	(1510)	(912)	(2077)
Monthly medical spending	194.0	112.9	308
	(1869)	(913.8)	(2689)
Monthly household consumption	1673	1233	2,307
	(1564)	(1082)	(1899)

Table 2.3 Effect of the NCMS on Health and Consumption

	Health (all family members)	Health (all working members)	Consumption	Log Consumption
	(1)	(2)	(3)	(4)
NCMS	0.251	0.0727	7.447	0.0224
	(0.707)	(0.752)	(108.7)	(0.0649)
Number of observations	12555	12555	12243	12243
Adjusted R-square	0.022	0.024	0.225	0.269

Note: Standard errors (in parentheses) are clustered at the county level. Health is the share of days in the past 28 days (in percentage points) in which all the working family members or all family members suffered from severe illness limiting daily activities. Each regression controls household size, percentage of children, household head's age and age square, household head's education, whether household head is single, wave and county fixed effects.
* p<0.1, ** p<0.05, *** p<0.01

Table 2.4 Effect of the NCMS on Health Expenditure

	Medical Spending	Log medical spending	Out-of-pocket Spending	Log out-of-pocket Spending
	(1)	(2)	(3)	(4)
NCMS	19.04	0.0158	1.516	0.0003
	(89.45)	(0.172)	(87.40)	(0.172)
Number of observations	12555	12555	12555	12555
Adjusted R-square	0.006	0.093	0.005	0.092

Note: Standard errors (in parentheses) are clustered at the county level. Each regression controls household size, percentage of children, household head's age and age square, household head's education, whether household head is single, wave and county fixed effects.
* p<0.1, ** p<0.05, *** p<0.01

Table 2.5 First Stage Result for the Instrument Variable

	Household NCMS status
Proportion of households enrolled in NCMS in the community	0.995***
	(0.0130)
Number of observations	12,555
R-square	0.916

Note: Standard errors (in parentheses) are clustered at the county level. Regression controls household size, percentage of children, household's age and age square, household education, whether household is single, wave and county fixed effects.
* p<0.1, ** p<0.05, *** p<0.01

Table 2.6 Welfare Benefit of the NCMS (per month per recipient)

	Complete-information Approach	Optimization Approach
Welfare benefits		
Welfare effect on enrolled households, $\gamma(q)$	109.7 (49.203)	106.3
Transfer-term	71.4	50.6
Pure-insurance Term	38.3	55.7
Benchmarks **Welfare effects relative to:**		
gross costs, $\gamma(q)/G$	1.42	1.37
net costs, $\gamma(q)/C$	1.44	1.39
moral hazard cost, $G\text{-}T\text{-}N$	5	25.8

Notes: Estimates of welfare effects and moral hazard costs are expressed in RMB per month per enrolled household. Standard errors are bootstrapped with 500 repetitions.

Table 2.7 Sensitivity of Welfare Estimates on Degree of Risk Aversion and Consumption Floor

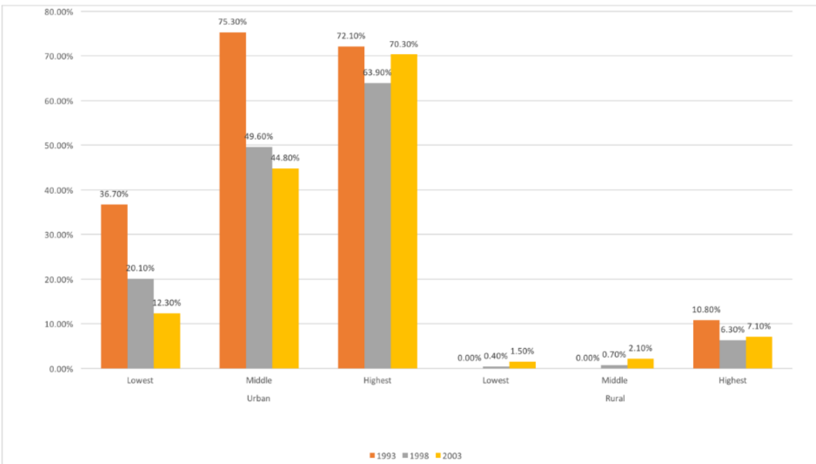
	I	II	III	IV	V
		Coefficient of relative risk aversion		Consumption floor	
	Baseline	1.2	3	100 RMB	500 RMB
Panel A : Welfare Relative to Gross Costs , $\boldsymbol{\gamma(q)/G}$					
Complete-information	1.42	1.40	2.57	1.55	1.20
Optimization	1.37	0.93	1.41	1.37	0.72
Panel B: Welfare Relative to Net Costs, $\boldsymbol{\gamma(q)/C}$					
Complete-information	1.44	1.42	2.61	1.57	1.22
Optimization	1.39	0.94	1.43	1.39	0.73

Table 2.8 Sensitivity of Welfare Estimates on Health Measurement

	I	II	III
	Baseline	Individual Health Measure	Shock born entirely by individual
Panel A: Welfare Relative to Gross Costs, $\boldsymbol{\gamma(q)/G}$			
Complete-information	1.42	1.174	1.55
Optimization	1.37	-	1.59
Panel B: Welfare Relative to Net Costs, $\boldsymbol{\gamma(q)/C}$			
Complete-information	1.44	1.220	1.57
Optimization	1.39	-	1.61

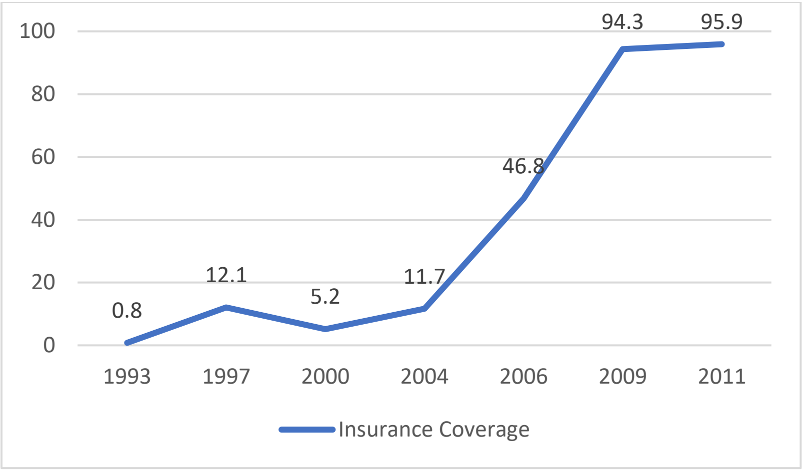
2.7 Figures

Figure 2.1 Health Insurance Coverage for Urban and Rural Residences by Income



Source: Yip and Hisao (2008)

Figure 2: Percentage of Rural Sample Covered by Any Type of Health Insurance



Source: Authors' calculation based on the CHNS data

Appendices

Appendix A.1 Estimating Outcome Distributions for NCMS Compliers

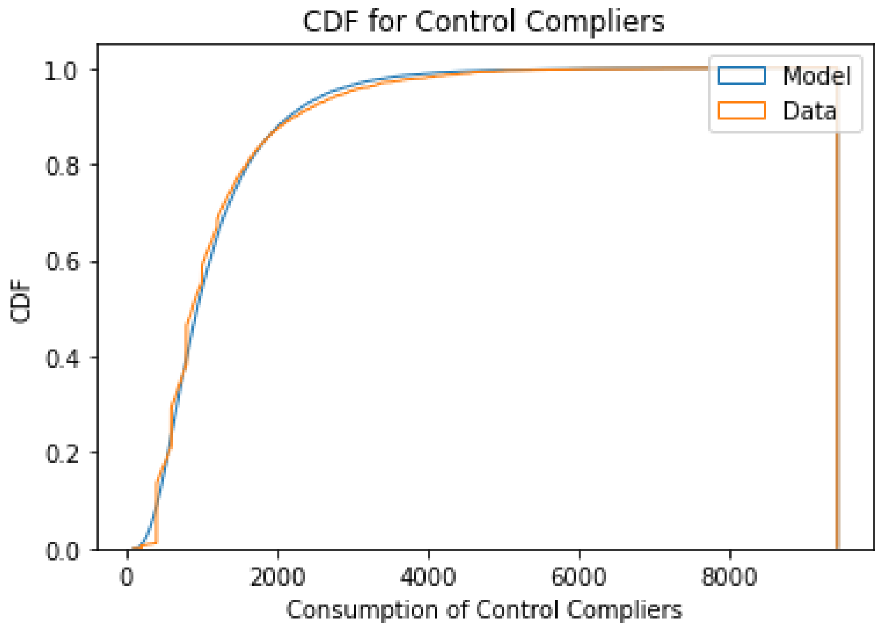
Let $f_g(x)$ denote the observed probability density function (pdf) x for group $g \in \{TC, CC, AT, NT\}$ where TC are the treatment compliers, CC are the control compliers, AT are the always-takers, and NT are the never-takers. In the sample, always-takers are defined as households who were enrolled in health insurance before the introduction of the NCMS to their residing county and never-takers are households who were not enrolled in the NCMS after the reform. I observe $f_{NT}(x)$, the distribution of x for never takers, as well as $f_{AT}(x)$ directly. The population fraction of never-takers, φ_{NT}, is given by the fraction of the treatment group that did not take up the program. Similarly, the population fraction of always-takers, φ_{AT} is given by the fraction of the control group that took up the program.

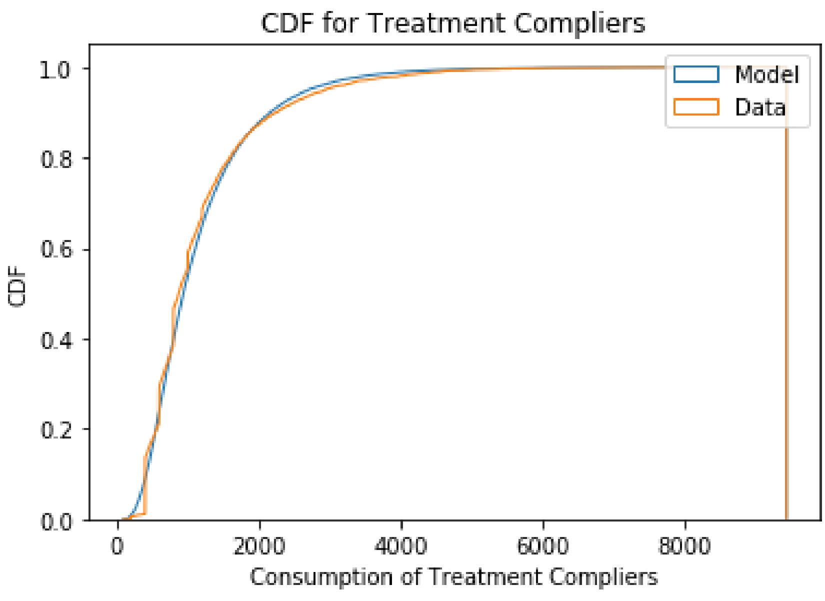
The population fraction of compliers is given by: $\varphi_C = 1 - \varphi_{AT} - \varphi_{NT}$. The distribution of x for compliers cannot be observed directly from the data. In the control group, those who were not enrolled in any health insurance are a mixture of never-takers and compliers. Similarly, in the treatment group, those who choose to enroll in the NCMS are a mixture of always-takers and compliers. Following Imbens and Rubin (1997), I could back out the distribution of compliers as: $g_{CC}(x) = \frac{\varphi_{NT}+\varphi_c}{\varphi_c} f_{NT}(x) - \frac{\varphi_{NT}}{\varphi_c} f_{CC}(x)$, and $g_{TC}(x) = \frac{\varphi_{AT}+\varphi_c}{\varphi_c} f_{AT}(x) - \frac{\varphi_{AT}}{\varphi_c} f_{TC}(x)$, where $g_{CC}(x)$ and $g_{TC}(x)$ are the potential outcome distribution of consumption for control compliers and treatment compliers respectively.

Assume the household consumption follows a log-normal distribution (Battistin, Blundell and Lewbel, 2009), I allow the parameters of the distribution to differ across the four groups: $LOGN(x|\mu^g, \upsilon^g)$ for $g \in \{TC, CC, AT, NT\}$, where $LOGN(x|\mu, \nu)$ is the CDF of a log-normal with mean and variance parameters μ and ν. I estimate the eight parameters using maximum likelihood estimation. Calculation of the maximum likelihood estimates is based on the EM algorithm (Dempster, Laird and Rubin (1977)).

To assess the goodness of fit, Figure 2.A1 plots the estimated and actual CDF separately based on NCMS county level offer status. As can be seen from these figures, the parametric model fits quite well.

Figure 2.A.1 Fitted and actual CDFs of consumption spending


CDF for Control Compliers
Model
Data
1.0
0.8
0.6
0.4
0.2
0.0
CDF
0
2000
4000
6000
8000
Consumption of Control Compliers


CDF for Treatment Compliers
Model
Data
1.0
0.8
0.6
0.4
0.2
0.0
CDF
0
2000
4000
6000
8000
Consumption of Treatment Compliers

Appendix A.2 Decomposition of welfare effects in the complete-information approach

To explore the underlying factors that drive the value of the welfare estimates, I decompose $\gamma(q)$ into two components: γ_c, welfare comes from consumption, and γ_m, welfare comes from health. γ_c is estimated based on the following equation given the additive nature of the utility function

$$E\left[\frac{c(0;\pi)^{1-\sigma}}{1-\sigma}\right] = E\left[\frac{(c(q;\pi)-\gamma_c)^{1-\sigma}}{1-\sigma}\right].$$

Naturally, γ_m is calculated as the difference between $\gamma(q)$ and γ_c. I further decompose the welfare effects operate from consumption and health into a transfer term and a pure-insurance term, similar as the optimization approach. The transfer component of γ_c is defined as

$$\gamma_{c,transfer} = E[c(q;\pi) - c(0;\pi)].$$

The pure-insurance component of γ_c is then: $\gamma_{c,ins} = \gamma_c - \gamma_{c,transfer}$.

Recall from section 3, health is produced according to a health production function $h = \tilde{h}(m;\theta)$. Substituting this into equation (4), we define the transfer component of γ_m as:

$$E\left[\frac{c(0;\theta)^{1-\sigma}}{1-\sigma} + \tilde{\phi}\tilde{h}(E[m(0;\theta)];\theta)\right] = E\left[\frac{(c(q;\theta)-\gamma_c-\gamma_{m,transfer})^{1-\sigma}}{1-\sigma} + \tilde{\phi}\tilde{h}(E[m(q;\theta)];\theta)\right].$$

$\gamma_{m,transfer}$ is interpreted as welfare associated with the change in health condition from the average change in medical spending due to the NCMS. The change in health condition is approximated as following:

$$\mathrm{E}[\tilde{\phi}\tilde{h}(E[m(0;\theta)];\theta) - \tilde{\phi}\tilde{h}(E[m(q;\theta)];\theta)] = \tilde{\phi}E\left[\frac{d\tilde{h}}{dm}\right]E[m(q;\theta) - m(0;\theta)].$$

The pure-insurance component of is $\gamma_{m,ins} = \gamma_m - \gamma_{m,transfer}$.

Evaluating the equation requires estimating the slope of the health production function $E\left[\frac{d\tilde{h}}{dm}\right]$ between $m(q;\theta)$ and $m(0;\theta)$. In the analysis, I use a simple OLS regression of the household medical spending on health measures, controlling log household size, share of children in the household, share of working-age adults in the household, age and age-squared of the household head, indicators for the education level of the household head, whether the household head is single, wave and county fixed effects. The slope of the health production function is estimated as the average effect of medical spending on changes in health measures. The regression result is presented in Table 2.A.1.

Table 2.A.1 Effect of Medical Spending on Health Measure

	Household Health Measure
Household Medical Spending (in 100RMB)	0.0130**
	(0.00475)
Number of observations	12555
R-square	0.028

Note: Standard errors (in parentheses) are clustered at the county level. Regression controls household size, percentage of children, household's age and age square, household education, whether household is single, wave and county fixed effects.
* p<0.1, ** p<0.05, *** p<0.01

Appendix A.3 First-Stage Regression Results using Different Instrument Variables

To compare the effects of different instrumental variables, I run the first-stage of 2SLS regression using county offer status and the duration of community-level NCMS availability. Table A.2 reports the results, regressing the household NCMS enrollment status against the county offer status and the duration of community-level NCMS availability. The result indicates that county offer status is highly correlated with the household's decision in participating in the NCMS while the duration is community-level NCMS availability is only weakly relevant. However, the R-square using proportion of households enrolled in the community excluding the observed household is higher than the county offer status, suggesting a stronger relationship.

Table A.2 First Stage Results Using Alternative Instrumental Variables

	Household NCMS status	Household NCMS status
County-offer Status	0.622*** (0.071)	
Duration of community-level NCMS availability		0.004 (0.012)
Number of observations	12,555	12,555
R-square	0.837	0.756

Note: Standard errors (in parentheses) are clustered at the county level. Regression controls household size, percentage of children, household's age and age square, household education, whether household is single, wave and county fixed effects.
* p<0.1, ** p<0.05, *** p<0.01

Chapter 3

Unemployment Insurance and Unemployment Insurance Savings Account

3.1 Introduction

The emergence of the Great Recession puts Unemployment Insurance (UI) back at the centre of political debate. Multiple extensions of UI benefits have been implemented over the last decade and the federal annual spending increased from $33 billion in 2007 to $155 billion 2010 (Congregational Budget Office, 2010). The length of UI benefits was extended, at the peak, to 99 weeks, causing a heated debate whether UI itself was to blame for the long unemployment duration. A natural proceeding question is therefore whether an alternative UI design could balance the dynamics between disincentive costs and insurance benefits.

To answer the question, I adopt the concept of Unemployment Insurance Savings Account (UISA), proposed by Feldstein and Altman (1998) and Hopenhayn and Hatchondo (2002), but combine it with the current UI to form a two-tiered unemployment insurance system. The system works as follows: each individual is required to save a fraction of his pre-tax wage income in a special individual Unemployment Insurance Savings Account during employment. When unemployed, instead of joining UI, he withdraws an amount equal to the current UI benefits from his personal UISA until he depletes the account. If by then, the individual is still unemployed, he would be eligible for the UI benefits for maximum 26 weeks. The UISA earns a market rate of return on existing balances and is merged into the individual's pension account upon retirement.

The advantage of adding UISA in the unemployment insurance system is that by internalising the cost of unemployment, incentives are improved. The second layer of usual UI provides the necessary safety net and guarantees protection for individual unemployment risks. As a form of self-insurance, UISA has the advantage of inducing little moral hazard effects. But it has been criticised for potential impacts in crowding out precautionary savings as well as lack of redistribution Therefore, the key issues in considering the two-tiered unemployment insurance system are whether it could reduce unemployment duration, whether it is welfare improving compared to the current program, and how valuable is the system compared to its efficiency costs.

To evaluate the two-tiered unemployment insurance system and its alternative designs, I propose a life-cycle model that allows me to study individual savings, labour supply and job search intensities under non-separable preferences. Moral hazard arises as workers can decide to quit their jobs during employment, not accept a job offer or not active in job search during unemployment. In addition, I assume workers can save at the market rate but cannot borrow. The savings in the model capture the precautionary motives.

Estimates of the model parameters are obtained using microeconomic data from the National Longitudinal Survey of Youth 1979 (NLSY79). Key parameters of the model are structurally estimated through Indirect Inference Method, minimising the distance between the life-cycle data profiles from NLSY79 and the simulated life-cycle profiles generated by the model. Finally, with the estimated parameters, I conduct counterfactual policy simulations to analyse the effects of proposed two-tiered unemployment insurance system through varying policy parameters: (i) rates of contribution to the UISA. and (ii) the replacement rate of the UI benefits. The ability to evaluate these questions in a coherent, unified framework is one of the main benefits of the paper. The metric for individual welfare is the consumption equivalent that keeps expected utility at the start of life constant as policy changes.

The literature on the UI program, surveyed in the next Section, contains both reduced form papers attempting to estimate the extent of adverse incentives created by the program and its insurance value, as well as sophisticated structural analyses designed towards assessing the consequences of reforming the program. As with most structural models, the value of the paper relative to reduced form analyses is that I can conduct counterfactual analysis of potential reforms, that have not been experienced in the past or that are too costly to assess in a randomized evaluation context, to the current UI program. Relative to existing structural analyses, I stress the importance of many model features: non-separable preferences, job search efforts, permanent skill shocks, and interactions with social welfare programs. Further, I study the effects of novel unemployment insurance policy reforms, and subject the model to various validity tests.

I find that financing unemployment through individual mandatory saving significantly reduce the unemployment duration especially for young workers. Compared to the existing unemployment insurance program, workers under the UISA are more likely to exit from unemployment and take up job offers. Consistent with the findings from the previous studies, the UISA foster long-term saving and facilitate consumption smoothing over the life-cycle. Workers under the UISA consume less when young but more when old. Overall, including the UISA on top of the existing unemployment insurance leads to a welfare gain of 1%.

In addition to reduce unemployment duration, I find that moral hazard effects exist in the two-tiered unemployment insurance program. A more generous program not only leads to longer unemployment duration but also lowered incomes over the life-cycle due to loss of working years. Under the two-tiered unemployment program, workers consume more under a less generous program and accumulate higher amount in individual mandatory saving account.

The rest of the paper proceeds as follows. Section 3.2 reviews the related literature. Section 3.3 presents the life-cycle model of labour supply, consumption, and job search. Section 3.4 discusses the data used for analysis. Section 3.5 presents the identification strategy and results. Section 3.6 conducts the counterfactual analysis and evaluates the welfare consequences of the two-tiered unemployment insurance system. Section 3.7 presents the robustness analysis results with varying relative risk aversion. Section 3.8 concludes.

3.2 Literature Review

A large literature studying the effects of UI on unemployment have focused on labour supply behaviours during unemployment and reached a general consensus that more generous UI program leads to longer unemployment duration, suggesting the disincentive effects of UI. The rise of replacement rate and extension of benefit duration, impact the labour supply behaviours adversely by decreasing search intensity and increasing reservation wage. Through studying various extensions of UI benefits during recession periods, Card and Levine (2000), Farber and Volletta (2015) and Farber, Rothstein, and Valletta (2015) found small but significant negative effects of UI on the exit rates of unemployment and expected unemployment duration. Taking advantage of a change in maximum UI benefit in New York State, Meyers and Mok (2014) confirm the conclusion from previous studies that higher UI payments lead to longer unemployment duration (Meyer, 1990; Katz and Meyer, 1990). Card et al. (2015) extends the literature by examining the elasticity of UI duration with respect to weekly benefit and concludes that UI durations are more responsive during recessions than prerecession, in a range of 0.6 to 0.9. I compare the implied elasticity of employment with respect to UI benefit from my model with the estimates in the literature.

Despite a long literature of the disincentive effect, the provision of UI brings support to individuals during unemployment who would otherwise suffer from reductions in consumption (Gruber, 1997; Browning and Crossley, 2001). A recent stream of research suggests that labour supply responses to variations of UI benefits can be decomposed of liquidity effects and "moral hazard" effects (Shimer and Werning, 2008; Chetty, 2008). Chetty (2008) points out that the effect of UI on unemployment duration is mainly due to liquidity effect for constrained individuals and substitution effects for the unconstrained. Based on this conclusion, the increase of unemployment duration due to UI would be socially beneficial as it allows the liquidity constrained individuals to search longer, who would otherwise have to take jobs earlier than desired. Rothstein (2011) also argues that UI could increase the measured unemployment by inducing individuals, who would otherwise drop out of labour force, to search longer. Utilising kinks in the scheduled UI benefits, Landais (2015) confirms the existence of significant liquidity effects and show that a small increase of UI duration could be welfare improving.

However, extended search duration due to UI does not necessarily lead to better jobs. Using a series of age discontinuities in benefit duration in Germany, Schmieder, von Wachter, and Bender (2012, 2013) show that a prolonged unemployment spell induced by extended UI benefits leads to a decline in weekly earnings: approximately

0.6 to 0.8 percent for each additional month out of work. Card, Chetty and Weber (2007) found similar result that the increases in the search duration induced by UI have little effect on subsequent job match quality, using various discontinuities for extended UI and severance pay eligibility in Austria.

The balance between providing liquidity supports and mitigating the disincentive effects leads to a stream of research discussing the optimal designs of UI. There has been an influential theoretical literature on optimal UI designs but in stylised models, thus difficult to connect to the data (Hopenhayn and Nicolini, 1997; Shimer and Werning, 2008; Lentz, 2009). Specially, unemployment policies appear to vary substantially across countries. In the US, benefits are usually paid only during the first six months of unemployment with little supports afterwards (i.e. Food Stamps). In countries such as Belgium and Sweden, the unemployed could receive same benefit amount forever, while in Germany, the unemployed continue to receive a less generous support, unemployment assistance (UA), upon the exhaustion of UI. The diversified unemployment policies increase the difficulty in interpreting the results of empirical studies regarding optimal UI designs. For example, using data from Germany, Hann and Prowse (2015) suggests an optimal policy design focuses mainly on Social Assistance, a government program that provides a universal household income floor, with a minor role of UI. Such a design would be difficult to apply from the US perspective.

Under the context of the US, recent papers have proposed two alternative designs for the current UI program. Koehne and Kuhn (2015) suggest an asset-tested UI policy and show the welfare improvement is minimal given the distorting saving incentives. Proposing an age-dependent scheme, Michelacci and Ruffo (2015) show that redistributing unemployment insurance over the life cycle, increasing for the young and decreasing for the old, are welfare-improving. Both designs are based on the insights that moral hazard can be reduced by financing consumption during unemployment through individual assets and are less prone to individuals with liquidity constraints. However, the asset-tested UI design could lead to disincentive in asset accumulating, larger drop in consumption at the start of unemployment and reduce the internalisation of the unemployment costs (Koehne and Kuhn, 2015).

The concept of Unemployment Insurance Savings Account (UISA) is first proposed by Feldstein and Altman (1998) as an alternative to the traditional unemployment system. Orszwag and Snower (2002) and Stiglitz and Yun (2005) both show that allowing liquidity during unemployment, either by mandatory saving or by borrowing against future pension fund, could be welfare-enhancing compared to the current system. Following the practice of Feldstein and Altman (2007), Rodrigues (2008) and Vodopivec (2008) simulate the introduction of UISA in Portugal and Slovenia and show the feasibility of the design with little distortion in distributional effects. Empirical evidence of UISA is scarce because few governments had implemented such a policy. Several recent papers evaluate the reduced-form effects of

UISA reforms in Latin-American countries (Ferrer and Riddell, 2009; Hartley et al. 2010) but fail to deliver consistent conclusions.

The paper closest to mine is Setty (2017). Setty (2017) proposes a policy design with the combination of UI and UISA, and shows that the new system requires lower unemployment replacement but delivers higher welfare benefits. The innovative part of his framework is that he proposes a two-tiered hybrid system, which is similar to my design of the unemployment insurance system. However, he models the second-tier of benefits indefinitely, rather than 26 weeks as the current system. The unemployment insurance program in Setty (2017) does not interact with other government transfer programs and the UI benefit replacement schedule is a constant proportion of pre-unemployment wages, which ignores actual minimum and maximum UI benefit levels. As a result of these shortcomings, the effect of an unemployment insurance system combining UISA and UI on unemployment duration is likely to be overstated. It remains an open question whether, in the context of a more realistic mode, a two-tiered unemployment insurance is welfare improving.

3.3 Life-Cycle Model

3.3.1 Overview

I specify a model where individuals make consumption, labour supply, and search effort decisions to maximise lifetime expected utility:

$$\max_{c,p,s} V_t = E_t \sum_{m=t}^{T} \beta^{m-t} U(c_m, p_m, s_m)$$

where β is the time discount factor, E_t the conditional expectation based on information available in period t, p a discrete indicator of employment status, and c consumption. Time is measured in months. Individuals live for T periods, may work from age 23 to 62, and face an exogenous mandatory spell of retirement of $T_R = 10$ years until the end of life. The date of death is known with certainty. There is no bequeath motive and health status.

For those in the labor force, each period proceeds as follows. i) Unemployed individual chooses the amount of search efforts. ii) Individual decides on whether to accept the job offer, which arrives as a result of the individual search productivity and search intensity, or wait longer. iii) Employed individual observes the market wage and unemployed individual observes the unemployment insurance status. iv) Individual makes consumption and saving decisions. v) The employment status is updated as a result of job destruction, quit or accepted job offer. The model imposes sufficient risks regarding individual unemployment, productivity and unsuccessful job searches. Once an individual enters retirement compulsory at 63, there are no further opportunities for job search or labor supply decisions. Individuals collect social security benefits, which are paid according to a formula observed in reality. Social security benefits, together with assets individuals voluntarily accumulated over the working years, are used to finance consumption during retirement.

3.3.2 Preference

The per-period utility function of a worker at age t is given by

$$U(c_t, p_t, s_t) = \frac{(c_t \exp(\eta p_t))^{1-\rho}}{1-\rho} - \frac{s_t^2}{2}$$

where c_t is monthly individual consumption, and p_t employment status at age *t*, and s_t search decision at age *t*; ρ is the worker's coefficient or risk aversion. Employment brings a utility loss determined by the value of η. The specification of the utility function implies that consumption and work are Frisch complements and thus the marginal utility of consumption is higher when working. I adopt this specification based on findings that consumption and leisure are not additively separable within a period (Heckman, 1974; Blundell, Browning, and Meghir, 1994; Attanasio and Weber, 1995; Low, 2005). Search intensity increases the probability of job offers during unemployment but leads to decrease of utility enjoyed by the worker.

3.3.3 Wage Process

I assume that the logarithm of wages at age-*t* in the data are governed by the process:

$$\ln w_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + u_t + e_t\,.$$

w_t is the hourly wage rate, u_t the permanent component of wages, e_t the transitory error component. The permanent component of wages follows a random walk process:

$$u_t = u_{t-1} + \zeta_t .$$

The random shock to the permanent process ζ_t is assumed to follow normal distribution with mean zero and variance σ_ζ^2, and is independent over time. The transitory component e_t is assumed to be normally distributed with variance σ_e^2 and independent over time. This relatively simple wage process captures much of the observed wage profiles, especially after conditioning on education (Low, 2005). The wage is bounded below so that the individual will always receive a job offer with a non-zero wage. The wage process is not conditional on participation, thus the model abstracts from on-the-job human capital accumulation and the wage rate grows with age whether or not individuals participate.

3.3.4 Labour Market Frictions

Each period, an employed individual experience a job destruction with a probability δ. An employed individual who is not laid off decides whether to retain or quit the job. For unemployed individuals, at the beginning of the periods, he first chooses his search intensity s_t. The arrival of job offers depends on the individual search intensity. Following Hann and Prowse (2015), let χ_t denote a worker's search productivity. The probability of a worker with search intensity s_t, receiving a job offer at period t is

$$\lambda_t = (1 - \chi_t) s_t$$

where $\log(c_t) = c_1 + c_2 age + c_3 age^2 + c_4 1(educ \geq 12)$. An individual who receives a job offer decides whether to accept that offer and become employed or to reject it and remain unemployed.

The transitions between employment and unemployment allows for both exogenous and endogenous decisions. Employed individuals lose their jobs either because of an exogenous separation or an endogenous quit. Unemployed individuals remain unemployed because of either lack of job offers or rejection of one. The presence of endogenous decisions is an essential component of the model since it implies that unemployment is determined within the model and depends on the unemployment policy.

3.3.5 Unemployment Insurance

The Unemployment Insurance (UI) is a state-federal program that aims to provide workers with insurance against spells of involuntary job loss. It was set up based on the recognition that labour markets were imperfect, and the resulted involuntary unemployment could cause individuals experiencing severe hardships. The purpose of the UI benefit is to help individuals ease the burden of involuntary unemployment without unduly affecting the job search incentives. The general program features are similar across states but differ substantially in terms of eligibility requirements, benefit levels, and maximum duration[20]. The policy this paper focuses on is the program in place after the major amendments in 1976, though many minor revisions have been implemented since then.

The receipt of the UI benefits requires the following condition: (1) An individual must file a claim; (2) A worker must have worked more than the essential minimum number of weeks and have earned higher than the earning requirement in the base period[1]; (3) The job separation must be involuntary. To continue receiving the UI benefits, a claimant must be available for work and active in job search throughout the unemployment spell. The weekly UI benefit amount is set to be at least one-half of the worker's weekly wage loss, limited by the maximum weekly benefit amount. To insure adequate coverage, the maximum weekly benefit amount should be high enough to cover 80 percent of the insured workers, among whom, if unemployed, could receive at least half of the usually weekly wages. The eligible individuals would receive a proportion of the past average earnings for maximum 26 weeks.

The actual award of UI benefits is a combination of coverage provisions, an individual's decision to apply for benefits, and state eligibility standards. In my model, I make the following assumptions to capture the most salient features of the current

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[20] Details can be found in the Department of Labour publication Unemployment Insurance: State Laws and Experience

program. First, I assume that those who qualify for UI are automatically covered without filing a claim, and receive it for maximum 6 months. Second, an individual is initially eligible if he was working in the month prior to the unemployment, has earned a weekly average of at least 80 dollars, and was laid off from work (e.g. $E_t^{UI} = 1$). The UI benefits are computed as:

$$UI_t = \max\{\min\{\gamma^{UI} y^{UI}, M\}, m\},$$

where γ is the replacement rate and y^{UI} the average weekly earnings, calculated based on gross income during the 12 months prior to unemployment. *M* represents the maximum weekly benefit and *m* the minimum. Third, to continue the benefit receipt, an individual must be active in job search at every period during the benefit entitlement period.

3.3.6 Government Transfer

I assume that the government provides an income floor through a universal means- tested program. Following Low and Pistaferri (2015), the program has three characteristics: (i) it is mean-tested only on income rather than on income and assets; (ii) the program provides cash benefits; and (iii) the take-up is 100%. The gross income for the program is defined as

$$y_t^{gross} = w_t h p_t + (UI_t E_t^{UI})(1 - p_t)$$

giving net income of $y_t = (1-\gamma_w) y_t^{gross} - d$, where d is the standard deduction for computing Food Stamp allowances. The value of the program is $W_t = \bar{T} - 0.3 \times y_t$, where $\bar{T}$, the maximum payment, is set assuming a household with two adults and two children. Individuals are eligible if net income is below the poverty line ($\underline{y}$), denoted as $E_t^W = 1$.

3.3.7 Social Security

After retirement, individuals only incur a consumption-savings problem. Reflecting the current rule, the individual's pension depends on this Average indexed Monthly Earnings (AIME), which is approximately his average income during this 35 highest earning years. The value of Social Security is given by

$$ss_t = \begin{cases} 0.9 \times AIME & AIME \le a_1 \\ 0.9 \times a_1 + 0.32 \times (AIME - a_1) & a_1 < AIME \le a_2 \\ 0.9 \times a_1 + 0.32 \times (a_2 - a_1) + 0.15 \times (AIME - a_2) & a_2 < AIME \le a_3 \\ 0.9 \times a_1 + 0.32 \times (a_2 - a_1) + 0.15 \times (a_3 - a_2) & AIME > a_3 \end{cases}$$

where a_1, a_2, a_3 are thresholds taken from legislation.

3.3.8 Intertemporal Budget Constraint

The inter-temporal budget constraint during the working life has the form

$$c_t + a_{t+1} \le [(1-\gamma_w) w_t h] p_t + UI_t E_t^{UI} (1 - p_t) + W_t E_t^W + (1+r) a_t$$

where a_t represents the assets at the beginning of the period. r is the return to saving. w_t is the hourly wage rate and h is the fixed number of working hours (150 hours per month). During employment, a worker of age t pays income taxes that constitutes γ_w fraction of their labour income. Taxes are used to finance the UI and Social Security benefits. The details of tax are described in Appendix A. Individuals are assumed not allowed to borrow against future earnings: $a_t \geq 0$. Once the individual is retired, his inter-temporal budget constraint follows:

$$c_t + a_{t+1} \leq (1+r)a_t + ss_t$$

where ss_t represents the income from social security.

3.3.9 Optimal Life-Cycle Behaviour

Optimal decisions depend on the state variables, denoted as $\Omega_t = \{a_t, \exp_t, age, u_{t-1}, y^{UI}, y_t^{gross}, AIME\}$, preferences denoted as $\Theta = \{\eta, \rho, \beta\}$, and the parameters that determine the data generating process for the state variables denoted as $X = \{\alpha_1, \alpha_2, \alpha_3, \alpha_4, \sigma_\zeta^{\ 2}, \sigma_e^{\ 2}, \delta, \chi_1, \chi_2, \chi_3, \chi_4, \gamma^{UI}, M, m, \overline{T}, d, \underline{y}, a_1, a_2, a_3, r, \gamma_w\}$.

I denote the value function when employed as V_t^E and is written as:

$$V_t^E(\Omega_t) = \max_{\{c_t\}}\{U(c_t, p_t = 1) + \beta\delta E_t V_{t+1}^U(\Omega_{t+1}) + \beta(1-\delta)E_t \max\{V_{t+1}^E(\Omega_{t+1}), V_t^U(\Omega_{t+1})\}$$

where $V_{t+1}^U(\Omega_{t+1}) = \max\{V_{t+1}^A(\Omega_{t+1}), V_{t+1}^N(\Omega_{t+1})\}$ represents the value of being unemployed. Losing job, laid off or quit, would put the individual for at least one period of unemployment. Combining the uncertainty of job search, individuals would have a strong preference to not quit the job. When unemployed, there are two states the individual can be: unemployed and not searching for jobs, V_t^N , unemployed and searching for jobs V_t^A . The value function for unemployed and searching for jobs is given by

$$V_t^A\{\Omega_t\} = \max_{\{c_t, s_t\}}\{U(c_t, p_t = 0, s_t) + \beta\lambda_t E_t \max\{V_{t+1}^E(\Omega_{t+1}), V_{t+1}^U(\Omega_{t+1})\} + \beta(1-\lambda_t)E_t[V_{t+1}^U(\Omega_{t+1})]$$

The value function for unemployed and not searching for jobs is:

$$V_t^N(\Omega_t) = \max_{\{c_t\}}\{U(c_t, p_t = 0) + \beta E_t[V_{t+1}^U(\Omega_{t+1})] .$$

The optimal search intensity is the amount of effort that leaves the individual indifferent between searching and staying unemployed, and thus described as:

$$s_t^* = \arg\max_{s_\in[0,1/\chi_t]}\{V_t^A(\Omega_t), V_t^N(\Omega_t)\} .$$

In the model, active search does not guarantee a successful job offer but cause disutility to the individuals. Therefore, individuals would have incentives not to search for jobs whenever the situation allows, reflecting the moral hazard behaviours in labour supply in the real data.

Upon retirement, the individual's choice problem ends since he could no longer search or work. The retirement problem entails only a consumption-savings decision. The value function for the retirement individual is

$$V_t^R(\Omega_t) = \max_{\{c_t\}} \{U(c_t) + \beta E_t[V_{t+1}^R(\Omega_{t+1})]\}$$

subjective to the budget constraint.

3.3.10 Model Solution

There is no analytical solution for the model. The model has to be solved numerically by backward recursion from period T, solving at each period for the value functions. To solve the model, I follow an approximation method developed by Keane and Wolpin (1994).

3.4 Data

I use the National Longitudinal Survey of Youth 1979 (NLSY79) for the model estimation. The NLSY79 is a longitudinal survey of 12,686 individuals from the cohort born between 1957 to 1964. They have been sampled annually from 1979 to 1994 and biennially from 1994 to 2012. The NLSY79 has several advantages over other longitudinal datasets for this study: (i) It contains extensive information on each individual’s labour market behaviour, educational outcomes, government program participation, assets and income. (ii) It provides a week-by-week record of individuals’ full work history including job-to-job transitions and the resulting wage each time, as well as the gaps in employment. (iii) The NLSY79 has very rich information regarding the reason of unemployment.

The sample selection is as follows. I focus on working-age male heads of household aged between 23 and 55 to estimate the model. Individuals who are missing more than three survey rounds are excluded. The final sample consist of 1,904,400 month-individual observations, for 6,348 male respondents.

The NLSY79 asked individuals to report every job the respondents held currently or since the last interview. At the first interview, respondents older than 18 were required to identify each job held since age 18, and those who were younger than 18 reported job history between age 15 to 17. Therefore, I could obtain a complete record of individuals' work history without left-censoring. At each interview, respondents are required to report the start and end date of any job held since last interview. In addition, a weekly record of each respondent's labour market status (e.g. working, out of the labour force) are reported from January 1st 1978. Combining all the information, I construct a monthly employment indicator for each individual and the duration of unemployment spells. I classify employed in a given month if respondents work at least one week in that month.

Table 3.1 reports the summary statistics of the sample (pooling data for all years). Individuals in the sample on average achieve 12.65 years of education. The average employment rate is 80.3% with an average unemployment duration of 2.82 months. 40% of the sample are married. And the average hourly wage rate is 9.14 USD.

3.5 Identification

This section describes the identification strategy. The unknown parameters of the model are identified in two steps. In the first step, I calibrate some of the parameters in X based on findings from the literature. In the second step, I use the numerical methods described in Section 3.10 and estimated data generating process for the state variables to simulate life cycle profiles for hypothetical individuals. The parameters are estimated using Indirect Inference Method by matching a set of moments from the NLSY79.

3.5.1 Pre-determined Parameters

The values of relative risk aversion coefficient ρ and the inter-temporal discount rate β are fixed. I set the coefficient of relative risk aversion ρ equals to 1.5, taken from Low et al. (2005), whose model of consumption also allows for non-separable labour supply. Following Kaplan (2012), β is set to be 0.964 on a monthly basis. The replacement rate of UI benefit, γ^{UI}, is fixed as 0.5, reflecting the average replacement rate of the current US unemployment insurance program. The maximum (M) and minimum amount (m) of weekly UI benefits are set as \$450 and \$45. The monthly maximum value of payment for universal means-tested program, is set as \$649, assuming a household size of four. The detailed setting of Social Security can be found in Appendix A. Finally, I set the interest factor as r = 0.016 on an annual basis and assume a life-span of 50 years with the last 10 years in compulsory retirement.

3.5.2 Internally Estimated Parameters

Identification of the remaining structural parameters of interest ($\eta, \delta, \chi_1, \chi_2, \chi_3, \chi_4, \alpha_1, \alpha_2, \alpha_3, \alpha_4, \sigma_\zeta, \sigma_e$) is achieved by Indirect Inference (see Gourieroux et al., 1993, Smith, Jr, 1993, and Gallant and Tauchen, 1996). This simulation-based estimation method relies on matching moments from auxiliary model, estimated on both real and simulated data, generated using the decision rules and other equations of motion described by the life-cycle model. Parameter of interests are chosen to minimise the distance between the moments of the auxiliary model estimated from the observed data and the moments of the auxiliary model estimated from the simulated data. The closer the link between the moments of the auxiliary equations and the structural parameters, the more reliable is the estimation.

To provide credible identification of the parameters, auxiliary moments are selected to reflect individuals' choices: how much to consume, whether to quit if employed, whether to search for jobs and whether to accept the arriving job offer if unemployed. Since age is an important factor in the labour supply behaviours, I choose auxiliary moments conditional individuals' age group. Table 3.1 in Appendix C describe the auxiliary model parameters and link these parameters to the identification of the life-cycle model.

The adopted auxiliary model contains 44 one-parameter sub-models that are sufficient to identify all parameters. Following Low and Pistaferri (2015), the indirect inference estimator of the parameters of the life-cycle model is defined as

$$\widehat{\omega} = argmin(\hat{\phi} - \hat{\phi}(\omega))'\Sigma(\hat{\phi} - \hat{\phi}(\omega))$$

where $\hat{\phi}$ denotes the vector of auxiliary model parameter estimates obtained from the real data, and $\hat{\phi}(\omega)$ denotes the auxiliary model parameters estimated using the simulated data with parameter value ω. The diagonal weighting matrix Σ has diagonal elements equal to the inverse of the variance of each of the auxiliary model parameters, estimated using bootstrapping with clustering at the individual level. Standard errors are obtained using the formula provided by Gourieroux et al. (1993).

3.5.3 Indirect Inference Results

In this section, I present the results on the moments matched by Indirect Inference and estimates of the structural parameters. Targeted moments are divided into five panels: wage moments, flows into and out of employment, employment rates, and unemployment duration. Details of the moments are in Table 3.4.

Figure 3.1 shows the life-cycle profile of the hourly wage rate. On average, hourly wage rate increases 30 percent from age group 23 to 30 to age group 31 to 35 but drops to 16% for every five-year age gap until age 50, and further slows down to 7% from age 50 to 55. The auxiliary moments of log hourly wage rates are very closely replicated by the simulated moments for all age groups. However, the effects of education and working experiences on hourly wage rate are lower in the data than in the simulation, but qualitatively the effects are similar.

In Figure 3.2, I examine the flows into employment from unemployment by age. These moments capture individuals' willingness to take-up job offers and exit from unemployment. The model predicts higher take-up rate than the data, indicating a smaller disutility in employment. However, the model captures the general trend: the likelihood to transit from unemployment into employment decreases with age, reflecting the volatility of the early career.

Figure 3.3 reports the flows into unemployment by age. In the model, there are two channels for unemployment: involuntary layoff and voluntary quits of exiting jobs. In the data, quits are infrequent since a worker would not be eligible for benefits. The model simulates the flows from employment into unemployment well for age group 23 to 35 but over estimate for age group 36 to 50.

Figure 3.4 compares the data and the model employment rate over the working age. Overall, the fit is good, capturing the light increase in employment in ages 25 – 36 and the subsequent drop for older ages. Young workers in the model have relatively lower levels of assets while older workers have relatively high levels of savings, some of which were accumulated for precautionary reasons against unemployment and income shocks. Therefore, towards retirement, workers who become unemployed by an exogenous shock tend to reject job offers and receive unemployment benefits for six months. The results are consistent with the observations of Michelacci and Ruffo (2015), Setty (2017) that moral hazard increases with age.

Figure 3.6 describes the distribution of unemployment duration in the model relative to the data. The model performs reasonably well in matching the relative moments for age 23 to 35 but underestimate the unemployment durations for older age.

In Table 3.2, I report the Indirect Inference parameter estimates corresponding to these moments. Individuals with at least 12 years of education earns on average 37% more in hourly wage rate. Wage increases with age, reflecting the accumulated returns to human capital. I estimate that job is destroyed on average every 26 quarters. Individual search productivity decreases with age but increases with education.

3.5.4 Implications and External Fit of the Model

In this section, I discuss the implications of the estimates for the unemployment insurance and the extent of self-insurance. I compare predictions of the model with evidence from the predominantly reduced form literature. This is a way to verify that the model can reproduce statistics about the UI program that were not explicitly targeted by the estimation procedure (external validity).

The reduced form literature on UI has analysed the incentive costs of UI by looking at a number of behavioural response, particularly the elasticity of the hazard rate with respect to benefits. Since employment is associated with disutility, worker's employment decision is driven by the tension between enjoying higher consumption when employed and exerting an effort that reduces their utility. The elasticity of the hazard rate with respect to benefits captures this tension. The higher the elasticity, the more sensitive workers are to unemployment benefits. The elasticity is calculated as the change in the hazard rate in responses to a change in the replacement rate of UI benefits. Two recent studies using SIPP data show that the elasticity is -0.53 for Chetty (2008) and -0.36 for Michelacci and Ruffo (2015). In my model, this elasticity is at the lower end of this range of estimates (my estimate is -0.19).

An important part of the model is individual's ability to self-insure through asset accumulation. In the model, individuals could only accumulate through liquid assets while in the data individuals could have both liquidity financial wealth as well as illiquid assets. Therefore, I do not match moments using the asset data. Figure 3.7 shows the life-cycle asset profile of both data and the simulation. The simulation in general captures well the asset accumulation especially around retirement. In addition to asset, consumption is another important measurement of welfare. Unfortunately, NLSY79 do not provide consumption information and there I could not match the consumption profile from actual data. Figure 3.8 describes the life-cycle consumption where it shows a clear hump shape, consistent with the literature.

3.6 Unemployment Insurance Savings Account

The most important use of the structural estimation is the ability to analyse the effects on welfare and behaviour of alternative policy designs. In this section, I evaluate the effects of combining unemployment insurance savings account with unemployment insurance, forming a two-tiered unemployment insurance program. In addition to the existing policy instruments: replacement rate (γ^{UI}) and benefit duration, the two-tiered program has two extra features: UISA deposit rate (ϕ) and withdraw rate (ϖ).

The system works as following. Each individual is required to save ϕ percent of the pre-tax wage income in his UISA during employment. When encounter an unemployment spell, the individual would first withdraw from his own UISA. The eligibility requirements for UISA withdraw is the same as the eligibility criteria for current UI. The amount an individual could withdraw from the UISA during unemployment is equal to the current UI benefit (UI_t). Upon the depletion of the UISA, if the individual is still unemployed, he would be eligible for UI and receive it for maximum 26 weeks.

UISA earns a market rate of return on existing balances and becomes available to individuals upon retirement. The balance of UISA is subjective to an upper bound of $\overline{M}$. The balance of UISA is computed as:

$$Q_t = \sum_{t=1}^{T} (1+r)^{t-1} [\phi w_t p_t - UI_t (1-p_t) E_t^{UI}].$$

Under the two-tiered UI model, the individual inter-temporal budget constraint before retirement becomes:

$$c_t + a_{t+1} \leq [(1-\phi) w_t h] p_t + UI_t E_t^{UI} (1-p_t) + W_t E_t^{W} + (1+r) a_t - \tau_t .$$

At the first period of retirement, the remaining balance of UISA is available to the individual and becomes part of the assets.

3.6.1 UISA Deposit Rate

In the first experiment, I consider the effects of varying UISA deposit rates. Focusing on the transition from unemployment to employment, a worker who has a job offer faces several disincentives to accept job offers. First, accepting the offer is associated with disutility from work. Second, the worker could enjoy unemployment benefit while unemployed. Third, a worker who experiences a low-income draw may wait for a better draw, similar to the basic McCall search model. Table 3.3 displays statistics by age group for monthly income, UISA amount, unemployment duration, employment rate and probability transit into employment conditional on being unemployed the last period for three levels of deposit rates: ϕ = 0, 1% and 4%.

Compare the life-cycle income profiles, the two-tiered unemployment insurance program does not have much effects. Compared to the baseline scenario (ϕ = 0), the two-tiered program significantly increase the employment rate and reduces the unemployment duration for age 23 to 45. Workers who are 46 years old and above would stay longer in unemployment. The results indicate two effects of the two-tiered program: (i) it effectively reduces moral hazard costs associated with the traditional unemployment insurance and encourage labour participation especially for the younger workers; (ii) it might encourage early retirement of older workers who experience an unemployment spell given the high amount accumulated in individual UISA.

I also analyse the consumption decisions of workers and how these decisions are affected by different levels of UISA deposit rates. As Figure 3.6 shows, there is a little difference in the life-cycle profile of average monthly consumption between the baseline and the alternative program. Under the two-tiered program, workers consume less from age 23 to 50 but enjoy higher consumption from age 50 and onwards. Compared with worker from the baseline, workers enjoy, on average $200 less each month in age 23 to 50, and on average $300 more from age 51 to 55. The results indicate that the two-tiered program facilitate a better transfer of resources over the life-cycle. On average, the two-tiered unemployment insurance program increase the overall welfare by 1% over age groups. Increasing the UISA deposit rate from 1% to 4% does not change the welfare measurement much.

3.6.2 Generosity of the Two-tiered Program

In addition to the deposit rate, another important feature of the UISA is the withdraw rate. Earlier literature has shown that changes in the replacement rate of the UI have significant effects on individuals' labour supply choices. In this section, I investigate the effects of alternating the generosity of the program by varying replacement rate. To compare with the results from first experiment, I set the deposit rate at 4% and vary the replacement rate. Table 3.4 displays statistics by age group for income, unemployment duration, employment rate, average UISA amount and percentage transit into employment conditional on being unemployed the last period for three levels of replacement rate.

Comparing the life-cycle income profiles, workers earn less from age 36 and above under a more generous two-tiered insurance program but not differences from age 23 to 35. Compared with workers with a replacement rate of 50%, workers on average earn $200 less each month from age 36 to 45 and $800 less each month from age 46 to 62. The results could be explained by the loss of working experiences which lead to lower human capital returns. The findings on employment rate and unemployment duration support the same argument. Under a more generous program, workers are less likely to accept job offers and have a longer unemployment duration. Figure 3.7 shows the monthly consumption level under different levels of program generosity. Workers end to enjoy a lower consumption level from age 23 to 45 under a less generous program but enjoy a higher consumption level from age 46 to 62.

Combining the results from Table 3.3, it shows that a less generous two-tiered unemployment insurance program could effectively reduce the moral hazard costs and increases labour participation especially for the young workers without compromising much of the consumption. A generous two-tiered unemployment insurance program harms total welfare not only by reducing consumption but also the life-cycle incomes. The findings are consistent with Schmieder et al (2012, 2013) that prolonged unemployment spell induced by high UI benefits could leads to decline in earnings.

3.7 Conclusion

In this paper, I study the effects of an alternative unemployment insurance using a life-cycle framework. One of the major concerns for providing unemployment insurance is the associated moral hazard costs. Individuals stay unemployed longer because of lower costs of unemployment. The UISA is a mandatory individual savings accounts that can be used only during unemployment or retirement. Combining the UISA and the UI would both provide insurance and reduce moral hazard costs.

I empirically evaluate the proposed two-tiered unemployment insurance system through a life-cycle model, which allows individual savings, labour supply and job search intensities under non-separable preferences. The simulations show that the two-tiered unemployment insurance program effectively reduces moral hazard behaviours by reducing the unemployment duration and increasing employment rate. The UISA helps to foster long-term saving by reducing consumption for younger workers and increasing for the older. Compared to the existing unemployment insurance, the two-tiered program improve the workers' welfare by 1%.

Tables

Table 3.1 Summary Statistics

Variable	**Mean**
Age (years)	32.43
	(9.93)
Education (years)	12.65
	(2.54)
Unemployment duration (months)	2.82
	(14.09)
Employed	0.803
	(0.398)
Unemployed	0.054
	(0.226)
Non-employed	0.147
	(0.354)
Assets (USD)	27,487.3
	(42,046.5)
% Married	0.40
	(0.490)
Hourly wage rate (USD)	9.14
	(9.48)

Note: USD in 1982 dollar.

Table 3.2 Estimated Parameters

Parameter	Estimates
Panel A: Wage Equations	
Intercept	-7.61
Age	0.1409436
Age square	-0.1661994
Education >= 12 years	0.368478
Working experience	0.0045
S.D for permanent productivity shock	0.09
S.D for transitory productivity shock	0.004
Panel B: Preference and Labor Market	
Disutility or working	-1.5
Job destruction rate	0.03
Panel C: Search Productivity	
Intercept	0.090514
Age	0.0433493
Age square	-0.065403
Education >= 12 years	0.0246287

Table 3.3 Moments for Deposit Rates

	ϕ= 0	ϕ = 1%	ϕ = 4%
Age[23,30]			
Income ($K)	1.684	1.646	1.571
UISA Amount ($K)	-	0.585	1.771
Unemployment Duration	3.628	3.314	3.259
Employment Rate	0.868	0.871	0.883
Probability of transiting into employment given unemployed at t-1	0.261	0.271	0.276
Age[31,35]			
Income ($K)	2.893	2.912	2.839
UISA Amount ($K)	-	1.019	1.79
Unemployment Duration	3.804	3.158	2.525

	ϕ= 0	ϕ = 1%	ϕ = 4%
Employment Rate	0.888	0.918	0.919
Probability of transiting into employment given unemployed at t-1	0.267	0.306	0.365
Age[36,40]			
Income ($K)	4.14	4.258	4.047
UISA Amount ($K)	-	1.019	1.95
Unemployment Duration	3.433	3.401	2.71
Employment Rate	0.87	0.907	0.918
Probability of transiting into employment given unemployed at t-1	0.276	0.305	0.354
Age[41,45]			
Income ($K)	5.235	5.596	5.399
UISA Amount ($K)	-	1.376	2.095
Unemployment Duration	3.857	3.445	3.749
Employment Rate	0.815	0.903	0.906
Probability of transiting into employment given unemployed at t-1	0.308	0.294	0.284
Age[46,50]			
Income ($K)	6.238	6.499	6.531
UISA Amount ($K)	-	0.822	2.077
Unemployment Duration	3.321	3.266	3.483
Employment Rate	0.851	0.766	0.866
Probability of transiting into employment given unemployed at t-1	0.274	0.277	0.251
Age[51,55]			
Income ($K)	6.924	7.018	7.047
UISA Amount ($K)	-	0.747	1.244
Unemployment Duration	3.219	3.266	3.419
Employment Rate	0.821	0.793	0.643
Probability of transiting into employment given unemployed at t-1	0.299	0.282	0.242
Age[56,62]			
Income ($K)	6.667	6.721	6.354
UISA Amount ($K)	-	0.237	0.674
Unemployment Duration	7.786	3.897	9.479
Employment Rate	0.421	0.549	0.383

	ϕ= 0	ϕ = 1%	ϕ = 4%
Probability of transiting into employment given unemployed at t-1	0.122	0.221	0.111

Table 3.4 Moments for Replacement Rates

	replacement rate = 40%	replacement rate = 50%	replacement rate = 60%
Age[23,30]			
Income ($K)	1.622	1.571	1.619
UISA Amount ($K)	1.727	1.771	1.748
Unemployment Duration	3.737	3.259	4.816
Employment Rate	0.855	0.883	0.832
Probability of transiting into employment given unemployed at t-1	0.231	0.276	0.185
Age[31,35]			
Income ($K)	2.859	2.839	2.837
UISA Amount ($K)	1.845	1.79	1.6
Unemployment Duration	3.564	2.525	6.213
Employment Rate	0.911	0.919	0.826
Probability of transiting into employment given unemployed at t-1	0.269	0.365	0.149
Age[36,40]			
Income ($K)	4.067	4.047	3.875

	replacement rate = 40%	replacement rate = 50%	replacement rate = 60%
UISA Amount ($K)	1.936	1.95	1.699
Unemployment Duration	3.936	2.71	6.384
Employment Rate	0.901	0.918	0.825
Probability of transiting into employment given unemployed at t-1	0.279	0.354	0.152
Age[41,45]			
Income ($K)	5.498	5.399	4.955
UISA Amount ($K)	2.088	2.095	1.805
Unemployment Duration	3.145	3.749	9.187
Employment Rate	0.908	0.906	0.798
Probability of transiting into employment given unemployed at t-1	0.278	0.284	0.108
Age[46,50]			
Income ($K)	6.379	6.531	5.901
UISA Amount ($K)	1.617	2.077	1.49
Unemployment Duration	3.848	3.483	3.68
Employment Rate	0.768	0.866	0.742
Probability of transiting into employment given unemployed at t-1	0.264	0.251	0.289
Age[51,55]			

	replacement rate = 40%	replacement rate = 50%	replacement rate = 60%
Income ($K)	6.894	7.047	6.134
UISA Amount ($K)	1.678	1.244	1.106
Unemployment Duration	3.753	3.419	3.969
Employment Rate	0.716	0.643	0.64
Probability of transiting into employment given unemployed at t-1	0.194	0.242	0.252
Age[56,62]			
Income ($K)	6.021	6.354	5.432
UISA Amount ($K)	0.258	0.674	0.348
Unemployment Duration	8.825	9.479	5.506
Employment Rate	0.204	0.383	0.334
Probability of transiting into employment given unemployed at t-1	0.108	0.111	0.161

Table 3.5 Targeted Moments

Mean of:	Observed	Simulated
Panel A: The Log Wage Function		
Log wage | Age [23,30]	-4.86	-4.599
	(0.006)	
Log wage | Age [31,35]	-4.49	-4.016
	(0.008)	
Log wage | Age [36,40]	-4.235	-3.659
	(0.01)	
Log wage | Age [41,45]	-4.072	-3.407
	(0.012)	
Log wage | Age [46,50]	-3.921	-3.239
	(0.013)	
Log wage | Age [51,55]	-3.853	-3.148
	(0.02)	
Log wage | High exp	-3.909	-3.4004
	(0.011)	
Log wage | High educ	-4.553	-3.551
	(0.007)	
Variance of log wage	0.646	0.428
Panel B: Flows into Employment		
Full-time employment | Age [23,30] & Unemp. at t-1	0.126	0.271
	(0.002)	
Full-time employment | Age [31,35] & Unemp. at t-1	0.097	0.287
	(0.003)	
Full-time employment | Age [36,40] & Unemp. at t-1	0.083	0.282
	(0.003)	

Mean of:	Observed	Simulated
Full-time employment | Age [41,45] & Unemp. at t-1	0.067	0.298
	(0.003)	
Full-time employment | Age [46,50] & Unemp. at t-1	0.05	0.264
	(0.002)	
Full-time employment | Age [51,55] & Unemp. at t-1	0.04	0.296
	(0.003)	
Panel C: Flows into Unemployment		
Involuntary layoff | Age [23,30] & Emp. at t-1	0.03	0.0293
	(0.004)	
Involuntary layoff | Age [31,35] & Emp. at t-1	0.027	0.029
	(0.004)	
Involuntary layoff | Age [36,40] & Emp. at t-1	0.02	0.0282
	(0.004)	
Involuntary layoff | Age [41,45] & Emp. at t-1	0.013	0.0279
	(0.004)	
Involuntary layoff | Age [46,50] & Emp. at t-1	0.02	0.0286
	(0.005)	
Involuntary layoff | Age [51,55] & Emp. at t-1	0.027	0.0281
	(0.007)	
Panel D: Employment Status		
Full-time employment | Age [23,30]	0.838	0.878
	(0.003)	
Full-time employment | Age [31,35]	0.862	0.905
	(0.004)	

Mean of:	Observed	Simulated
Full-time employment | Age [36,40]	0.869 (0.004)	0.867
Full-time employment | Age [41,45]	0.848 (0.005)	0.814
Full-time employment | Age [46,50]	0.809 (0.005)	0.847
Full-time employment | Age [51,55]	0.771 (0.009)	0.824
Panel E: Unemployment Duration		
Unemployment Duration | Age [23,30]	3.045 (0.127)	3.628
Unemployment Duration | Age [31,35]	3.767 (0.319)	3.804
Unemployment Duration | Age [36,40]	4.998 (0.761)	3.433
Unemployment Duration | Age [41,45]	4.875 (0.854)	3.857
Unemployment Duration | Age [46,50]	7.256 (1.110)	3.321
Unemployment Duration | Age [51,55]	8.168 (2.261)	3.219

Figures

Figure 3.1 Life-cycle profile of Hourly Wage Rate

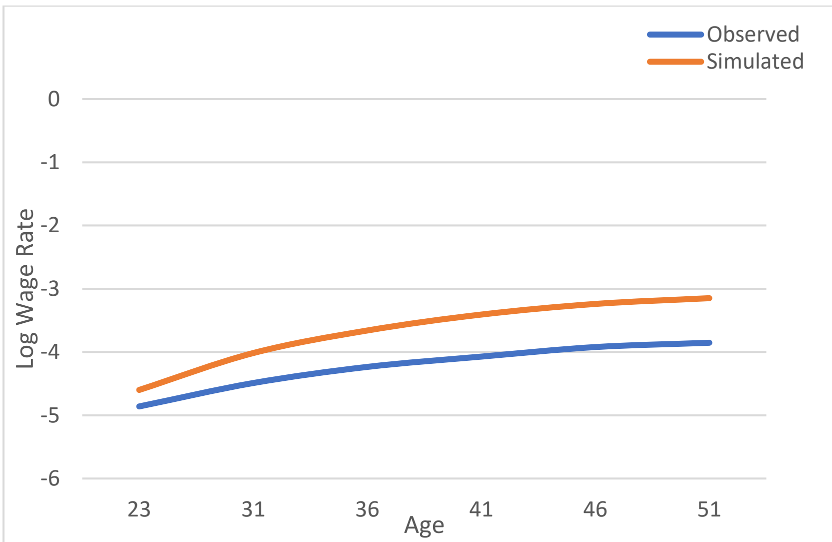


Figure 3.2 Flows into Employment from Unemployment

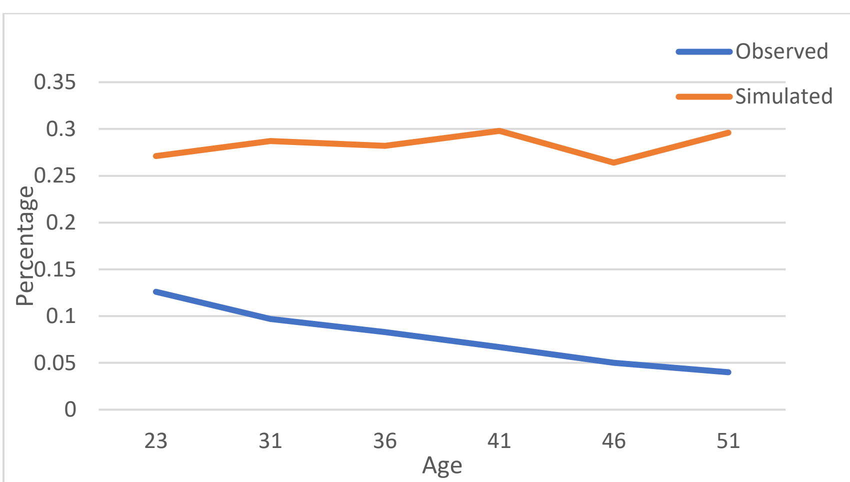


Figure 3.3 Distribution of Flows into Unemployment from Employment

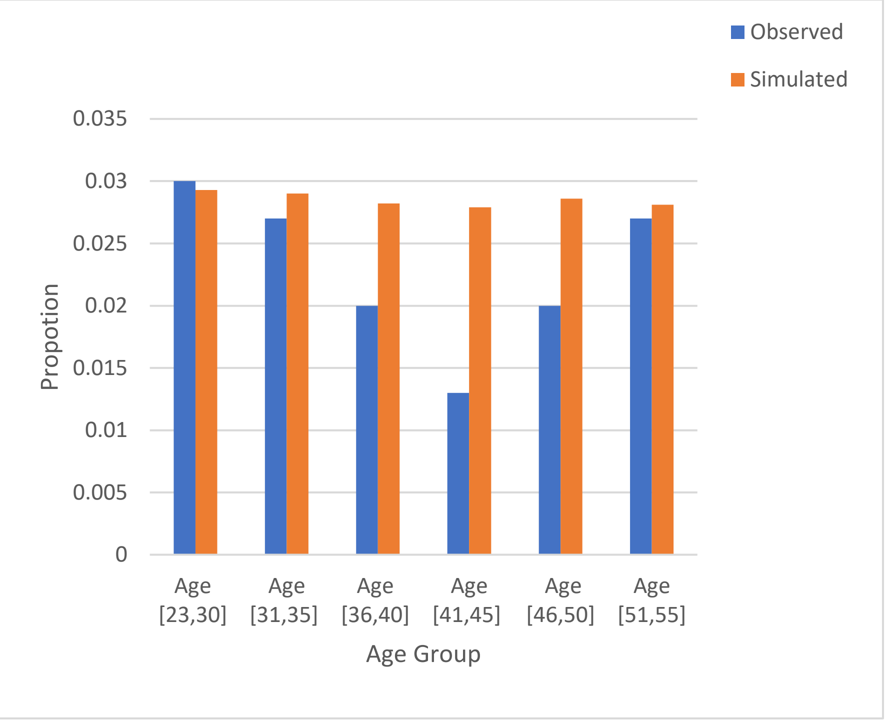


Figure 3.4 Employment Rate over the Working Age

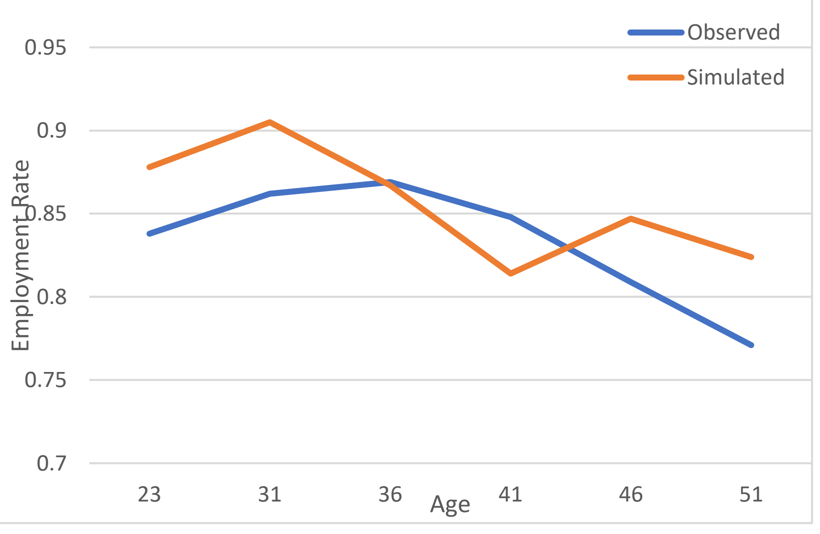


Figure 3.5 Unemployment Duration

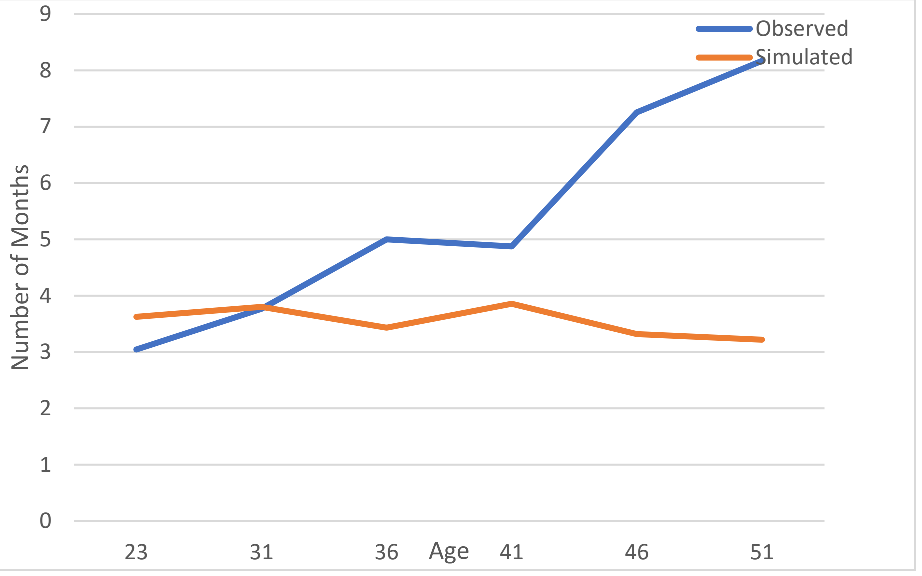


Figure 3.6 Monthly Consumption

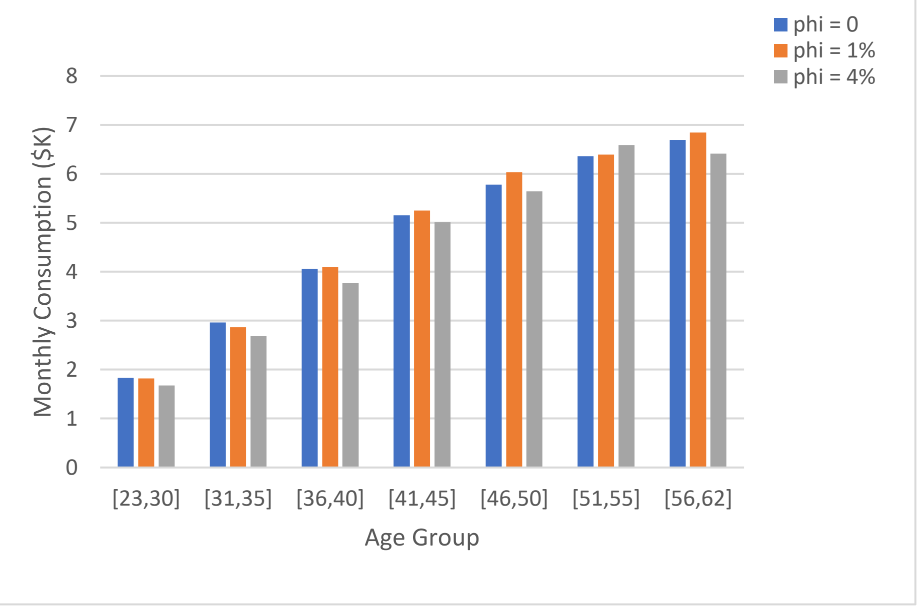
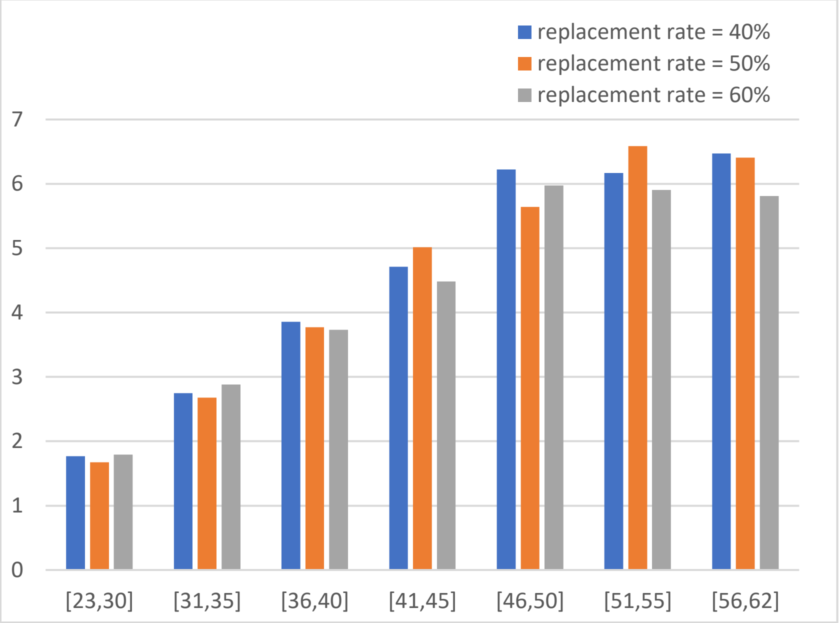


Figure 3.7 **Monthly Consumption for Different Replacement Rate**



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