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Measuring Catastrophic Health Expenditure: Innovation and Validation

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by

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Abstract

This research attempts to provide an innovative approach to measuring Catastrophic Health Expenditure (CHE) that captures the dynamics of household assets globally. CHE is a major cause that pushes households into poverty or forces households already in poverty into even deeper poverty. The study estimates how dynamically measured CHE affects a household's assets by exploiting a panel dataset with a plethora of household financial information. The innovative approach is then validated by comparing the accuracies of future CHE incidence prediction, using the CHE indicators in the current period along with other household characteristics, fitted into a machine-learning classification algorithm.

Keywords: Catastrophic health expenditure, health expenditure, health insurance, poverty alleviation, illness-caused poverty, measurements of CHE, asset dynamics, innovation, validation, machine learning

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Chapter 1: Introduction

Countries and organizations around the world work hard on carrying out policies and programs to alleviate poverty. According to the World Bank's estimation, 10% of the world's population lived on less than $1.90 a day in 2015. Global organizations including the United Nations and the World Bank have announced their mission of ending extreme poverty by 2030. Despite this, the World Bank estimates the world is not on track to achieve these goals by 2030 (World Bank Group, 2018). For instance, they estimated in 2018 that the number of people living in poverty in the Sub-Saharan Africa region had increased to 413 million in 2015 from 278 million in 1990. This demonstrates how, unfortunately, alleviating poverty is not an easy task. Many studies have shown that poor health is associated with low income (Bartel and Taubman, 1979; Brazenor, 2002; Kraut et al., 2001; Mcintyre et al., 2006). Callander and Schofield (2015) argued that among poor individuals, those with low income and poor health or with poor health and insufficient educational attainment are more likely to stay in chronic poverty than those whom are merely low-income individuals. Therefore, multidimensional poverty measures including health as a factor are a useful tool to accurately target those who are in need of aid for poverty alleviation.

Health is an important factor in analyzing poverty and poverty is often considered a leading cause of poor health. For instance, poverty often prevents individuals from accessing health care when needed and poor individuals tend not to be able to work as much as when they were healthy and thus lose earnings (Sala-i-Martin, X., 2005; Phipps, 2003). Furthermore, households with severely or chronically ill members reduce their daily consumption of goods and services to pay for drugs, health and wellness services, and other activities in seeking care. Among poor households ill household members, they are pushed into poverty or forced into deeper poverty not only due to paying for drugs that can mean the difference between life and death, but also forgone income (McIntyre et al., 2006). Thus, providing medical care, subsidies, and health insurance in impoverished areas does more than keeping people healthy. It might help people to escape from poverty (Mayer 2001). From a policy perspective, providing health insurance, subsidies, and medical care may also increase overall labor productivity through an increase in human capital (Bloom, Canning and Sevilla, 2004). Experiments attempting to find a suitable policy to help the poor with varying instruments, such as cash transfers, in-kind transfers, community-based development and microfinance loans have been conducted in diverse areas, including developed and developing countries (Cho and Honorati, 2013, Atkinson et al., 2013, Banerjee et al., 2015, Benhassine et al., 2015, Molyneux et al., 2016, Aker et al., 2016, Cahyadi et al., 2018). Helping the poor by providing healthcare access and health insurance directly was also considered by researchers as a method to combat poverty, along with how to efficiently allocate the budgeting of fund (Thorbecke and Berrian, 1992). Therefore, precisely determining who is truly in need of subsidies in healthcare and health insurance resource allocation is important in mitigating poverty from a health economics perspective. In other words, it is advantageous for governments and organizations would like to prevent people from falling into illness-caused poverty, but they want to do so in cost-effective ways.

The health expenditures that negatively affect households' basic consumptions and drive households into poverty are considered catastrophic (Wyszewianski, 1986; Berki, 1986; Xu et al., 2003; Wagstaff and Doorslaer, 2003). Empirical evidence of the prevalence of catastrophic health expenditure (CHE) has been observed by many researchers and organizations. Specifically, Xu et al. (2003) found that the proportion of households facing catastrophic payments from out-of-pocket (OOP) health expenses varied widely between countries. The proportion is especially high in some countries in transition, such as Vietnam and Zambia. In the later research using the same method (Xu et al. 2007), it is found that around 100 million households are pushed under the poverty level simply because they need to pay for the health services they use. More than 90% of these individuals live in low- income countries. Flores and O'Donnell (2016) measured the exposure of a household to particularly onerous medical expenses. These researchers aggregated the risk of medical expenditure exceeding a set of threshold they established, the loss due to predictably low consumption of other goods and the further loss arising from the volatility of medical expenses exceeding the threshold. Across the seven Asian countries that they estimated, risk was highest in Laos, then in China, with the lowest in Malaysia. While comparing the loss from the volatility of consumption below the threshold as a proportion of total loss, Laos has the greatest loss, followed by India and China, with Malaysia having the lowest amount of losses (Flores and O'Donnell, 2016).

Currently, various methods exist for the measurement of CHE globally. Specifically, four methods currently exist to determine whether a health expenditure is considered catastrophic for a household. The most commonly used method was proposed by Xu et al. (2003). They proposed a method of measuring CHE as an OOP expenditure that exceeds 40% of a household's “Capacity to Pay”. The second method concerns whether the OOP payment for health services exceeds a certain fraction of household income (Berki, 1986). The third method is whether a household’s health expenditure, including all sources of payments, exceeds a certain fraction of household income (Wyszewianski, 1986). The fourth method of measuring CHE is a household’s OOP exceeding the household’s “Ability to Pay” (Wagstaff and van Doorslaer, 2003). The difference between the “Capacity to Pay” in the first method of measurement and the “Ability to Pay” in the fourth is the “Capacity to Pay” is calculated by a household’s expenditure minus the household’s subsistence needs. In contrast, the “Ability to Pay” is the remaining income after paying for subsistence needs. More detailed information about these two methods including the measurement of subsistence needs is discussed in the next chapter.

The first method as proposed in Xu et al. (2003) is the most common method held in economic literature. To date, Xu et al.’s (2003) study has been cited by 1,912 papers. However, this measurement has several limitations, leading to the problem that many households with the risks of falling into poverty due to health expenditure might not be captured. First, this method uses a high threshold to determine CHE, where households' health expenditure below this threshold might be at the far left of the distribution for net income. Second, this method only captures the direct health expenditure, such as the spending on medicine and in-hospital, but not other health-related expenditure, such as the cost of seeking care and the forgone earnings for a household member in order to take care of the sick household member. Also, this method does not capture the importance of households' financial and physical asset that could dilute the catastrophe of a high health expenditure (Flores et al., 2008), which can make some households less affected by the other who hold less assets at the same income level. In addition, by using the same percentage of remaining income as the threshold of CHE for all the countries and regions, researchers neglect region-specific characteristics for households in various regional groups.

There exists a call for research to measure CHE more precisely. This study takes advantage of a panel dataset with a large survey scale, rich financial information to indicate households’ wealth, an accurate sampling design and strict interviewing rules leading to a significantly low rejection rate compared to other surveys. The goal of this research is to propose a more precise measurement of CHE and validate this method, thus distinct policies to achieve precision poverty alleviation can be made. In this study, we examine three research questions:

First, can we propose an innovative approach to measure CHE that captures the dynamics of poverty? Second, households with what kind of characteristics are more likely to face CHE than those without, using the new measurement of CHE? Finally, who, among the households faced CHE using the new approach of measure, were left behind by using the most commonly used measurement of CHE?

This is the first study to propose a measurement of CHE that captures the households' asset dynamics. Its main methodology to validate the proposed dynamic measurement is to estimate the impact of CHE on households' wealth, using both the conventional method and the innovative method, and to compare the difference in the identification of households facing CHE using both methods. The new approach distinguishes health expenditure that households are facing in a more precise manner so that following policies can be made to help households reducing the risk of CHE.

The rest of this thesis is divided in six Chapters: Chapter 2 provides a literature review of CHE and Illness-caused Poverty in China; Chapter 3 proposes an innovative methodology of measuring CHE from a dynamic perspective and the validation of the method; Chapter 4 describes the study setting, the choice of data, the selection strategy of sample and the construction of key variables; Chapter 5 provides evidence for estimating and validating the innovative method to measure CHE; Chapter 6 provides the conclusion of this study, compares the results of this study from other studies, discusses the possible explanations of the differences, and limitations of this study; and Chapter 7 presents policy implications.

Chapter 2: Literature Review: Catastrophic Health Expenditure and Illness-caused Poverty

Section 2.1 Why Measuring CHE: Evidence of Health Expenditure related Poverty

Health spending contributes significantly to poverty, and this happens in developing countries and some high-income countries lacking universal health insurance. Doorslaer et al. (2006), having analyzed eleven Asian countries (representing 79% of Asia's population), conclude that OOP payments remain the main health care tool in most of these Asian countries and result in millions of people trapped poverty. In addition, Doorslaer et al. (2007) have studied the impoverishing health expenditures of fourteen Asian countries (representing 81% of Asia's population). They discovered that the five countries where people rely the most on OOP to finance their health care have the highest incidence of catastrophic payments. Evidence from other developing countries outside Asia also show a high rate of healthcare expenditure related poverty. For example, Gotsadze et al. (2009) have found that the proportion of households having medical expenditures that brought them financial catastrophe increased from 2.8% in 1999 to 11.7% in 2007. In the US, despite higher average household incomes, health expenditure lies behind most bankruptcy claims (Himmelstein et al., 2005). In 2005, the WHO estimated that more than 44 million households globally faced health-related financial catastrophe on an annual basis, of which 25 million households were pushed below the poverty line. Xu et al. (2007) have found that 150 million people globally suffer financial catastrophe annually by paying for health services, based on a survey done in fifty-nine countries, covering 89% of the world population.

All the studies that address the distribution of health related poverty show that poorer households are exposed to greater catastrophic risk. For example, Wagstaff and van Doorslaer (2003) analyzed how OOP health payments impacted poverty in Vietnam for 1993 and 1998. They found that OOP health payments made more poor people poorer than non-poor poor. Other studies have found that, even in developed countries, OOP expenditures for health care as a proportion of income varied greatly based on income level. Berki (1986) considers out-of-pocket expenditures as a percentage of income by poverty level. 0.9% families with an income of at least $20,000, but 17.9% with less than $12,000 income, incurred expenditures amounting to 10% or more of their family income. These disproportionalities remain even at the substantially lower financial burden of out-of-pocket expenditures at 5 or more percent of income, it worth's noting that while a tenth of all families spent 10% or more of their income on medical care, among the poor almost a third did so. Similar disproportionalities are also observed in Serbia (Arsenijevic et al., 2013). The rural households, larger households and unhealthier households are more likely to face OOP expenditure that had a catastrophic effect. Even worse, after being deducted the OOP payments, the households above the absolute, relative and subjective poverty lines were pushed below those poverty lines.

Section 2.2 Global Policies and Interventions to Prevent CHE

Countries use prepayment mechanisms including social health insurance and tax-based programs to protect people from CHE. Many studies examined the effect of those mechanisms that reduce the OOP payments from patients. Knaul et al. (2006) conclude the three main methods for countries to finance their health systems: funds levied by the state through specific taxes and general taxes; contributions to social security through deductions or taxes; and private payments, which can be self-funded or private. However, government-financed and social insurance schemes established by mixing the three methods above, often do not protect all citizens from catastrophic and impoverishing health expenditures. No strong evidence exists that suggests the social health insurance system works better or worse to protect households from

CHE compared to tax-based systems, but the two prepayment mechanisms both work. In 2006, people in Turkey were better protected from catastrophic medical expenses by risk pooling/health insurance than in many other countries with comparable income levels at that time (Yardim, Cilingiroglu and Yardim, 2010). Gotsadze, Zoidze and Rukhadze (2009) have recommended policies to help the poor and chronically ill with CHE by including and expanding inpatient coverage and adding drug benefits. The three empirical researches mentioned above use on the measurement in Xu et al (2003).

Liang et al. (2012) have estimated the effects of New Cooperative Medical Scheme (NCMS) on health outcomes and on alleviating CHE in China, but they have no clear evidence that NCMS improves the health outcomes or alleviates CHE of China's rural population. Consistently, Wagstaff et al. (2018) have argued that it is not sufficient to reduce the incidence of CHE by increasing the share of GDP spent on health, based on the evidence from a retrospective observational study covering 133 countries between 1984 and 2015. Instead, increasing the share of total health expenditure that is prepaid, through taxes and mandatory contributions is sufficient to reduce CHE.

Various interventions are also conducted through randomized controlled trials. In the developed countries, for example, the RAND health insurance experiment and the Oregon health insurance experiment randomly assigned people health insurance with different coverage plans. In addition, when the Affordable Care Act was carried out, some researchers, collaborating with Covered California, conducted a randomized assessment of individuals choosing to purchase insurance and choose an insurance plan. Patient behaviors of the above experiments were followed (Taubman et al., 2014, Baicker et al., 2014). In the developing countries, for example, the delivery of health insurance is bundled with other financial services by microfinance institutions (Banerjee et al., 2014).

Section 2.3: CHE measurements

Measurements of CHE in health economic literature are different. Usually, the total medical expenditure of a household is considered “catastrophic” if it exceeds some fraction of household total income or expenditure in a certain period. Two papers published in 1986 gave the earliest measurements of CHE among all publications we could date back to: Berki (1986) points out that the threshold at which a level of out-of-pocket (OOP) expenditure becomes financially catastrophic should be measured relative to family income. He uses three thresholds: 5%, 10% and 20% of annual household income. Wyszewianski (1986) proposes a differentiation of a “financially catastrophic” expenditure versus a “high cost”. He argues that the former measurement is used when health expenditures are relatively large with respect to a family’s ability to pay, as determined by the annual income and the source of payments, such as insurance coverage; while the latter describes cases where health expenditures exceed a set amount regardless of the source of payment or ability to pay. He gave an example of CHE as the OOP health expenditure in a year that is greater than 15% of a household's annual gross income, while a high cost is the health expenditure in a year that exceeds $5000, regardless of that household's source of payment or ability to pay. Both papers that were the first to measure CHE used the United States as the location of research. In the Xu et al. (2003) study, expenditure is defined as catastrophic when a household's financial contribution to the health system exceed 40% of remaining income after subsistence needs have been met. A subsistence need is defined as the average food spending associated with the food share in total household spending in the country.

Empirically, researchers use the average food expenditure of households whose food share in total expenditure was in the 45-55 percentile range for the sample as a whole. The ability of a household to pay is defined as the annual gross income minus subsistence needs. They surveyed fifty-nine countries and found that the proportion of households facing catastrophic payments from OOP health expenses varied widely between countries. Wagstaff and van Doorslaer (2003) used an empirical research to compare two kinds of thresholds that evaluate health expenditure level. One threshold requires that OOP payments do not exceed a pre-specified proportion of pre-payment income, while the other requires that they do not exceed a share of the household's Ability to Pay, which is defined as the remaining income after a flat rate of "deductions", such as spending on food and other 'necessities'. The two authors compared the headcount and intensity of CHE using 2.5%, 5%, 10% and 15% as thresholds of the fraction of OOP over pre-payment income and the fraction of OOP over Ability to Pay. Buigut, Ettarh and Amendah (2015) apply both measurements: households' OOP spending greater than a certain fraction of income and households' OOP spending greater than a certain fraction of the capacity to pay as defined by Xu et al. (2003) in their study of Kenya slums.

The studies above use the proportion of households with health expenses exceeding some fraction of the ability to pay, which is defined as a part of total income or consumption, as an indicator of the prevalence of CHE. However, the method proposed in Xu et al. (2003) is the most widely used method and has been used among researchers to compare the spread of CHE country by country (Su et al., 2006; Xu et al., 2006; Van Doorslaer et al., 2007; Gotsadze et al., 2009; Yardim et al., 2010; Aidam et al., 2016; Wagstaff et al., 2018; Kang and Kim, 2018; Han and Gao, 2019). Other studies measure CHE with a threshold as the share of health expenditure, either OOP or the overall health expenditure, over household consumption or income. Recently, Wagstaff et al. (2016), for example, measures CHE when health expenditure exceeds 10% and 25% of household consumption. Using the dataset from 533 health surveys in 133 countries between 1984 and 2015, they estimated a global incidence of CHE of 9.7% in 2000, 11.4% in 2015 and 11.7% in 2010 at the 10% threshold.

These studies use the number of households facing CHE divided by the total number of households in a population as the prevalence of CHE. However, this method only measures the ex post level of spread of CHE, yet some researchers mistakenly use it also as a measurement for ex ante risk of CHE. Flores and O'Donnell (2016) criticizes this method for four reasons. First, it fails to identify the average risk of CHE in a population or the distribution of risk. And the information of a portion of households facing chronic illness and constant CHE is diluted by other households that never face a risk. Second, the method is a partial measure of risk of CHE that does not capture the variability of the expectation of burdensome expenses. Third, the fraction of income is set arbitrary and not easily reconciled with preferences. Last, informal insurance through saving and credit may cushion the impact of Out-Of-Pocket (OOP) that seems to be a large fraction of income.

Chapter 3: Methodology

In Section 3.1, I review the existing method most widely used for measuring CHE. In Section 3.2, I advance an innovative approach to measure CHE. In Section 3.3, I compare these two approaches to estimate how CHE impacts poverty. In Section 3.4, I compare the two approaches to measure the predictive power of CHE.

Section 3.1. The Most widely-used method

The most widely-used method, as Xu et al. (2003) suggests, categorizes health spending when it exceeds 40% of a household's capacity to pay. Capacity to pay is defined as the gap between total consumption and subsistence needs. Subsistence needs are defined as the mean of food consumption for the 45th to 55th percentile of household food share, where households are adjusted based on their size. Other research based on Xu et al. (2003) suggests a lower percentage of households' capacity to pay be used to determine CHE, such as 10% or 25%, rather than 40%. In this study, I provide the incidences of CHE based on 10% and 40% thresholds. To compare the consumption and income among households of different sizes, I adjust household income, consumption, and other expenditures according to the consumption equalization scale provided by Xu et al (2003) and given here:

$$eqsize = hhsize^{\beta},$$

where β for each year is obtained separately from the estimator in the following regression:

$$lnfoodexp = lnk + \beta lnhhsize + \sum_{i}^{N-1} province,$$

where $province$ represents a dummy variable of each province,

k is a constant,

$foodexp$ is the value of a household's total monthly food consumption, and

ln means natural logarithms.

The β was estimated with observation weights for each year. In this study, the $\hat{\beta}$ for 2011 is 0.15 (SD=.01, p=0.00, 95% CI 0.13-0.17), the $\hat{\beta}$ for 2013 is 0.12 (SD=0.01, p=0.00, 95% CI 0.11-0.14) and the $\hat{\beta}$ for 2015 is 0.10 (SD=.01, p=0.000=, 95% CI 0.09- 0.12).

Then, I adjusted all households' food expenditure by $eqsize$ and used the mean adjusted food expenditure within the 45th and the 55th percentile as the subsistence needs for each year:

$$eqfoodexp_{it} = \frac{foodexp_{it}}{eqsize_{it}},$$

where the money value was adjusted by CPI. The value of subsistence needs for 2011 is 538.00 (SD = 27.21), 767.02.00 (SD = 50.17) for 2013, and 646.62 (SD = 53.42) for 2015. Table 1 shows the incidence of CHE in our sample using this method with 10% and 40% as thresholds of health expenditure greater than a portion of capacity to pay and the ex-post risk of households in our sample facing CHE.

Section 3.2. The innovative method

The innovative and dynamic method proposed here defines a household having a CHE, based on three criteria:

(1) The household has fewer assets in the next period than that of the current period

(2) The household spends an amount on health expenditures

(3) The household's assets in the next period are not high.

An assumption behind the first criterion is that households that face CHE deliberately reduce their assets to compensate for their catastrophic expenditure. And a natural interpretation of the second and the third criteria is that households classified as facing CHE must have spent some amount of money on health, and such catastrophic payments either will push them into poverty or into deeper poverty. Households that did not spend anything on health are classified into non-CHE subgroup. This method relaxes the threshold of spending an absolutely large amount of money on health care and the threshold of medical expenditure exceeding a certain portion of income, consumption, or capacity to pay. This method has several advantages: for households that have a great amount of assets to smooth their everyday consumptions, an expenditure on health care exceeding 40% of their capacity to pay is not likely to drive the household into poverty, as long as the household can sell part of its assets to overcome the short-term obstacle. However, for households that have very few assets, even an expenditure in health care that appears to be a small amount can severely affect the households because they are so vulnerable. Following the notation of Adato et al. (2006), a household's aggregated asset level is represented by Asset Index—Λ_{it}, which is a fitted value of a household's total assets. This method compresses a household's multidimensional assets into a one-dimensional index. The Asset Index is calculated as:

$$\Lambda_{it} = \sum \widehat{\boldsymbol{\beta_j}} \boldsymbol{A_{ijt}}$$

Where $\hat{\beta}$ is estimated from:

$$\ell_{it} = \sum \beta_j A_{ij} + \varepsilon_{it}$$

I measure the Asset Index by aggregating all assets, including financial assets and non-financial assets, together. The financial asset includes a household's deposit, stock, bond, fund, derivatives, financial planning products, non-RMB asset, gold, cash and lending. The non-financial asset includes a household's agriculture asset, business asset, housing asset, land asset car asset and durable asset. The household livelihood (ℓ_{it}) is measured by household total consumption divided by subsistence needs adjusted by household size:

$$\ell_{it} = \frac{Consump_{it}}{Subsneeds_{it} * eqsize_{it}}$$

Households with $\ell_{it} = 1$ have total consumption exactly equal to the corresponding subsistence needs. The intuition behind this method is different kinds of assets a household holds have different rates of returns. When I reduce the dimension of the wealth measurement by generating a weighted sum of those assets all together, I assign the weights to those assets based on their ability of generating returns. According to Adato et al (2006), households with an Asset Index $\Lambda_{it} = 1$ are at the static asset poverty line at time t. Households with $\Lambda_{it} < 1$ are living under the static asset poverty line at time t. Also, the Asset Index is expressed in poverty line units (PLUs) and the dynamic asset poverty line was estimated at about 2.1 PLUs in Adato et al (2006). Jouseholds who hold an amount of assets under the dynamic asset poverty line proposed in Adato et al. (2006) in the next period, after paying for health expenditure and selling assets, are considered facing CHE. It does not matter if they are pushed into poverty or pushed into deeper poverty. After calculating the Asset Index for each household that was surveyed in 2011, 2013, and 2015, I used a local regression method (LOWESS) to estimate the relationship between the Asset Index in 2015 and the Asset Index in 2011.

Section 3.3 Measuring the impact of CHE on poverty

The impact of some household features and CHE on household assets are of interest. Theoretically, assets, especially financial assets, can act as an informal form of insurance when households face a disturbing amount of health expenditure (Flores et al., 2008). In the sample used in this study, does a catastrophic amount of health expenditure affect a household's asset holdings in the next period? What other household characteristics are significantly correlated with households' asset holdings in the next period? The innovative measurement of CHE, if proven validated, should be able to answer these questions above. Thus, I measured how an incidence of CHE in 2011 affects the Asset Index in 2013 with the following regression including both dummy variables and continuous variables:

$$\Lambda_{it} = \boldsymbol{\beta X_{it}} + \beta_c Cat_{t-2} + \alpha_i + \mu_{it}$$

Where X_{it} includes a set of time-variant characteristics in year t (t =2013). α_i is the time-invariant individual effect. Our model allows α_i to be correlated with the regressor matrix $\boldsymbol{X_{it}}$.

Section 3.3: Predicting CHE

Machine Learning strategies are used in this study to validate the dynamic measurement of CHE proposed in this study. Specifically, I use a Supervised Machine Learning method to predict if the household will face CHE in the future. The goal of using a machine learning model is to create a model that predicts whether a household faces CHE by learning simple decision rules inferred from the existed variables corresponding to households do and do not face CHE. Among all machine learning classifiers, I select a decision-tree classifier. The decision-tree classification model is a non-parametric model used to predict the response of a given dataset. It is a very powerful machine learning model that achieves high accuracy in many tasks while being interpretable. Also, it does not impose any assumption on the distribution of samples. In the decision tree diagram, each node has a decision rule that splits the data into two groups. If there is multicollinearity, the decision tree classifier will choose the best segmentation. In particular, decision trees are one of the most popular and simplest classification algorithms in machine-learning predictions and are easy to explain. In this study, I have a large dataset and four kinds of dummy variables in the prediction process: whether a household will reside in a rural area, whether the household head will be female, whether the household faced CHE in the current year and whether the household will be in one specific province. With these several independent variables including four dummy variables, if I choose a conventional linear regression model instead of a machine-learning classification tree, the inverse of the variance-covariance matrix of the regression might be too difficult to solve, and thus some regression regularization strategies must be introduced, which will make the model difficult to interpret.

Before building the decision-tree classifier, I first split the dataset randomly into two subsets: the training set and the testing set. Then, I trained the decision tree by using the information in the past and current period to classify our households into two groups: households facing CHE in the current year and households not facing CHE in the current year. After classifying if a household faced CHE in each year using both the measurement method proposed in this paper and the widely used method, I used a classification tree learning method with an information-entropy-minimization criterion to look for important characteristics that are associated with CHE happening to households. Each node in the decision tree represents an essential feature of the dataset that is related to the classification. By doing numerous calculations, the algorithm finds the most efficient order of the attributes and in that way the information entropy is minimized. In our case, the information entropy is defined as:

$$S = -\sum_{i=1}^{N} p_i \log_2 p_i$$

where S represents information entropy, p_i represents the probability of household having CHE. Entropy can be observed as a degree of information noise in the dataset. When all the records of a node belong to the same class, the information equals zero thus the node is called pure. A node is pure means the criteria in the node and nodes above form a good classifier. When all the records of a node are divided evenly into two groups, the information entropy equals one. This means the combination of the criteria in the node and nodes above does not classify the households well. I used Python 3.7 for the decision-tree classification method.

In this study, three decision trees were built. The first decision tree is designed to use the households' wealth information in the last period and some known demographic characteristics in the beginning of the current period to predict if a household will face CHE (measured by the innovative method) in the current period. The second decision tree is designed to use the household's wealth information and an indicator of CHE (measured by the innovative method) in the current period to predict if a household will face CHE (measured by the innovative method) in the next period. The last decision tree is built to use the household's wealth information and an indicator of CHE (measured by the conventional method) in the current period to predict if a household will face CHE (measured by the innovative method) in the future period. The accuracy scores of the second and the third predicting algorithms are compared to validate the dynamic measurement of CHE proposed in this study. The innovative method is validated if the accuracy score of the second decision-tree classifier is higher than that of the third decision-tree classifier.

Chapter 4 Study Setting and Data

Section 4.1 Study Setting: Poverty, Illness-Caused Poverty, and Poverty Alleviation in China

4.1.1. A Brief Review of Health and Healthcare in China

In 2003, the Chinese government took the first step in its healthcare reform, by landing a pilot project of a modest health insurance scheme covering some hospital expenses for rural residents, who were not covered by formal-sector programs. This health insurance’s premium was largely subsidized by the tax revenue from both the central government and the local governments. The scale of the subsidy differs in towns and cities, based on the poverty status of the households. For the poorest households, the premium was almost entirely subsidized—individuals only pay 10 Yuan (around 1.88 CAD) per person per year. In Eastern China where the local governments are richer compared to its counterparts in Western China, the subsidy was covered only by the local governments. However, for areas in Western China where the local governments have less funds, the premium was subsidized only by the central government. Moreover, non-poor households either pay a flat-rate subsidized premium or an income-based premium. The form of the healthcare coverage was a fee-for-service charge with some scale of reimbursement. The scale of reimbursement depends on the type of medication received, the patient’s residential district, the patient’s age and the hospital’s class. In 2009, the Free Market healthcare scheme was officially abandoned by the Chinese government and the New Cooperative Medical Scheme (NCMS) was officially launched, based on the pilot project upfront. Various strategies were adopted to fulfil one commitment of the Chinese government’s goals, which is to provide affordable basic health care for all Chinese people by 2020. Before the end of 2012, 95% of the population was enrolled in modest, but comprehensive, government subsidized coverage. The rate of each individual's coverage varies among people who live in neighborhoods with different economic developments. Many studies have documented China's progress towards universal health care together with its limitations (Wagstaff et al., 2009; Yip et al., 2012; Chen and Jin, 2012; Hou et al., 2014).

Before the reform in 2003, China had a "free market" policy for health care which was officially launched in 1984. Government subsidies to the health system fell to less than 5% from almost 100%, thus most hospitals had to become for-profit organizations. The price of health supplements became very high, so CHE put many families into poverty. There was also little evidence of enrollment in private health insurance was observed around 1984. This finding reflects the theorem, first formally discussed in Arrow's (1963) economic paper and then became common knowledge among economists that a free market for health insurance does not work due to asymmetric information. Arrow's (1963) paper exploited a new field of economics: Health Economics. Since then, numerous economists have researched on moral hazard and adverse selection in health insurance industry that has caused major failure in private health insurance market. Unfortunately, this theory was not acknowledged widely in China in 1984. During the period of time when the "free market" policy was in effect, urban residents were more fortunate in health care insurance than the rural residents in China. By 1985, in the rural area, only 5.4% of rural communities were estimated as maintaining their collectively funded cooperative medical care system by 1985; the rest of the rural communities were self-paying, according to Hsiao (1995). However, by 1989, about 50% of the urban population was insured by one of two types of insurance in 1989. The larger was to reimburse urban workers, which covered nearly 201 million workers and retirees of state-owned and large collective enterprises and their families. In 1994, the State Council conducted a pilot reform of the basic social medical insurance system for urban workers. According to Dong (2009), the pilot was carried out in Zhenjiang City, Jiangsu

Province and Jiujiang City, Jiangxi Province. This previous reform basically transformed China's health care to a wage-oriented social insurance plan. Li and Jiang(2017) mentions that when the Urban Employee Basic Medical Insurance(UEBMI) program was carried out initially in the mid-1990s, only 109 million employees of state-owned and collective enterprises were covered. Then, the New Cooperative Medical Scheme (NCMS) for rural residents and the Urban Resident Medical Insurance (URMI) program for self-employed and unemployed urban residents were carried out in the early 2000s and almost filled the gap of the universal health care coverage (UHC).

Researchers are curious about the progress and impact of the huge health insurance reform in China since 2003. Wagstaff et al (2009) find out that the NCMS has increased both outpatient and inpatient utilization and has significantly reduced the cost of deliveries, but it appears to have increased the cost of outpatient visits in village clinics. This limitation of NCMS is consistent with the curse that the more patients are insured, the more expensive type of care patients receive. Yip et al (2012) also argue that China must reform its incentive structures for providers, improve governance of public hospitals and institute a stronger regulatory system beside its huge and complex health-care reforms.

4.1.2. Poverty and Illness-caused Poverty in China

According to the World Bank's estimation, the poverty headcount in China at 1.90 USD a day (2011 PPP) in 2015 is 1,386.4 million. Although China's annual GDP growth remained above 6% (6.8% in 2017, which is more than twice of Canada's GDP growth in 2017), there are still many households left behind. Across all areas in China, there are significant differences in households' share of China's huge economic prosperity between rural and urban areas. Available evidence suggests that poverty is primarily a rural phenomenon (Meng, 2013). In a speech in

2015, President Xi Jinping set a national large-scale goal of lifting all 1.4 billion people out of poverty by 2020[1].

Illness-caused poverty exists in China, regardless of the huge reform in government-sponsored health insurance schemes. Ouyang reported in 2012 that 12.9% families in China suffer from a catastrophic level of health expenditures. This number was barely reduced from that of 2003, when health insurance started its rapid expansion. Although local governments received detailed guidelines on how to provide vulnerable households financial protection on health expenditure, they did not have corresponding resources to pay for those costly programs. Ouyang concludes the reason behind this situation is the 2-year slump in property markets in most provinces. Local governments rely on land sales to collect fiscal revenue, therefore they were largely affected when the land and housing prices plunged. Ouyang also argues that many expensive treatments, including imported oncology therapies, are not reimbursable at all. Additionally, rural patients who travel to big cities for higher quality of treatments have to pay a larger portion of their health services OOP, as restricted by the rule of reimbursement in their health insurance. These reasons above bring patients financial burdens even the patients are covered by some government-sponsored health insurance, such as NCMS. A recent research in 2018 (Wu, Yu and Nie, 2018) shows that the CHE ration in Jiujiang City is 14.2% in 2015, according to the data in the first half of the year from a hospital in Jiujiang City. Another research (Xu et al. 2018) has stated a much higher rate of CHE in China. According to the research, the occurrence rate of CHE in 2008 in rural China was 29.15% while that rate in 2013 declined to 23.62%. Meanwhile, the occurrence rate of CHE in urban China increased from 19.18% to 24.95% from 2008 to 2013. Thus, the overall rate for CHE remains high while the

1 The information was gathered from https://www.chinadailyasia.com/nation/201510/16/content_15330833.html

Chinese government has been putting a lot of effort and money in the campaign. Li et al (2012) has found that the rate of catastrophic health expenditure was 13% and the impoverishment rate was 7.5% by analyzing data from the Fourth National Health Service Survey that includes 55556 households locate both in rural and urban areas. Although health insurance coverage increased dramatically between 2000 and 2011, where the research by Li et al (2012) updated the record from the previous World health report 2000, the rate of CHE and its impoverishment was high. Among the 38945 households included in a study conducted by Li and others in 2013, there were 9.2% of households pushed into poverty by purchasing health services. Households headed by members covered of urban insurance schemes are significantly less poor than those without any insurance. However, rural households covered by NCMS have slightly higher rate of illness-caused poverty compared to those not covered.

As a large a complex healthcare reform going on, a number of studies tried to estimate the effect of those reforms on CHE illness-caused poverty. The study mentioned above (Li et al., 2013) concluded that NCMS failed to both prevent CHE and illness-caused poverty. A systematic review (Liang et al., 2012) on the effect of NCMS on health outcomes and alleviating CHE in China states that the results from previous studies focus on the relationship between NCMS and alleviating CHE in China were in conflict: Two studies suggested no effect (Wagstaff et al., 2007; MoH, 2007). Yan et al., (2009) found that NCMS reduced the incidence of CHE.

4.1.3. Poverty Alleviation in China

All developing countries have some forms of poverty alleviation programs. In China, the economic reform in order to achieve nationwide economic growth started as early as 1978. Deng Xiaoping, the leader of the economic reform stated “Let some people get rich at first”, which is similar to the “Trickle-down” theory. The rural sector was the first stage in which the reformers achieved poverty alleviation by reintroducing the distribution of private agricultural land in the early 1980s. This change stimulated rapid growths of the rural economy. However, since the mid-1980s, rural economic growth has not been fast, and rural income inequality has increased. As Khan (1998) commented, “China’s official poverty reduction strategy is based on the assumption that poverty is a rural problem.” Also, as the World Bank Group’s stated in 2010, China's poverty reduction plan before 1990 relied heavily on single-year and single-sector projects that could not overcome poverty in the most affected areas. In addition, the statistical system used to assess the location of the poor is limited. In 1993, China carried out the first pilot of Minimum Livelihood Guarantee (MLG or Dibao) in Shanghai, targeting to provide a safety net for the urban poor. This program was officially launched nationwide in 1999. Moreover, more projects of poverty alleviation, including those with assistance and cooperative from international organizations and some developed countries were carried out at the same time in the1990s. For example, debts of funds for the Southwest Poverty Alleviation project was approved by the World Bank in 1995, costing 486.40 million USD, and the Qinba Mountains Poverty Reduction Project was approved in 1997. Through efforts to better understand poverty adjusted through a rigorous monitoring and evaluation system, China lifted more than 600 million people out of poverty between 1981 and 2004 (World Bank Group, 2010). In 2013, Xi Jinping, the General Secretary of China first proposed “Precision Poverty Alleviation” by pointing out that “Poverty alleviation should be based on facts and in line with local conditions. Precision poverty alleviation is not only a sentence.” This proposal inspired policy makers to realize the multidimensional characteristics of poverty, and thus provide precise help to those with precise needs. The previous widely used channel to reduce poverty is providing cash transfers through a mean-test method on household income. Though simple to implement, this method can sometime be wasteful of resources. For example, households with income just above the threshold are not given financial assistance at the beginning, but once they fall below the poverty line due to a catastrophe, they should receive a great amount of cash transfers from the government to maintain their basic livelihood. In contrast, protective aids from the government can be less costly if ex-ante risks in some dimension of poverty can be detected.

Facing an illness that causes financial burden to a household can be one dimension of poverty. Therefore, preventing CHE plays an important role in China's poverty alleviation programs. Xu et al. (2007) showed that the incidence of financial catastrophe is negatively correlated with the dummy variable through which countries fund their health systems by some prepayment mechanisms either in tax or insurance form. Currently, there are two major cost-sharing health insurance supported by the central government that covers Chinese residents. The New Cooperative Medical Scheme (NCMS) is a voluntary program based on cost sharing between government and farmers. It covers mostly inpatient services and a few outpatient services. In the eastern China where the local governments are richer compared to the I stern country, the cost shares between the local governments, the central government and the farmers, while the corresponding cost shares only between the central government and farmers. Each farmer pays ¥180 premium on average per year since 2016. The Medical Insurance for Urban Employees (MIUE) scheme is a mandatory program based on cost sharing between employers and employees. Also, there are multiple health insurances supported by local governments. The Medical Insurance for Urban Residents scheme (MIUR) is for urban residents who are not covered by the MIUE and are co-financed by residents and local governments. The Critical Illness Insurance for Urban and Rural Residents (CIIURR) provides residents enrolled in MIUR or NCMS and have severe disease higher reimbursement limits. It was designed to prevent CHE on households. “Five Guarantee” service and the Minimum Livelihood Guarantee System provide additional stipends household.

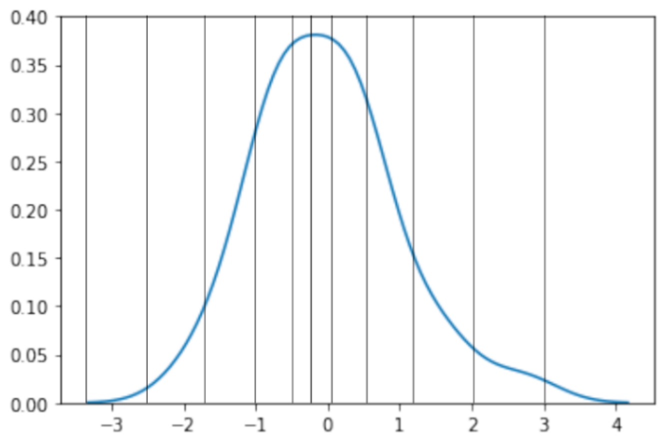
Besides, public and private health aid foundations allow reimbursement level as high as to 200 thousand Yuan, depending on the financial status of local governments or private foundations. Statistics from the monthly/seasonal/yearly report at National Health Commision website[2] showed that the health expenditure is largely covered by some sort of public health insurance. The total health expenditure in 2010 is 1998.039 billion Yuan and 28.7% was paid by either the central government or the local governments’ tax revenue, 36% was paid by societal health insurance and 35.3% was paid out-of-pocket by individuals. The total health expenditure in 2012 is 2784.684 billion Yuan. 30% was paid by the governments, 35% was paid by the society and 34.4% was paid out-of-pocket by individuals. The overall coverage, stipends and out-of-pocket health expenditure vary among households, based on different demographic characteristics and local policies, so it is hard to infer individual level coverage based on macro policy, thus I need field survey to get information of such things.

Section 4.2 Data: China Household Finance Survey (CHFS)

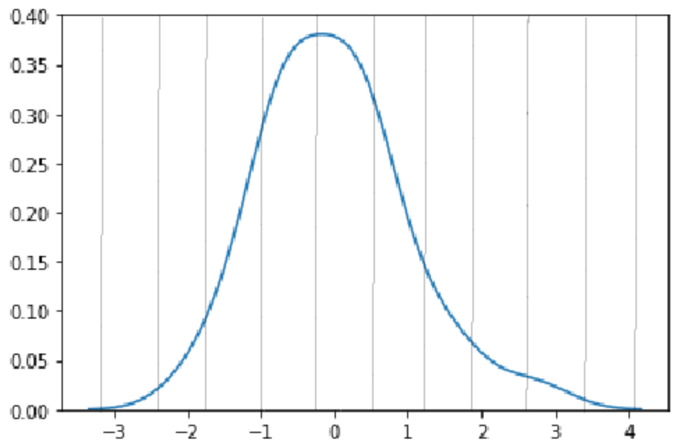
I use three sets of panel data obtained from the China Household Finance Survey (CHFS) to estimate and validate the CHE approach proposed in this study. The first set of panel data contains household information, the second contains individual information and the third has the sampling information indicating the location of each household and its sampling weight. The sampling weight design in CHFS increases the accuracy of the descriptive of statistics of the

[2] http://www.nhfpc.gov.cn/

CHFS data. The data center of CHFS designed to randomly select more households in the richest area and the poorest area compared to the not rich nor poor area. Also, they designed to randomly select more urban households in urban area and randomly select more rural households in rural area. As a result, richest households are more likely to be chosen in the richest area and the poorest households are more likely to be chosen in the poorest area, compared to completely random sample selection. Therefore, the richest and the poorest households are less likely to be underrepresented. For example, if I randomly select households in the population, I can get a figure like this:



Where the x axis represent an indicator of how rich a household is and the y axis represents the frequency of households having a certain indicator of fortune. Suppose the household fortune follow a normal distribution, there are more households having a fortune indicator close to the mean. The vertical lines represent a household being randomly selected to conduct a survey. As we can see, the relatively rich and relatively poor households are less likely to be selected compared to an average household. If we follow the sampling technique of CHFS, the households locate out of two standard errors are more likely to be chosen to conduct a survey, shown in the graph below:



CHFS also maintained its high quality of data accuracy with strict survey conduction rules. Once a household is randomly selected by computer, the survey conductors cannot change the sample to another household unless they are rejected by the selected household six times in the survey period at different time. Moreover, CHFS maintains its confidentiality of data, so that the rich households have less incentive to underreport their fortune, compared to the government sponsored surveys. In addition, CHFS keeps voice records of all surveys and randomly check the survey answer with voice records and call back for quality check at times, so that the rate of survey mistake is reduced. Compared to other similar surveys in China, CHFS has a critically low rate of rejection.

CHFS includes detailed household level and individual information. The household dataset contains 1207 variables in 2011, 2018 variables in 2013 and 2840 variables in 2015. The individual dataset contains 239 variables in 2011, 315 variables in 2013 and 292 variables in 2015. Our data includes the categories of variables outlined in Section 3.2.

Section 4.3. Sample Selection

I included all households surveyed in 2011, 2013 and 2015 datasets initially. There are 8,438 households in the 2011 dataset, 28,141 households in the 2013 dataset and more than 40,000 households in the 2015 dataset. I merged the individual survey dataset and the household survey dataset using the unique household identification number. Missing data were not imputed.

I used all observations to generate descriptive statistics and create variables that need sample percentile values, including subsistence needs, capacity to pay, and the measurement of CHE using the traditional, static method. Then, since our method of CHE measurement is dynamic, I selected those households who were surveyed both in 2011 and 2013 to estimate the impoverishment effects of CHE and for machine learning model training purposes. I dropped the observations with no asset data. To test the fitting accuracy of the machine learning model, I included the households who were surveyed both in 2013 and in 2015.

Section 4.4 Key Variables

- *Demographic Variables*: Demographic variables such as household head's gender, age, and education and whether the household is in a rural area, and the number of household members of working age.
- *Income*: The income variable is calculated as the sum of each household member's monthly salary, capital, and physical benefits, any type of dividend, and the household financial income and production income. Financial income includes any gain from financial products, such as bonds, stocks, insurance, and so on. Production income includes agriculture production, family business net gain and rent from land or real estate. The information for household assets and income is inclusive.

- *Assets*: The asset variable contains answers from 15 questions about financial assets, and answers from 27 questions about non-financial assets.
- *Consumption and Food Consumption*: The monthly consumption and food consumption were calculated for each household.
- *Total Health Expenditure*: The health expenditure data is not consistent in the surveys of 3 waves. In 2011, the variable is F2019 (The question is: How much did each household member spend on healthcare in the previous month before the survey). In 2013, F2019 represents the amount of health expenditure of each household member in the past year. In 2013, there is only 1 variable representing the household health expenditure: F2024, stating the amount of inpatient expenditure for each household member in the past year.
- *Healthcare coverage*: Questions in the surveys of 2011, 2013 and 2015 ask how much of a household's total health expenditure was covered by health insurance sponsored by public sections and how much was covered by private health insurance. However, the question in 2011 is inconsistent with the questions in 2013 and 2015. In 2011 the question asks how much of the total health expenditure which occurred last month was covered by some forms of insurance while the questions in 2013 and 2015 asked how much of the total health expenditure occurred in the whole past year was covered by some form of health insurance.
- *Out–of-Pocket Payments*: I use the value of the gap between the Total Health Expenditure and Healthcare Coverage as the Out- of- Pocket Payments. Different from the previous work (Flores and O' Donnell 2016), I do not deduct the amount of expenditure that is financed from informal insurance, such as selling assets, reallocating savings and borrowing. Flores and O' Donnell see the remaining expenditure after subtracting the amount of money financed by the informal insurance as the OOP because they treat informal insurance as

optimal. However, recent studies have found out that with households becoming poorer, their intertemporal choices become myopic. In other words, people tend to maximize shorter term utility after they become poorer.

- *Healthcare premium*: A question in the survey asks how much an individual in a household paid for the social healthcare premium in the past year. Another question asks how much an individual in a household paid for the private healthcare premium in the past year. I construct the variable of healthcare premium by using the aggregated number of the individual- level data within a household.

Chapter 5: Results

Section 5.1: Descriptive statistics

Descriptive statistics were generated for demographical variables, financial variables and health expenditure variables for households reside in rural areas and urban areas. Table 1 shows the frequency, mean and standard deviation for numerical variables, such as household size, happiness, and the age of the household head, income, expenditures and assets. Frequencies of categorical variables, such as the gender of the household head, are counted for households belongs to both the rural subgroup and the urban subgroup. In total, there are 8438 households in our panel dataset for the descriptive statistics. Among all the household head, 6171 are male while 2267 are female. In all waves of surveys, urban households, on average, are happier than rural households. They also have younger household heads, higher income, and higher monthly consumption, more financial and non-financial assets. However, rural households' OOP payments on health services, according to the 2013 survey and the 2015 survey, are higher than those of the urban households on average. This distortion is consistent with the findings from previous studies on the distribution of OOP payments.

Section 5.2 Comparison of CHE incidence, using the two measurements

Table 2 shows the incidence of CHE in our sample, using the conventional measurement of CHE (using 10% and 40% as thresholds) and the innovative approach proposed in this study. The percentage of household sample facing CHE using the static measurements is calculated by the number of households facing CHE being divided by the number of all households not missing OOP data in that year. One hundred and six households reported their OOP payments in the 2011 survey. Twenty-eight households in the 2013 survey and 4756 households in the 2015 survey have non-missing OOP data. The percentage of household sample facing CHE using the innovative approach is calculated by the number of households facing CHE being divided by the number of households without missing health expenditure data in that year. The large variance in the number of households having the OOP information reflects the difficulty of getting the data of reimbursement from household surveys. This difficulty might due to two reasons. First, since most of the government-sponsored health insurance in China work through a reimbursement channel, there might be of difficulty for household members to remember the specific amount of their health expenditures being reimbursed. Second, the question related to the amount of OOP payment in the 2011 survey asks how much of the household's health expenditure being reimbursed in the past month when the household was surveyed. Since illnesses do not often occur in all months to all households, surveyed households might not have applicable answers.

I applied our newly proposed measurement of CHE to all households in our panel dataset. Then, I summarized the characteristics of those households facing CHE in 2011 and of those did not. I also conducted statistical tests on the difference between each feature I are interested in. t-tests were conducted on numerical variables while chi-square tests were conducted on categorical variables. Table 3 in the Appendix I shows the results. The differences between each subgroup (CHE subgroup and non-CHE subgroup) on the age of household head, the hukou of the household head (urban or rural), the amount of household total expenditure, health expenditure, OOP expenditure on health services, financial assets in the past year and the current year and the amount of nonfinancial assets in the past year and the current year are significant. Surprisingly, the difference between the two subgroups on the household total monthly income is not significant. This finding validates the idea that the income factor does not play an important role when a great amount of health expenditure happens to a household. Households with enough assets, including financial assets and non-financial assets are less vulnerable than those without, because they can always sell out some of their assets to overcome a short-term obstacle.

Section 5.3 Results from Estimations

Three variables are found significant in a multivariate analysis with provincial factor controlled (Table 4). The factor that a household facing CHE in 2011 significantly plays a negative role in the household's asset holdings in 2013. In a single-variate OLS estimation, this factor is still crucial. However, this factor is not significant, when we measure the CHE dummy variable by the static method. On the contrary, whether a household resides in rural area and whether a household has a female household head are significantly correlated with a household's asset index in the next period.

Statistical tests are conducted on the variables having significant effect in the multivariate analysis, between the subgroup of household facing CHE, measured by different approaches. Households classified facing CHE, measured both by the static approach and the dynamic approach, are considered "True Positive". Households classified facing CHE by the static approach but not the dynamic approach are considered "False Positive" and households classified facing CHE by the dynamic approach but not the static approach are considered "False Negative" (Table 5). The financial asset factors, especially the stock holdings, differ significantly between the true positive and the false positive subgroups. Those households considered facing CHE using the old method but not the new method hold significantly more financial assets than those who truly faced CHE. These "False Positive" households also held significantly higher amount of car asset when surveyed in 2011. The "False Negative" households, however, spent less on health services, both by all means and by OOP payments, specifically. They are not considered facing “CHE” measured by the static method because their OOP spending does not take up a large portion of their household income, but in the next wave of survey, their asset holdings declined.

Section 5.4 Results from the Machine-Learning Classifications

Asset index, household income, household size, household health expenditure, household asset holdings, net wealth and the age of household head are considered in the decision-tree classifier (Figure 1). I used information entropy as the criterion of the decision tree. The information gain is a decrease in entropy. The information gain calculates the difference between the entropy before segmentation and the average entropy after segmentation of the data set based on the given attributes. I also controlled model complexity to avoid over fitting for the specific training dataset. It is controlled by setting the maximum depth of the tree equals 30 and the minimum samples per leaf equals 30. The accuracy score of this classifier is 49.69% (rounded to the second decimal). Health expenditure less than or equal to 0.25 in the previous survey wave is chosen to be the first criterion to separate the training dataset into two groups and to gain the largest information entropy decline. This also shows that in our training dataset, all households (1,205) spent less than or equal to 0.25 Yuan in 2010 did not face CHE at all. The second split selected by this tree, in order to achieve the largest information entropy decline, is whether a household’s asset in 2011 is less than or equal to 47075.0 Yuan. Then, whether the adjusted household size in 2011 is less than or equal to 1.249 and whether a household’s asset index is less than or equal to 0.373 are chosen by the model in order to classify households into two groups, obtaining the largest information gain. The fifth layer of criterion, if a household’s amount of assets in 2011 is less than or equal to 13,000 classifies the samples with an entropy equals zero. This means that, in our training dataset, if a household satisfies five conditions: The household's health expenditure in 2010 is greater than 0.25; its total asset in 2011 is greater than 47075.0; its asset index in 2011 is greater than 0.373; the age of its household head is greater than 67.5; its total asset in 2011 is less than or equal to 13,000, then this household faced CHE in 2011 for sure.

Figure 2 shows the best decision-tree classifier to segregate households into two groups: whether they face CHE in 2015 or not, based on their CHE status in 2013, when we use the innovative method to measure CHE. The accuracy score of testing this algorithm of classification on a testing dataset is 74.64%. The conventional method of measuring CHE status in 2013 was used in the decision-tree classifier in Figure 3. With this measurement applied, the accuracy score of testing the corresponding algorithm on a testing dataset falls to 68.75%. These accuracy scores represent the fraction of number of observations correctly classified over the total number of observations being classified in each case.

Chapter 6: Conclusions and Discussions

This study contributes to the measurement of CHE in three ways. First, it is the first study that proposes an approach to measuring CHE that captures the asset dynamics reflecting households' wealth and vulnerability. Second, it examines any significant correlation between household characteristics widely used in previous literature measuring the poverty situation and CHE. It accomplishes this by using a rich panel data set contains various household and individual wealth information. Third, it describes the characteristics of households who actually face CHE but were left behind using the previous, static method of CHE measurement. The precision of the estimates is enhanced by simple statistical corrections. The accuracy of the prediction is also improved by measuring CHE, using the innovative method rather than the conventional method. These contributions are important for both descriptive and policy purposes.

Further studies could focus on two aspects: improving the accuracy of predicting CHE and exploring the causal relations between household characteristics and CHE. In this study, we take advantage of detailed household wealth information and have found that whether a household is facing CHE, whether a household resides in a rural area, and whether a household is led by female are significantly correlated with a household's asset holdings. Also, we have found significant differences between households that are facing CHE and those that are not. These differences include several household characteristics (i.e., the age of the household head, the household's total expenditure, the household's health expenditure, OOP payments, the amount of financial asset holdings, the amount of non-financial asset holdings and the household's rural-urban status). However, we have not explored any causal relations between the household characteristics mentioned above and CHE. In order to accomplish this, methodological tools, such as structural equation modeling, can be applied to future studies. One big challenge here is the current dataset I use in this study, despite its detailed asset information, does not have information on the health status of individuals or households. Whether a person is in good health or not directly affects how much she is going to spend on healthcare. This lack of health information, in surveys, reflects the fact that survey designers have not realized the important role that health plays in a household's wealth accumulation and the society's economic growth.

With households' previously mentioned health information, the accuracy of predicting CHE in future studies is likely to be improved. Good health can improve labor productivity (Bloom, Canning and Sevilla, 2004). Therefore, further improving a household's wealth, health status should be a crucial feature when we classify households into CHE group and non-CHE group. Thus, the accuracy of prediction is likely to increase in further studies, when access to health data is granted.

In this study, the prediction of accuracy, with the use of the innovative measurement of CHE, is higher than that of using the conventional method. However, this result is open to interpretation. One possible controversial argument is the machine-learning classifier using the conventional method lacks training data. Currently, we have 90 observations in the training dataset. This is the result of only a few households replying, in the survey interview, as to how much of their health expenditure, in the past year, was covered by health insurance. On the one hand, we can interpret this lack of data in OOP payments as a signal showing the difficulty of interviewees to recall their OOP payments information in the past year. Therefore further studies may try to link the administrative data from the health services sector to household characteristics and obtain more reliable and detailed OOP payments. On the other hand, we must embrace the uncertainty that, with more information on OOP payments obtained, the accuracy of using the conventional measurement of CHE to predict CHE in the future will surge. The other possible controversial argument is the selection of the “CHE” and the “non-CHE” labels. The current labels of selection in this study are based on the dynamic method to measuring CHE. However, the ideal method of selection could be, if no constraint applied, based on the information of whether a household was pushed into poverty or deeper poverty due to health payments. Unfortunately, this information is not given in the dataset used in this study.

The asset index for each year is calculated as a weighted sum of all household assets. The weight ($\hat{\beta}$) assigned to each type of asset is estimated as the marginal contribution to a household’s livelihood ($\ell_{it} = \sum \beta_j A_{ij} + \varepsilon_{it}$). This marginal contribution of one type of asset may vary across years. In the country where the sample households are from, both the value and the return of a financial asset may fluctuate significantly, leading to a decrease in the asset index. Households that are holding this type of asset, as long as they pay some amount of money on health services, might be classified in the CHE group. In this case, the household classified as facing CHE does not actually face a catastrophe in health expenditures but rather a broader financial catastrophe. This is a potential limitation of this approach because households facing other catastrophes might be classified as CHE households, when in fact their slide into poverty is not due to CHE.

Chapter 7: Implications for Policy

Not only are the households facing CHE different from those are not, using the innovative measurement of CHE proposed by this study, but the differences between the two subgroups of households are also likely to call for distinct policy attitudes and responses, in order to achieve precision poverty alleviation. Allen (2017) concludes the situation that households face absolute poverty as "when necessity displaces desire". However, for households facing CHE, the situation they are facing is not merely a necessity displaces desire. Their conditions are even worse. The drugs and other health services they seek for the sick household members displaces resources that are crucial to the whole household, such as the household's asset holdings, investments in human capital (nutrition, education, training, etc.) and the quality of the necessities. Having considered the problems above, I call for specific efforts on strategies toward alleviating poverty precisely.

First, given the significant empirical results of estimating the correlation between CHE and households' wealth, policy makers should have deep thoughts and careful considerations on the overall health status of households along with the amount of expenditures spent on health services, when the policy makers try to identify who are in need of some kinds of help from the government. The results from this study show that, among a household's all characteristics to be considered, health expenditure plays a significant role. According to these results and along with the strategy of China's Precision Poverty Alleviation project, multidimensional characteristics, especially health expenditures, should be applied to identify poverty.

Second, policies to protect households from CHE should be implemented in poverty alleviation projects. Shown in the results, the indicator of CHE is significantly correlated with the aggregated asset index. On the one hand, this finding may provide an empirical ground of the assumption in Flores and O'donnell (2016)'s study that households can fund OOP payments each time through savings, sale of assets, borrowing or other informal insurance. On the other hand, this finding can be explained as household sell out their valuable asset to tackle CHE in the short term, but leave themselves less assets and become more vulnerable in the long term. Policymakers can use the information provided in this study to better targeting financial risk protection strategies. For example, providing pooled-risk health insurance to vulnerable households might be useful on reducing the risk of household members to get sick or sicker, and then the expectation of household labor productivity will increase correspondingly.

Third, detailed information on multidimensional characteristics should be gathered to predict CHE that might happen in the following years. The next problem policymakers face, after they are convinced that strategies on protecting households from CHE in order to further prevent households pushed into poverty or into deeper poverty, is how to precisely predict if households will face CHE in the next period, using all information they gather in the current period. Machine learning methods can be of help to some extent. In this study, with a lack of the direct cause of CHE— health status, we achieved an accuracy rate of 74.64%. This result sheds a light on the possibility of using detailed information from many aspects, including a household's human capital stock, household financial and non-financial asset dynamics, household's socioeconomic status and some exogenous feature such as the province or county a household resides in, to predict if a household is likely to face CHE in the next periods.

Finally, interventions and policies should have strong theoretical and empirical background, and be documented and evaluated carefully. All interventions and policies must be designed on a sound theoretical framework that recognizes the interplay between poverty and poor health. Also, evidence from empirical studies and every procedure of the implementation of the policies or interventions shall be systematically collected. By following this protocol, estimation and prediction algorithms can be monitored and modified in order to obtain more effectiveness of the policies or interventions toward precision poverty alleviation.

Appendix. Tables and Figures

Table 1. Descriptive Statistics of the Sample from CHFS

		Urban			Rural		
		N	Mean	SD	N	Mean	SD
Household Size							
	2011	5194	3.20	1.41	3244	3.82	1.69
	2013	18778	3.21	1.45	9363	3.94	1.84
	2015	25286	3.50	1.56	12003	4.22	1.95
Happiness (1-5)							
	2011	5193	2.29	0.85	3243	2.32	0.92
	2013	18771	2.35	0.85	9358	2.51	0.90
	2015	25250	2.31	0.83	11993	2.42	0.88
Household Head Age							
	2011	5193	47.84	14.87	3244	52.64	13.07
	2013	18771	49.46	15.30	9362	53.44	12.98
	2015	25279	52.66	14.67	12002	55.44	12.71
Male Household Head							
	2011	3473	_	_	2698	_	_
	2013	13056	_	_	8240	_	_
	2015	17627	_	_	10529	_	_
Female Household Head							
	2011	1721	_	_	546	_	_
	2013	5715	_	_	1123	_	_
	2015	7659	_	_	1474	_	_
Income-monthly							
	2011	5194	6378.39	16923.34	3244	2951.26	8046.34
	2013	18778	5932.27	13002.75	9363	2687.74	5982.52
	2015	25286	6556.64	15850.25	12003	3063.58	7862.08
Expenditure-monthly							
	2011	5194	4549.58	6988.09	3244	2331.417	4958.01
	2013	18778	4351.74	5602.34	9363	2420.52	3134.30

2015	25286	4683.88	5524.10	12003	2738.96	3492.78
Health Expenditure						
2011	4578	450.19	2932.75	2996	293.20	2182.41
2013	18501	250.38	801.20	9309	198.58	535.67
2015	24078	552.31	1790.45	11466	479.33	1532.94
Out of Pocket Expenditure						
2011	228	178.31	991.57	39	57.93	166.42
2013	208	119.61	287.50	7	149.67	185.89
2015	23365	328.77	1204.44	10998	341.90	1065.67
Food Expenditure						
2011	692	1097.00	982.79	2342	862.89	979.63
2013	2481	1645.53	2867.69	6930	1192.13	1532.33
2015	2766	1277.43	2922.68	7356	989.75	955.95
Financial Asset						
2011	5194	91452.45	322113.50	3244	23761.11	94871.11
2013	18778	79379.16	237895.50	9363	19959.87	88840.04
2015	25286	133562.20	490971.30	12003	26172.5	195753.2
Non-financial Asset						
2011	5177	862793.60	1578664.00	3232	274008.3	707800.9
2013	18776	848282.80	1450814.00	9363	293484.8	618817.8
2015	25260	925270.60	1569703.00	12002	308983.2	697195

Note: Sample selection weights were adjusted for numerical statistics.

Table 2. Incidence and the percentage of CHE households in the sample

Threshold	10%		40%		Innovative Approach	
Year	Incidence	% of Sample	Incidence	% of Sample	Incidence	% of Sample
2011	14	13.21	2	1.89	1724	37.6
2013	4	14.29	0	0.00	1514	27.50
2015	1592	33.47	573	12.05		

Note: The “% of Sample” in static measurements are calculated by the number of households facing CHE being divided by the number of households without missing OOP data in that year. The “% of Sample” in the innovative approach is calculated by the number of households facing CHE being divided by the number of households without missing HE data in that year.

Table 3. Characteristics and test results of households facing CHE and not facing CHE

	N	Mean	SE	Statistical Test
Household Size				
Non-CHE	3361	3.64	0.03	t-value=0.40
CHE	1724	3.62	0.04	p=0.34
Happiness (1-5)				
Non-CHE	3,360	2.32	0.02	t-value=1.00
CHE	1,723	2.29	0.02	p=0.16
Household Head Age				
Non-CHE	3,361	50.35	0.22	t-value=-8.47
CHE	1,724	53.64	0.32	p=0.00
Income-monthly				
Non-CHE	3,361	2839.47	98.10	t-value=-0.05
CHE	1,724	2846.88	84.10	p=0.48
Expenditure-monthly				
Non-CHE	3,361	2459.12	103.59	t-value=-2.38
CHE	1,724	2874.96	136.42	p=0.01
Health Expenditure				
Non-CHE	3,141	175.64	19.07	t-value=-7.28
CHE	1,444	819.04	123.56	p=0.00
Out of Pocket Expenditure				
Non-CHE	67	35.84	10.60	t-value=-3.82
CHE	39	231.84	64.95	p=0.00
Food Expenditure				
Non-CHE	1,589	914.36	23.66	t-value=0.02
CHE	726	913.59	43.28	p=0.49
Financial Asset in 2011				
Non-CHE	3,361	19881.52	791.61	t-value=-4.01
CHE	1,724	25574.80	1247.72	p=0.00
Financial Asset in 2013				
Non-CHE	3,361	45820.79	1599.22	t-value=8.69
CHE	1,724	25115.82	1158.57	p=0.00
Non-financial Asset in 2011				

Non-CHE	3,361	241229.70	5129.15	t-value=-5.44
CHE	1,724	288951.00	7082.50	p=0.00
Non-financial Asset in 2013				
Non-CHE	3,361	404011.40	7857.46	t-value=13.9
CHE	1,724	238450.30	6473.81	p=0.00
Rural				
Non-CHE	1657	–	–	
CHE	778	–	–	
Non- rural				Pearson Chi2=7.95
Non-CHE	1704	–	–	p=0.01
CHE	946	–	–	

Table 4. Determinants of Asset Index in 2013

	Static Measurement			Dynamic Measurement			Dynamic Measurement		
	Coef.	SE	p value	Coef.	SE	p value	Coef.	SE	p value
CHE in 2011	-0.60	0.53	0.26	-0.26	0.02	0.00	-0.28	0.02	0.00
Rural	-0.56	0.17	0.00	-0.36	0.02	0.00			
Female Household Head	-0.36	0.18	0.04	-0.11	0.02	0.00			
Province fixed effects	Yes			Yes			No		
N	106			5085			5085		

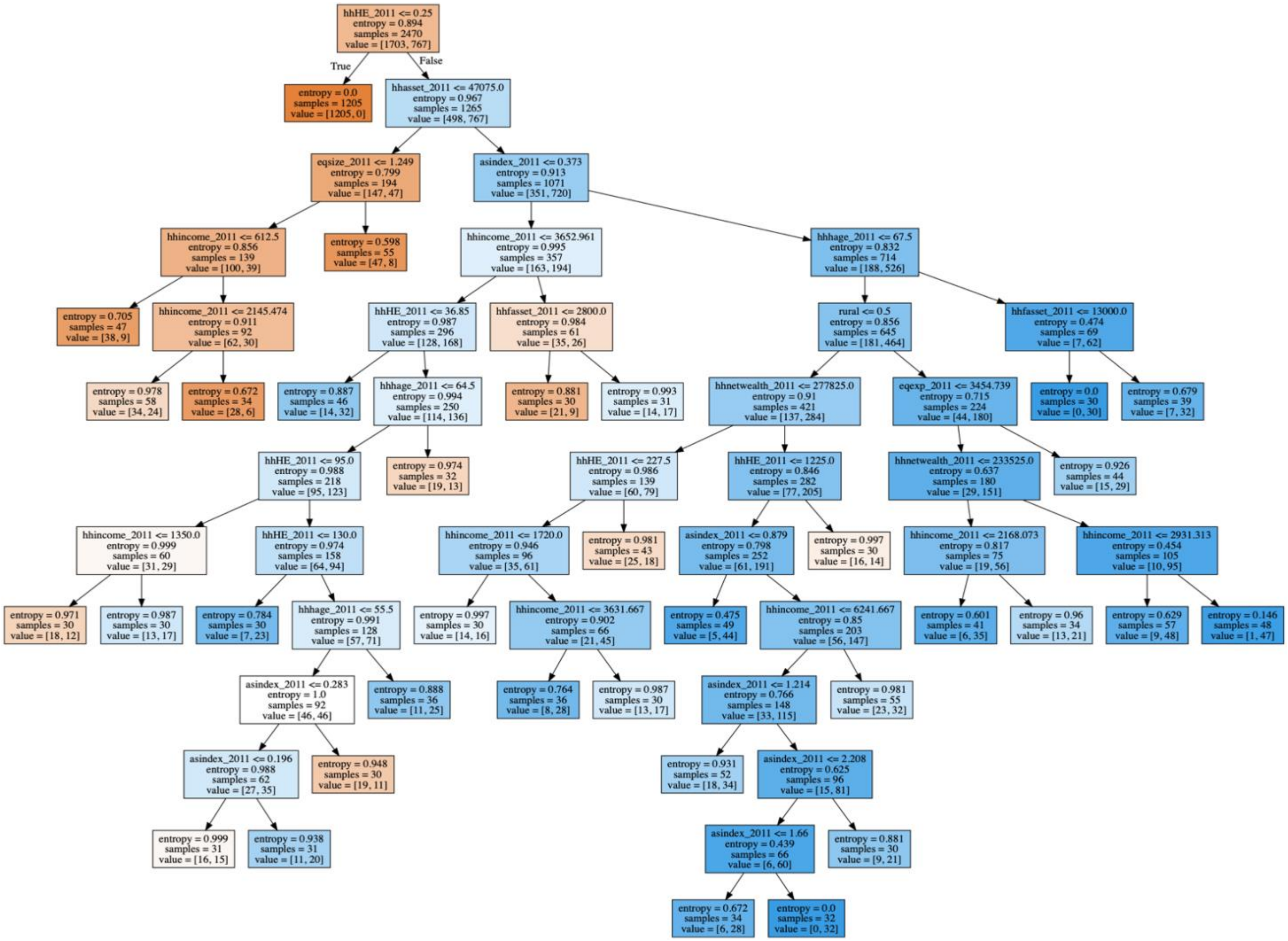
Table 5. Characteristics of households facing CHE and of those not facing CHE

	True Positive(N=11)		False Negative(N=28)		False Positive(N=3)	
	Mean	SE	Mean	SE	Mean	SE
Household Size	2.91	0.46	3.46	0.20	3.00	0.00
Health Expenditure	800.23	205.06	137.82***	29.46	363.33	89.50
OOP	646.82	176.60	68.81***	15.57	363.33	89.50
Income	3849.08	627.75	5679.56	1525.65	5081.64	1666.09
Financial Asset	32886.36	11458.72	74355.36	19593.52	114933.30**	86841.16
Nonfinancial Asset	337559.10	72563.31	469369.50	63610.25	352923.30	120412.50
Car Asset	6250.00	4356.36	11619.05	5386.29	31850**	28150.00
Durables	10786.36	3117.63	12393.57	2143.95	11650.00	10187.53
Housing Asset	350000.00	72014.66	446923.10	60449.65	296666.70	132957.80
Land Asset	63666.67	20792.09	77628.38	21151.04	70000.00	–
Deposit	28110.00	8766.03	66254.76	19652.49	68666.67	67172.25
Stock	0.00	0.00	3785.714*	1687.46	16666.67***	16666.67
Cash	1877.27	521.51	7271.43	3613.18	2933.33	1618.99

Lending	30000.00	20000.00	51250.00	18526.45	–	–

Note: t-tests were conducted between households classified in the true positive (facing CHE both measured in the old method and the new method) subgroup and the false negative (facing CHE using the innovative method proposed by this study but is missed using the old measurement). T-tests were also conducted between households classified in the true positive subgroup and the false positive (facing CHE using the old method but not facing CHE using the innovative method proposed by this study). *: 0.05<p-value≤0.1; **: 0.001<p-value≤0.05; ***: p-value<0.001.

Figure 1. A Decision Tree Classifier with Household Wealth Information



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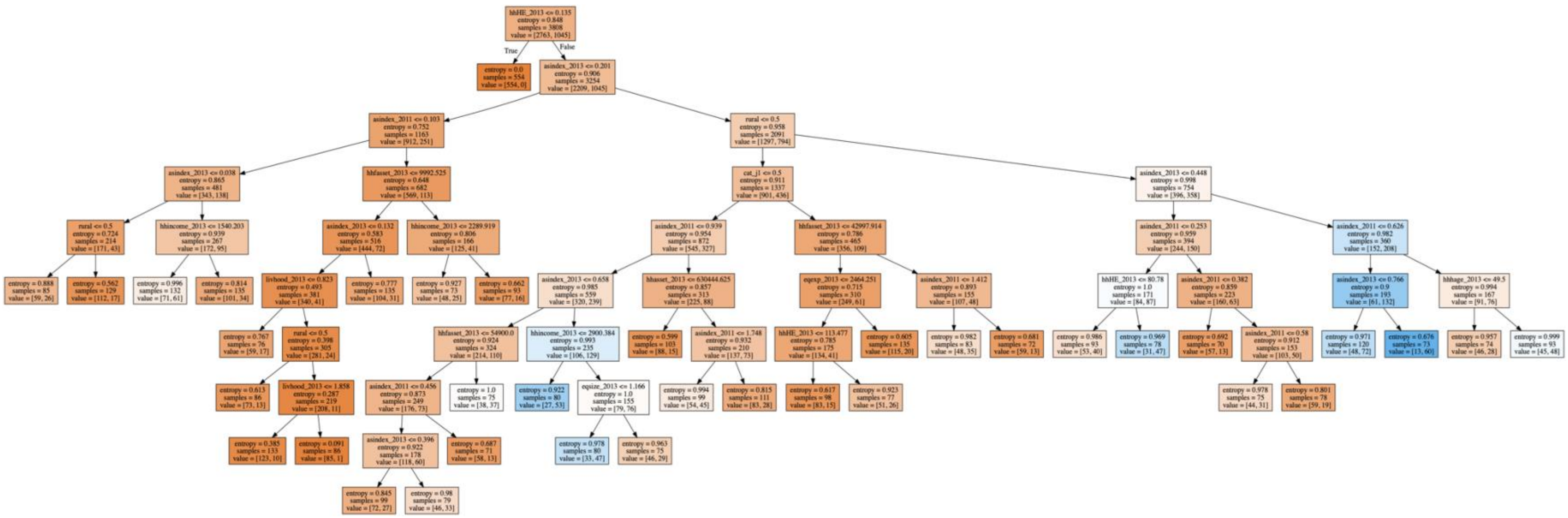
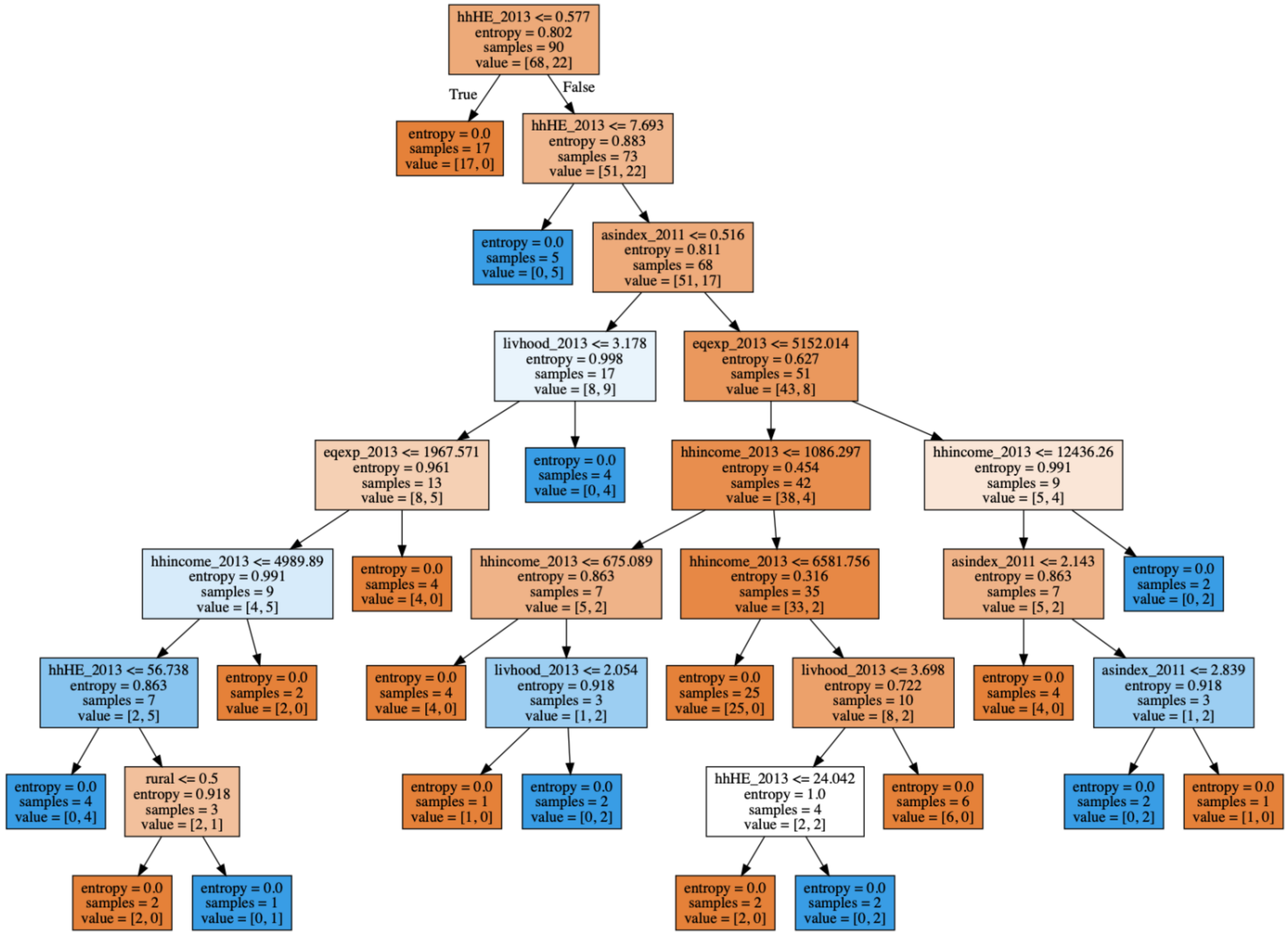
Results from Decision Tree Classifier using Sklearn library via Python 3.0. Criterion = 'entropy', Max Depth of the tree = 30, Minimum samples per leaf = 30, Minimum Impurity Decrease=0.0001. hhincome = household monthly income, eqsize = equalized household size, hhhage = the age of the household head, hhHE = household monthly average health expenditure, asindex_2011 = household asset index in 2011, hhfasset = household financial asset, hhnetwealth_2011= household net wealth in 2011.

Figure 2. A Decision Tree Classifier with Household Wealth Information and CHE Information of the Previous Years



Results from Decision Tree Classifier using Sklearn library via Python 3.0. Criterion='entropy', Maximum depth=30, Minimum samples per leaf=70. The accuracy score of testing is 74.64%. The innovative method of measuring CHE is applied on measuring CHE in 2013 and CHE in 2015.

Figure 3. A Decision Tree Classifier with Household Wealth Information and CHE Information of the Previous Years



Results from a Decision Tree Classifier using Sklearn library via Python 3.0. Criterion='entropy', Maximum depth=30, Minimum impurity decrease=0.0001. The accuracy score of testing is 68.75%. The conventional method is applied on measuring CHE in 2011. The innovative method is applied on measuring CHE from 2013 to 2015.

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