ESSAYS ON SUBSIDIZED HEALTH INSURANCE AND HEALTH-RELATED QUALITY OF LIFE

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A Thesis Submitted to the School of Graduate Studies in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy

Doctor of Philosophy (2018) (Health Policy Program)	McMaster University Hamilton, Ontario
Title:	Essays on subsidized health insurance and health-related quality of life
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Number of pages:	165

Abstract

This dissertation comprises three main chapters, book-ended by an introduction and a concluding chapter. Chapters 2 and 3 examine the impacts of health insurance programs in the Philippines and Indonesia on healthcare utilization, healthcare expenditures, and health outcomes. Chapter 4 then examines the age-related trajectories of health-related quality of life of Canadians with diabetes.

In Chapter 2, we examine the impact of the national health insurance program of The Philippines on maternal and health outcomes among poor mothers. We find that the program is associated with greater likelihood of prenatal care visits, facility-based birth delivery, and post-natal care, and the impact is most pronounced among the poorest women, but we do not observe improvements in birthweight. In Chapter 3, we evaluate the impact of Jamkesmas, the largest subsidized health insurance in Indonesia, on healthcare utilization, health outcomes, and healthcare expenditures. We find that Jamkesmas is associated with higher probability of using outpatient care and inpatient care and lower out-of-pocket healthcare expenditures, but no significant impact on catastrophic healthcare expenditures and health outcomes. In Chapter 4, we characterize the age-related-trajectories of health-related quality of life of Canadians with diabetes. We find that women and low-income individuals with diabetes experience a lower health-related quality of life trajectories, but there is no evidence

that the rate of deterioration of their health-related quality of life is faster than their counterparts without diabetes.

Acknowledgement

I would like to express my gratitude to the following people who have supported me not only during the course of writing this thesis but throughout the PhD degree.

Firstly, I would like to thank my supervisors, Prof. Jerry Hurley and Prof. Arthur Sweetman. To Prof. Hurley for his guidance, humility and compassion that will resonate throughout my career as a researcher. I consider him as one of my greatest mentors. I thank him for teaching me the value of a good story and precision in academic research. To Prof. Sweetman for helping me develop many of the econometric skills I know today. I thank him for constantly pushing me to do better.

To my committee members, Prof. David Feeny and Prof. Emmanuel Guindon for their intellectual guidance. I had many memorable interactions with Prof. Feeny. I must say he is the man behind why I finished my PhD in four years. I admire his remarkable wisdom and passion. He taught me how to listen and discern. I will always be a student of Prof. Feeny.

To CHEPA and the HP Program under the leadership of Prof. Schwartz and Prof. Abelson for creating an excellent learning environment. To Ms. Lydia Garland for her unwavering support. Like any PhD student, I had many ups and downs, but Lydia was always there cheering for us. To my classmates and friends in the program for making my PhD life interesting. I cannot name all of them, but I want to mention Christina Hackett and Young Jung. Without these two amazing people, this important chapter of my life will

never be complete. Christina is one of the most intelligent and caring person I know. Young is not only my roommate, but a brother (from another mother).

To my roommate and friend in Toronto, Rishab Mehan for all the fun memories. I have learned from him the importance of solitude, humility, and compassion, which are the essential qualities of a truly great researcher. To my relatives in Hamilton for being my second family. They took care of me when I was still navigating my new life in cold Canada. To my former colleagues, mentors and friends at CGHR- University of Toronto, Prof. Prabhat Jha, Sujata Mishra and Hyacinth Irving for giving me the platform to pursue my passion for global health. To Beverly Ho for being my inspiration, and for pushing me to do better. She was always there from start to finish.

Lastly, to my family for their never-ending support and understanding. I dedicate my PhD degree to my parents. Without them this accomplishment is worthless.

Disclaimer

The analysis of Chapter 4 was conducted at Statistics Canada's Research Data Centre (RDC) at McMaster University. The RDC is supported by funds to the Canadian Research Data Centre Network (CRDCN) from the Social Sciences and Humanities Research Council (SSHRC), the Canadian Institute for Health Research (CIHR), the Canadian Foundation for Innovation (CFI), and Statistics Canada. Although the research and analysis are based on data from Statistics Canada, the opinions expressed do not represent the views of Statistics Canada.

Preface

Chapter 2 was written under the supervision of Prof. Arthur Sweetman and Prof. David Feeny.

Chapter 3 was written under the supervision of Prof. Jeremiah Hurley, Prof. David Feeny, Prof. Arthur Sweetman, and Prof. Emmanuel Guindon.

Chapter 4 was written under the supervision of Prof. David Feeny.

Table of Contents

List of Tables

List of Figures

List of Appendices

Chapter 1: Introduction

This dissertation comprises three main chapters. The first two main chapters examine the impacts of expanding health insurance programs in the Philippines and Indonesia on healthcare utilization, healthcare expenditures, and health outcomes. The last main chapter examines the age-related trajectories of health-related quality of life of Canadians with diabetes.

The two chapters on expanding health insurance evaluate the policy interventions of two countries in various stages on the path towards universal health coverage. Philippines and Indonesia, both low- and middle-income countries, have rapidly expanded government-sponsored health insurance targeted at the poor population. With respect to third main chapter, Canada, a high-income country has a long history and tradition of universal health coverage. The focus is on the burden of disease over time in a population with universal health coverage in a high-income country.

Chapter 2 evaluates the impact of the national health insurance program in The Philippines on maternal and child health outcomes among poor women. The Philippines was one of the first developing countries to introduce a health insurance program as part of the government's promise of universal health coverage. The strategy used progressive targeting: identify the poor households and subsidize their health insurance premiums. However, almost 20 years after the program's inception, there is little

empirical evidence on the effectiveness of the program in reducing inequalities in maternal and child health outcomes among the poor. We use semi-parametric and non-parametric propensity score matching estimators to examine the impact of the national health insurance program on pre-natal care car visits, facility-based birth delivery, post-natal care and birthweight among poor Filipino mothers.

Chapter 3 examines the impact of the expansion of Jamkesmas, the largest subsidized health insurance scheme in Indonesia, which targets the poor and near-poor population. Jamkesmas shares many similar features with the national health insurance program in the Philippines, particularly the decentralized identification of beneficiaries. In this study, we use a fixed-effects model applied to a 15-year of longitudinal data to examine the impact of Jamkesmas on healthcare use, health outcomes, and out-of-pocket healthcare expenditures. The unusual richness of the dataset allows us to examine the impact of Jamkesmas on a wide-range of healthcare utilization and health outcomes variables, including anthropometric, biochemical, clinical, and self-reported measures. Using these different measures allows us to examine the impact of health insurance from different viewpoints regarding the individual's health status, which is important given the multi-dimensional concept of health. We also examine the temporal effects of Jamkesmas, which is a longstanding limitation in many empirical studies on health insurance.

In recent years, the global push towards universal health coverage has encouraged many governments in low- and middle-income countries to expand

subsidized health insurance programs. Philippines and Indonesia are examples of these countries. The goals of these programs are to improve healthcare access, financial protection, and health outcomes. Despite the rapid adoption of health insurance programs in many low- and middle-income countries, their impacts are not well understood. The findings in Chapters 2 and 3 provide an important insight: despite the promising impacts of health insurance on healthcare use, health insurance expansion alone may not improve health outcomes. This finding should stir discussions, especially in low- and middle countries that consider health insurance expansion as the primary (even sufficient) intervention required to improve health outcomes. In addition to supply-side reforms such as ensuring availability and quality of healthcare facilities, population-based non-healthcare interventions are critical. The social determinants framework identifies factors that influence the health of the population such as income and social status; employment and working conditions; physical environments; personal health practices and coping skills; healthy child development; gender; and culture (Marmot, 2005).

Chapter 4 provides an understanding of dynamics of health in Canada. Although Canada has yet to complete its "not-yet" universal health coverage—which is currently limited mainly to physician and hospital services, it has a long history of progressive and inclusive social protection policies (Ross et al., 2011). In this chapter, we use a multi-level model on 16-years of longitudinal data to characterize the age-related trajectories of health-related quality of life of Canadians with diabetes. We found that women and

low-income individuals with diabetes experience a lower health-related quality of life (i.e., Health Utilities Index Mark III) trajectories, but there is no evidence that the rate of deterioration of their health-related quality of life is faster than that for their non-diabetic counterparts. Our finding differs from a trajectory study conducted in the United States, where significantly faster deterioration was observed among persons with diabetes than persons without diabetes (Chiu & Wray, 2010). This is consistent with the findings by Papanicolas, Woskie & Jha (2018) that American with diabetes are 90 percent more likely to have avoidable hospitalization compared to their Canadian counterparts. The study provides evidence that persons with diabetes have the ability the 'compress morbidity' and sustain a rate of deterioration similar to healthy individuals, perhaps because of universal coverage and/or progressive social policies.

In conclusion, the three main chapters are motivated by a desire to understand government efforts in improving healthcare access, financial protection and health outcomes of its citizens. Although we only examine three countries, their experiences should provide valuable lessons for governments in strengthening their own health systems.

Chapter 2: Impact of the Philippine health insurance program on maternal and infant health outcomes among poor mothers

2.1. Introduction

Universal health coverage (UHC) is now part of many global commitments including the 2030 Sustainable Development Goals (World Health Organization, 2015; United Nations, 2017). UHC aims to provide access to needed healthcare services to all citizens without financial hardship (World Health Organization, 2010). In recent years, many low and middle-income countries, where access to basic healthcare services remains a problem, have introduced government-sponsored health insurance programs as a strategy to achieve UHC (World Health Organization, International Bank for Reconstruction and Development & World Bank, 2017).

The Philippines was one of the first developing countries to adopt a government-sponsored health insurance program when, in 1995, the Philippine Congress enacted a national health insurance program. The introduction of the program was part of the government's promise of UHC. The Philippine Health Insurance Corporation or PhilHealth, a government-owned corporation acts as a third party payer. It collects premiums from members as well as premium subsidies from local and national governments and reimburses accredited private and public healthcare facilities. However, almost twenty years after its inception, there is little empirical evidence regarding the extent to which the national health insurance program has improved access to healthcare and health outcomes among the poor population.

The Philippines is committed to improving maternal and child health. The national strategy is to improve healthcare access by increasing the national health

insurance program coverage rate among poor households and by including maternity care services in the benefits package. To achieve this, mothers are encouraged to obtain the recommended number of prenatal care visits, deliver newborns in healthcare facilities and to have postnatal check-ups. In 2003, PhilHealth started paying for family planning, pregnancy and delivery services (Philippine Health Insurance Corporation, 2003).

In this study, we estimate the impact of national health insurance on maternal and infant health outcomes among poor mothers who delivered newborns from 2010 to 2013. Using semi-parametric and non-parametric matching to estimate average treatment effects, we analyze data from the 2013 National Demographic and Health Survey (NDHS) which contains five outcomes that cover the spectrum of pregnancy: (1) obtaining the recommended number of prenatal care visits, (2) birthweight (continuous), (3) low birthweight (binary), (4) healthcare facility-based delivery and (5) postnatal care visits.

2.2. Philippine health sector and the National Health Insurance Program

Infant and maternal mortality remain a problem in the Philippines. There has been no remarkable reduction in maternal and infant mortality in the country from 2000 to 2014 compared to countries in southeast Asia. In fact, maternal mortality surprisingly increased from 162 to 221 per 100,000 live births between 2006 and 2011 (Picazo, Ulep & de la Cruz, 2013). Disaggregating these national averages by socio-economic status

reveals substantial inequalities. In 2013, infant mortality in the poorest wealth quintile was 54 infant deaths per 1000 livebirths compared to 11 infant deaths per 1000 livebirths in the richest quintile (Philippine Statical Authority & ICF International, 2014).

The Philippines has a mixed public-private healthcare system. In 2010, almost 60 percent of hospitals and primary care clinics were privately owned, while most of the rest were controlled by local governments. The healthcare system is decentralized, with provinces and municipalities delivering health services. The distribution of healthcare facilities is uneven. In affluent provinces, there can be up to 2 beds per 1,000 population compared to 0.2 beds per 1,000 in poor provinces (Lavado, Ulep, Pantig, dela Cruz, Aldeon & Ortiz, 2011).

The national health insurance was to have been the major source of healthcare financing, with PhilHealth as the sole purchaser of healthcare services. However, the program has suffered from a low coverage rate, shallow benefits, and limited financial support (Romualdez, dela Rosa, Flavier, Quimbo, Hartigan-Go, Lagrada & David, 2011). There are four types of national health insurance program membership based on premium payments: (1) mandatory for formal employees, (2) voluntary for informal employees, (3) non-paying for senior citizens, and (4) sponsored for subsidized households. Members' children aged 21 years and below are covered as beneficiaries. In 2013, only 65% of the population was covered by the program. The sponsored program allows poor households to be included. Local governments identify and enroll poor households, with the premium subsidy cost-shared with the national government.

However, local government units have leeway in identifying and enrolling households, which led to high variation across provinces. In practice, local governments can actively identify and enroll eligible households, or passively let households approach local government units to be included in the program. Silfverberg (2014) finds that a significant number of eligible poor households were not enrolled and that there were also households enrolled in the program that are not considered poor. The latter is the so-called “political poor”.

2.3. Literature review

Universal health coverage (UHC) has a long history in many industrialized countries. However, in developing countries, it only started gaining momentum at the turn of the 2ist century (World Health Organization, International Bank for Reconstruction and Development & World Bank, 2017). In the last two decades, UHC has been adopted as a national policy in many low- and middle-income countries, and is now part of many global commitments including the 2030 Sustainable Development Goals (United Nations, 2017). UHC provides access to needed healthcare services to all citizens and serves a strategy to achieving health system goals that all countries should aim for, which are better health outcomes, improved financial protection, and a responsive health system (World Health Organization, 2000).

Each country has its own mechanism for providing access to needed healthcare services. However, in most low- and middle-income countries, the common approach to

UHC is through demand-side programs. These programs often entail progressive targeting: identifying a specific population (usually the poor, near-poor and vulnerable population groups), and purchasing health care services on their behalf via output-based payments (Cotlear, Nagpal, Smith, Tandon & Cortez, 2013).

Despite the growing number of countries that implemented government-sponsored health insurance as a strategy to achieve UHC, the impacts of these programs remain inconclusive (Giedion, Alfonso & Diaz, 2013; Lagarde & Palmer, 2011; Spaan et al., 2012). In Chapter 3, we provide a more detailed review of the impacts of health insurance programs on healthcare utilization and health outcomes in low- and middle-income countries. We only focus on maternal and child health outcomes in this section.

2.3.1. Impact on the use of maternal healthcare services

There are a few studies that evaluate the impacts of government-sponsored health insurance on maternal and child outcomes in low-and middle-income countries. All the studies we found in the literature are descriptive without any attempt to elicit causal impacts, and none is based on random controlled trials. It is also hard to draw general conclusions from limited empirical studies because the findings vary across outcome measures, and even within specific outcome measure, the findings vary across context or scheme.

Facility-based delivery (i.e. giving birth in a healthcare facility) and skilled birth attendance (i.e. delivery is assisted by a health professional) are the most commonly used outcome measures in empirical studies, and most findings show a positive association. The findings from different geographical areas in sub-Saharan Africa (e.g. Rwanda), Asia (e.g. India, China, Turkey) and Latin America (e.g. Peru and Colombia) show positive association between government-sponsored health insurance and facility-based delivery and skilled-birth attendance (Hong, Ayad & Nagabo, 2011; Lu et al., 2011; Devadsan et al., 2011; Bogg, Wang & Diwan, 2002; Celik & Hotchkiss, 2000; McQuestion & Velasquez, 2006; Giedon et al., 2010). However, a number of studies show no association. For example, Kozhaminnil, Valera, Adams & Degnan (2010) demonstrate that the Philippine health insurance program is not associated with increased healthcare facility-based delivery. However, unlike our study, they do not examine the heterogeneity of impact across population groups, and do not distinguish between sponsored (i.e. subsidized members) and non-sponsored (i.e. voluntary and mandatory members) components of the program.

Ante-natal care is also used as an outcome measure. Most studies demonstrate a positive association between government-sponsored health insurance and the probability of women receiving any antenatal care visits, and the probability of women receiving at least four antenatal care visits (i.e. the number of prenatal care visits recommended by the World Health Organization). Some empirical studies however show no association. Long et al (2010) show that China's New Cooperative Medical

Systems (NCMS) has no detectable impact on the use of antenatal care. Similarly, Smith & Sulbach (2008) demonstrate no detectable effects of health insurance on the probability of receiving at least four antenatal care visits or receiving antenatal during the first trimester in Ghana and Mali.

2.3.2 Impact of health insurance on health outcomes

There is little empirical evidence in the literature about the relationship between health insurance and maternal and child health outcomes in low- and middle-income countries, and research findings show contradictory results. We only found one study that investigates the impact of government-sponsored insurance on maternal mortality that addresses endogeneity. Chen & Jing (2012) find China's NCMS has no detectable impact on maternal mortality. Barros et al (2002) also find that neonatal mortality decreased over time as insurance coverage expanded. However, their analysis is descriptive, and is based on trend data.

Similarly, the evidence for the relationship between health insurance and birthweight is limited in developing countries. We only found two studies. Cercone et al. (2012) show that insured mothers in Costa Rica had a lower probability of having a low birthweight newborn. In contrast, Gideon et al. (2010) find that insured mothers in Colombia are more likely to have low birthweight. The authors do not explain this unexpected finding.

2.4. Methods

In the impact evaluation literature (e.g., Heckman, Ichimura & Todd, 1997; Caliendo & Kopenig, 2008; Imbens & Rubin, 2015; Smith & Sweetman, 2016), the effect of a policy or program intervention is counterfactually described as the expected value of the difference between a relevant outcome, Y, for each member *i* of the treated group, (i.e. $Y_{i1,}$ which measures the health outcome of public insurance plan member *i*), less the predicted outcome for that same individual if not treated (i.e. Y_{i0}, the outcome for the same member i if that person were not a member):

$$\Delta_i = E[(Y_{i1}) - (Y_{i0})]. \qquad (1)$$

While equation (1) cannot be estimated for any individual, its average can be estimated using data from a successfully executed analysis with a sufficiently large sample because the distribution of observed and unobserved characteristics for the treated and non-treated groups are, on average, the same except for the treatment. High-quality non-experimental sources of exogenous variation may also be used to obtain estimates of causal impacts because, like well-executed experiments, they provide treatment and comparison groups that, on average, have (perhaps conditional on covariates) the same distributions of unobserved characteristics.

In observational data where there is no source of exogenous variation, estimating program effects is not straightforward due to, especially, the presence of

selection into treatment which results in biased estimates if not adequately addressed. At issue is that the treated and non-treated groups may differ on unobserved dimensions that affect the outcome of interest. Under certain conditions, we can elicit causal impact of the program by first estimating their counterfactual outcome of members assuming they had not joined the national health insurance and then differencing it from their observed outcome. The identifying assumption, sometimes called conditional independence, is that the conditioning variables employed are sufficient to render the distributions of unobserved variables in both the treatment and comparison group approximately the same in large samples. Beyond the concept of conditional independence, the potential outcome observed on one unit is also assumed to be unaffected by the particular assignment to treatments of other units (known as the Stable Treatment Value Assumption or SUTVA in statistics, and as the assumption of no general equilibrium effects in economics).

In all three cases – experiments, quasi-experiments and situations without a source of exogenous variation – if the identification is credible, the estimated difference is commonly called the average treatment effect for the treated (ATET). If M=1 for members and M=0 for non-members, then

$$\Delta_i = E(Y_{i1} | M_i = 1) - E(Y_{i0} | M_i = 1) \qquad (2)$$

where the right-hand side is a counterfactual estimate of members' expected outcome if they had not been treated. The credibility of the impact estimate depends on the quality of the counterfactual with well-executed randomized experiments or credible sources of naturally occurring exogenous variation providing high-quality counterfactuals. For estimates without a source of exogenous variation, that is for those relying on the conditional independence assumption such as in this study, the identification of causal impacts relies on conditioning on observable variables (using matching and/or regression techniques) that render the treatment variable independent of the error term.[1] If the identifying assumption is thought not to be credible, then the estimates can be interpreted as descriptive differences (i.e. conditional correlations that are not causal) in outcomes conditional on observed characteristics.

In our context, $\mathrm{E}(\mathrm{Y_{i0}}|\mathrm{M_i} = 1)$ is estimated using those who are not treated to generate a counterfactual for those who are treated. In recent years, there have been many methodological advances to address this problem, and propensity score matching (PSM) is the most widely used technique in the impact evaluation literature when there is not exogenous variation. A propensity score is the probability of joining the program conditional on a given set of explanatory variables (Rosenbaum & Rubin, 1983). It can be defined as e(X) = Probability(W=1|X). The propensity score is then used to balance

[1] According to Heckman & Robb (1985), conventional selection bias approaches rely on strong distributional assumption. In practice, regressors (X's) are assumed to be independent of the error term. However, in theory, they do not need to be independent. See Heckman & Robb (1985; 250). See also Smith & Sweetman (2016) for an interpretive introduction to these issues.

observed variables so as to eliminate all observed and by assumption unobserved differences, except for the treatment, that are relevant to the outcome between the member (treatment) and non-member (comparison) groups that are relevant to the outcome. If the identifying assumption is credible then, in this case, $\mathrm{E}(\mathrm{Y_{io}}\,|\mathrm{e(X)}, \mathrm{M_i} = 1)$ is equal to $\mathrm{E}(\mathrm{Y_{i0}}|\mathrm{e(X)}, \mathrm{M_i} = 0)$. The ATET is then

$$\Delta = \mathrm{E}(\mathrm{Y_{i1}} \mid \mathrm{e(X)}, \mathrm{M_i} = 1) - \mathrm{E}(\mathrm{Y_{i0}}|\mathrm{e(X)}, \mathrm{M_i} = 1)$$

$$= \mathrm{E}(\mathrm{Y_{i1}} \mid \mathrm{e(X)}, \mathrm{M_i} = 1) - \mathrm{E}(\mathrm{Y_{io}}\,|\mathrm{e(X)}, \mathrm{M_i} = 0) \qquad (3)$$

2.4.1. Specification of propensity score function

In this paper, we employ a framework adopted from Trujillo, Portillo & Vernon (2005) in specifying the propensity score function. Membership status among the poor depends on two general points: the government's decision to offer the premium subsidy and a mother's ability to seek benefits. Although the national government recommended an objective tool for identifying poor households, local governments still have leeway regarding whom to enroll. Arguably, the operation of the government's decision to offer a subsidy is a function of its governance, fiscal and administrative capacity. On the demand-side, the individual's capacity to seek or accept a subsidy is a function of the net benefit (including financial and psychic costs) that can be derived from being enrolled in the program. Hence, it is influenced by health status, previous exposure to healthcare services, socio-economic characteristics and community

characteristics. In the estimation of propensity scores, we use a logit regression model for the semi-parametric matching, and a kernel smoothing regression for the non-parametric matching. The logit regression model is:

$$\Pr(\text{Enrolled} = 1) = \mathrm{F}(\mathrm{a} + \mathrm{b}_1\mathrm{X}_1 + \mathrm{b}_2\mathrm{X}_2 + \mathrm{b}_3\mathrm{X}_3) \quad (4)$$

Where F is the cumulative distribution function for the logistic distribution, "a" is an intercept, the "X_n" are vectors of variables with "n" indexing the three groups of characteristics, and the "b" are coefficients to be estimated.

2.4.2. Matching estimators

After estimating the propensity scores using a logit regression model, we investigate whether the average propensity score and the mean of each explanatory variable are approximately equal for members and non-members. In practice, a variety of matching techniques are commonly used including nearest neighbor, stratification and kernel weighting. Caliendo & Kopenig (2008), and Frolich, Huberg & Wiesenfarth (2015) provide details about the advantages and disadvantages, estimation procedures, conditions and assumptions for each matching method. In this study, we employ local linear matching (LLM), which is a non-parametric estimator that uses a prediction from a local linear regression for each counterfactual estimate. One of the advantages of using LLM is lower variance as more information is used (Caliendo & Kopenig, 2008). We then

check if the means of the covariates are equal for member and non-members are balanced using t-tests. If the means are not statistically significantly different, or if the difference is less than 10 percent, the means of the covariates are regarded as approximately equal for members and non-members.

Inference for the ATET uses non-parametric percentile-t clustered bootstrapping with 999 replications to estimate the p-values and confidence intervals. We re-center each bootstrap t-statistic around the sample's coefficient estimate (Cameron & Trivedi, 2010; Signh & Xie, 2010). Cluster bootstrapping is required since we include province-level (macro) variables in regressions using individual-level data. Cluster bootstrapping accounts for intra-cluster (intra-province) correlations that might otherwise render our standard error estimates inconsistent.

As an alternative to semi-parametric PSM, we also use inverse probability weighting (IPW). IPW assigns greater weight to those comparison group members with higher estimated propensity scores (Hirano & Imbens, 2001; Imbens, 2004). We derive weights from the propensity score, e (X) using the following IPW estimator:

$$\triangle = \mathrm{N}^{-1} \sum_{\mathrm{i}=1}^{\mathrm{N}} \frac{\mathrm{M_i Y_i}}{\mathrm{e(X)}} - \mathrm{N}^{-1} \sum_{\mathrm{i}=1}^{\mathrm{N}} \frac{(1-\mathrm{M_i})\mathrm{Y_i}}{1-\mathrm{e(X)}} \qquad (4)$$

where N is the total number of subjects. M is the treatment and Y is the outcome.

The aforementioned estimators use a parametric logit regression model to estimate the propensity score. Although parametric models can provide estimates of the

true propensity score, they do not usually guarantee suitable approximations. Estimators based on a non-parametric propensity score have demonstrated the lowest possible asymptotic variance (Li, Racine & Woolridge, 2008; Hahn, 1998). In Monte Carlo trials, Frolich, Huberg & Wiesenfarth (2015) find that non-parametric regression outperforms all other semi-parametric estimators in estimating ATET. As a third option, we therefore follow the method of Li, Racine & Woolridge (2008) and Hall, Racine & Li (2007) in estimating the propensity scores using a kernel smoothing non-parametric regression model.

For all three estimators, we estimate the effect of national health insurance on the abovementioned maternal and infant health outcomes across subgroups. These include the difference in the ATET between the 1st and 2nd wealth quintiles, the difference between urban and rural, the difference between uniparous and multiparous, as well as the difference between low and high educational attainment. We also calculate the effect size (Cohen's d) to examine the clinical importance of our estimates. Cohen's d is calculated using the following formula: $([\text{Mean}_{\text{Group1}} - \text{Mean}_{\text{Group2)}}]/\text{SD}_{\text{pooled.}})$. Cohen arbitrarily classifies effect size as small, medium or large using the cut-off values of 0.2, 0.5 and 0.80, respectively (Cohen, 1988).

2.4.3. Data

We use the nationally representative 2013 National Demographic and Health Survey (NDHS) conducted by the National Statistics Office of the Philippines. The NDHS

has households', individuals' and women's modules; 14,808 households were interviewed with a 99.4 percent response rate. Among those interviewed, 16, 437 women of reproductive age were identified as eligible respondents for the women's module with a 98.4 percent response rate. It is possible that more than one woman in a household were interviewed. On average, there are 2 women of reproductive age per household in the Philippines (Philippine Statistical Authority and ICF International 2014). In this study, the household and women's modules are merged. We also employ aggregate data such as the prevalence of poverty, a governance index,[2] public health expenditure per capita and the number of hospital beds per capita for the 81 provinces from the websites of the Philippine Statistical Authority and Department of Health.

Because it is more policy relevant, the study focuses only on poor mothers who experienced at least one pregnancy in the three years prior to the survey. Mothers belonging to the first and second quintiles of wealth scores are considered poor and mothers belonging to higher socio-economic quintiles are excluded from the sample. The variable wealth score was generated by the Philippine Statistical Authority using principal component analysis of selected tangible household assets. The sample size for

[2] Governance index (GI) is a weighted arithmetic average of the Economic Governance Index (EGI), the Political Governance Index (PGI) and the Administrative Governance Index (AGI). The Economic Governance Index is calculated using fiscal-related indicators such as revenue collection, social services expenditures, and macro-economic indicators (e.g. inflation, unemployment, poverty gap). The Political Governance Index (PGI) is calculated using the following indicators: crime solution efficiency and voter's turn out rates. The Administrative Governance Index is calculated using school-related (e.g. drop-out rates, classroom-student ratio) and road, electricity and telephone-density indicators. The Philippine Statistical Authority officially releases the GIs of provinces.

analysis is 2,642 women: 1,497 national health insurance members (treatment group) and 1,145 non-members (comparison group).

We use five dependent variables, four of which are binary and one which is continuous: (1) obtained the recommended number of prenatal care visits (at least 4 prenatal care visits during pregnancy), (2) delivered in healthcare facility (private or public), (3) birthweight (in grams), (4) having a normal birth weight (2500 grams or more, binary) and (5) obtained at least one postnatal care visit within two months after delivery. We also explore log transformed birth weight and a lower cut-off point for normal birth weight (1500 grams or more) as outcome variables; because the results are similar, we do not present the results in this paper. The outcome variables address the spectrum of pregnancy care and outcomes.

The explanatory variables used to predict the probability of being enrolled in national health insurance (the propensity score) are grouped into three: individual-level, pregnancy-related and community characteristics. The first comprises individual and household-level variables measuring women's socio-economic status (wealth score, marital status, educational attainment, employment and gender of the household head) and health and demographic variables (age, obesity, smoking status, history of chronic disease and an indicator for eating a balanced diet). Socio-economic and health demographic characteristics reflect a number of factors including mothers' ability to weigh the costs and benefits of being enrolled in national health insurance. The health-

related characteristics capture the mothers' inclination to use medical care. In this study, we use variables that capture both chronic and preventive aspects of healthcare.

The second group contains pregnancy-related variables (presence of symptoms related to pregnancy, pregnancy intentions, and parity), which may influence mothers' decision to enroll in the program. For instance, multiparous mothers may be more likely to be aware of the benefits of health insurance during pregnancy.

The third group comprises characteristics of the province of residence (urbanity, region, poverty prevalence, governance index, public health expenditure per capita and the number of hospital beds per 1000 population) that might both influence mothers' decisions to seek insurance and government's capacity to enroll poor households. Characteristics of the province such as poverty prevalence and quality of governance are also thought to influence the enrollment practices of local government units. Provinces with high poverty prevalence tend to have a higher share of households eligible for the premium subsidy from the national government. Communities with a better political environment as measured by the governance index are more likely to identify poor households properly and efficiently. Supply-side characteristics of the area such as availability of healthcare facilities and medical equipment play a large role in determining enrollment (Mebratie, Sparrow, Yilma, Alemu & Bud, 2015). We measure the number of hospital beds per 1000 population and public healthcare expenditure per capita to proxy the availability of services in the province.

2.5. Results

Table 2.1 displays the unconditional means of these outcome variables and tests whether they differ by health insurance membership status. The percent of mothers with both the recommended number of visits and facility-based delivery are higher among members compared to non-members, but the means for postnatal visits and birthweight are not statistically significantly different. The smaller sample size for birthweight is due to a large number of missing observations. Table 2.2 presents a descriptive analysis of health insurance membership status and individual explanatory variables.

For semi-parametric propensity score matching, we estimate the propensity score of being enrolled in the national health insurance using a logit regression model. This is followed by matching the treatment and comparison groups using local linear regression to re-weight the comparison group. One necessary condition for matching to work is common support in the data for the two groups (i.e. overlapping propensity score distributions). After exploring our data, we impose common support by trimming the one percent of treated observations for which the propensity score density of the comparison is lowest; fourteen observations are removed because there are not comparable comparison group members. Lastly, we check the quality of matching by assessing the extent of balancing achieved on the two matched samples (i.e., t-tests for equality of means in the two samples). Table 2.3 shows that the characteristics of covariates of health insurance members (treatment) and non-members (comparison)

are balanced as ascertained by statistically insignificant p-values (except for mother's education) and less than 10 percentage bias in all covariates, which is the most commonly used cut-off point.

Table 2.4 presents the ATET of health insurance for different maternal and infant health outcomes using three estimators. Out of the five outcome variables, only the three utilization measures are statistically significantly different for the member and non-member groups: recommended prenatal care visits, healthcare facility-based delivery and postnatal care visit. Poor mothers enrolled in the national health insurance display a higher probability of obtaining the number of recommended prenatal care visits, of delivering newborns in healthcare facilities and obtaining at least one postnatal care visit within two months after delivery (except for postnatal care visit using semi-parametric estimator for which the ATET is not statistically different from zero).

Turning to birthweight (see the discussion section regarding sample size), the coefficients are all statistically insignificant; this is consistent across the three estimators of ATET. Further, the point estimates suggest national health insurance coverage actually reduces birthweight. The large standard error and wide confidence intervals of the average treatment effects on birthweight might be in part attributable to small sample size. Of the 2, 642 sample, 792 were excluded due to non-response.

We also estimate the effect of national health insurance coverage across potentially important subgroups. These include the difference in the ATET between the first and second wealth quintiles, urban and rural geographies, uniparous and

multiparous mothers, as well as mothers with low and high educational attainment. Results show that in all subgroups, the effects of national health insurance on recommended prenatal care visits, healthcare facility-based delivery and postnatal care visit are each statistically significant for at least one of the three ATET estimators (Table 2.5). However, the effect of national health insurance on birthweight (both continuous and binary specifications) in all subgroups is consistently statistically insignificant across the three estimators. In urban areas, the ATET of national health insurance on healthcare facility-based delivery is higher than in rural. The ATET of national health insurance on the recommended number of prenatal care visits is also higher among mothers belonging to the first wealth quintile compared to the second. Similarly, the ATET for recommended prenatal care visits is also higher among mothers with low educational attainment. Among uniparous mothers, the ATET on healthcare facility-based delivery is larger compared to multiparous mothers, and the ATET of national health insurance on recommended prenatal care visits is smaller. Although it may appear that there are differences in the point estimates between subgroups, these are statistically insignificant as witnessed by the overlapping confidence intervals.

For the three estimators to provide results that may be interpreted as causal, an assumption that is referred to using terms such as unconfoundedness or conditional independence is required. It means that selection bias is only due to observed characteristics (Imbens and Rubin, 2015). We argue that the NDHS includes the variables

needed for the empirical strategy to, at least approximately, satisfy this condition in accordance with the framework by Trujillo, Portillo & Vernon (2005).

2.6. Discussion

Our study reveals that poor mothers who are covered with the Philippines' national insurance program have a higher probability of obtaining the recommended number of prenatal care visits, of giving birth in a healthcare facility and of having a postnatal care visit within two months after delivery. However, there is no statistically significant effect on birthweight. There are several explanations for why the program did not produce a health improvement on this dimension. First, public health insurance can increase healthcare utilization, but healthcare services may not be a major determinant of health status (e.g., Smith, 1999; Chen et al., 2007). The social determinants of health framework suggests that health is determined not only by healthcare interventions but by a plethora of physical, environmental and other socio-economic conditions (Smith, 1999; Evans & Stoddart, 1990). Second, the lack of program effect on health status might be a reflection of the poor quality of healthcare services. Limited policy attention is given to the quality of healthcare services especially in government-run hospitals and clinics where poor mothers usually seek maternal and childcare services. Hence, despite the higher quantity, the poor quality of healthcare services may have limited the effects on health status (Chen et al., 2007).

Our study also shows that the effect of the national health insurance program is, on two dimensions, somewhat larger for the most vulnerable population. The effect of the program on recommended prenatal care and postnatal visits is larger among mothers in the poorest quintile and among mothers with low education. In contrast, while positive for our entire sample, the effect on healthcare facility-based delivery is statistically insignificant for this subgroup. Healthcare facility-based delivery might be prohibitively expensive because of the high non-medical and medical costs incurred outside the insurance benefit (e.g. transportation costs). More importantly, the lack of effect of the program on healthcare facility-based delivery may also signal the lack of healthcare facilities in poor areas. This is consistent with the lack of a significant effect of health insurance on facility-based delivery among mothers living in rural areas. Although there is an interesting pattern in the point estimates, the overlapping confidence intervals suggest that the differences in ATET between subgroups are not statistically significant. We conducted an ex-post power calculation to determine if the statistical insignificance can be attributed to the small sample size. Our calculation indicated that with our current sample size the power of the test is low (less than 80%);hence, we cannot make airtight inferences.

From clinical and economic standpoints, it is important to assess not only statistical significance but also how quantitatively meaningful the average treatment effects of the program are. Unfortunately, clinical importance is not always well-defined. As described above, one common, if ad hoc, the method for assessing a “minimal

clinically important difference" or a "clinically meaningful difference" is to calculate Cohen's d. By this metric, the effect of the program on prenatal care visits is clinically important. The Cohen's d from the IPW and non-parametric estimators are above the cut-off point recommended for an effect size (ATET) to be considered clinically important (a Cohen's d of ≥ 0.2 is considered clinically important). In contrast, the Cohen's d for healthcare facility-based delivery and postnatal care visits is < 0.2 for all estimators. This suggests that even though the ATET estimates for healthcare facility-based delivery and a postnatal care visit are statistically significant, they may not be "clinically" important. Comparing across groups, while the effect sizes of the program on optimal prenatal care visits in the lowest wealth quintile and low education groups are clinically important, they are not for the second lowest wealth quintile and high education groups. The effect sizes on other outcomes are not clinically important in both wealth quintile and education groups.

Despite the judgment of potential importance for the recommended prenatal care visit following from Cohen's d, the lack of a statistically significant effect of the program on birthweight suggests that the overall effect does not have much policy relevance – at least not on this important dimension. However, some might argue that this statistical insignificance might be due to the small sample size – assuming an "important" effect to be quite modest given that our point estimate is quite close to zero. We, therefore, conducted an ex-post power calculation to determine how large the sample size would need to be to detect a clinically important difference. In the case

of the proportion with normal birthweight (i.e., above 2500 grams), we would need a sample size of approximately 1, 052 to detect a clinically important difference. Assuming a 0.20 Cohen's d, the clinically important difference between health insurance members and non-members is 0.10. However, we observed a statistically insignificant ATET of about 0.01 with our current sample size (n=1.810). The difference between the observed ATET and the clinically important ATET (0.01 vs. 0.10) is statistically significant (p value=0.000). Our interpretation is that the "true" impact of health insurance on birthweight is zero to trivially small. If there were a clinically important difference in the proportion of normal birthweight between member and non-member, the model should have detected it with our current sample size.

Overall, our study supports the literature in questioning the effectiveness of health insurance, or at least these particular insured services, as the only policy tool for improving population health status, especially in developing countries. Also the results support further discussions on the feasibility of health insurance as a conduit for the delivery of effective interventions in the health insurance benefit plan.

In terms of research implications, our study calls for a more rigorous impact evaluation of health insurance in developing countries. In spite of our efforts to use propensity score matching to identify the causal relationship between the national health insurance program and maternal and child outcomes, we might have not fully met the assumption of unconfoundedness. Our results might, therefore, be interpreted by some readers as identifying correlations (or covariance) conditional on the regressors

in our model rather than as causal parameters. While this modifies the interpretation of our results, we think that the questions about the program's effectiveness in improving birthweight – a common and useful proxy for health status – remain. An implication of this argument is that governments should engage in a well-designed community effectiveness experiments (or, more broadly, introduce some source of exogenous variation in treatment) to evaluate this important initiative. Such experiments would convincingly reduce the effects of selection bias and generate valid evidence on the causal impacts of programs such as the one studied here.

Lastly, there is also a limitation inherent in our data that might affect the validity of our estimates. In this study, we used self-reported birth weight as a child health outcome and, given the low response rate (792 respondents out of 2, 642 did not report), aside from measure error our estimates might be biased because of who responds. There is a systematic difference between mothers who reported birthweight and those who did not. Mothers who did not report birthweight are more likely from the poorest wealth quintile, have low educational attainment, and living in rural areas.

2.7. Conclusion

Our key conclusion is that the Philippines' national health insurance program moderately increases the utilization of healthcare services among poor women during pregnancy. This impact is somewhat larger for the most vulnerable population -- mothers in the poorest quintile and/or with low education. With these findings, we can

say that the Philippine national health insurance program improved healthcare access among the poor, which supports the main thrust of UHC. However, the lack of detectable impact on the health status of infants as measured by birthweight for any group suggests that health insurance expansion alone might not be a sufficient to improve health outcomes. A policy implication of our results is that it is important for less developed countries like the Philippines to complement health insurance expansion with other effective interventions.

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Table 2.1. Unconditional probability and means of the outcomes, by health insurance membership status

	Member (n)	Non-member (n)
% of women with recommended number of prenatal visit	0.80 (1,497)	0.73 (1,145)*
% women who delivered in healthcare facility	0.49 (1,496)	0.47 (1,145)*
% women with normal birthweight children	0.78 (774)	0.78 (1,036)
Mean birthweight (in grams)	2952.2 (1,036)	2929.2 (774)
% of women with post-natal visits within two months after delivery	0.86 (1,496)	0.84 (1,141)

Notes:

1. Source of data: 2013 National Demographic and Health Survey
2. The number of observations are in parenthesis (n). The lower sample size for birthweight is due to missing observation and non-response.
3. Recommended number of prenatal visit means at least four visits, while post-natal visit means at least one visit to a health facility within two months after delivery.
4. Birthweight in grams
5. Asterisk (*) means there is statistically significant difference ($p<0.05$). Chi-square or t-test

Table 2.2. Descriptive statistics of selected variables, by health insurance membership status

Explanatory Variables	Member	Non-member	p value
Age during pregnancy (Mean) [1]	29.99	26.26	0.000
Currently working (%)[2]	0.51	0.39	0.000
Marital status			
Single (%)	0.01	0.03	0.002
Married (%)	0.97	0.93	0.000
Others (%)	0.02	0.04	0.002
Wealth index scores[1]	-106,488.10	-99,298.49	0.001
Mother's education			
No education (%)	0.02	0.05	0.001
Primary (%)	0.36	0.34	0.220
Secondary (%)	0.49	0.52	0.250
Tertiary (%)	0.12	0.10	0.060
Female as head[2]	0.07	0.10	0.007
Experience symptoms during pregnancy[2]	0.66	0.67	0.530
Parity (number of births) [1]	4.15	2.97	0.000
Pregnancy intentions			
Wanted (%)	0.69	0.73	0.016
Unwanted (%)	0.14	0.17	0.130
Mistimed (%)	0.17	0.10	0.000
Current smoker (%)[2]	0.05	0.06	0.130
Obese (%)[2]	0.10	0.09	0.300
Eat balanced-diet (%)[2]	0.23	0.22	0.700
Family history of chronic illness (%)[2]	0.28	0.26	0.210
Living in urban (%)[2]	0.19	0.29	0.000
Poverty prevalence of the province[1]	36.57	35.95	0.350
Governance index of the province[4,]	116.97	119.62	0.000
Public health expenditure of the province [1]	145.77	148.86	0.570
Number of hospital bed per 1000 population[1]	0.86	0.86	0.930

Notes:

1. Continuous variables. The values are expressed as means
2. Binary variable. The values are expressed as proportions
3. Region variable is not included to maximize space
4. The higher the governance index, the better governance level.

Table 2.3. Balancing covariates

	Member	Non-member	% bias	t-value	p-value
Age (squared)	942.89	939.95	0.70	0.19	0.85
Age during pregnancy	29.99	29.89	0.40	0.10	0.92
Currently working	0.51	0.48	5.60	1.51	0.13
Married	0.97	0.96	2.20	0.71	0.48
Other marital status	0.02	0.01	3.50	1.27	0.20
Wealth scores	-110000	-110000	0.50	0.15	0.88
Primary education	0.36	0.36	0.40	0.11	0.91
Secondary education	0.49	0.47	3.90	1.07	0.29
Tertiary education	0.12	0.15	-9.50	-2.35	0.02
Living in urban area	0.19	0.19	1.10	0.33	0.74
2.Region 2	0.03	0.03	2.10	0.56	0.58
3.Region 3	0.05	0.05	-1.30	-0.34	0.73
4.Region 4	0.05	0.05	-0.30	-0.08	0.94
5.Region 5	0.03	0.04	-1.70	-0.50	0.62
6.Region 6	0.04	0.04	-0.30	-0.10	0.92
7.Region 7	0.05	0.04	3.80	1.13	0.26
8.Region 8	0.08	0.07	4.50	1.17	0.24
9.Region 9	0.08	0.08	0.50	0.13	0.89
10.Region 10	0.06	0.06	-3.30	-0.92	0.36
11.Region 11	0.06	0.07	-5.40	-1.28	0.20
12.Region 12	0.09	0.08	5.10	1.34	0.18
13.Region 13	0.07	0.06	5.70	1.46	0.15
14.Region 14	0.07	0.07	-3.30	-0.86	0.39
15.Region 15	0.06	0.06	-0.90	-0.23	0.82
16.Region 16	0.07	0.08	-2.60	-0.69	0.49
17.Region 17	0.09	0.10	-0.80	-0.25	0.80
Female as head	0.07	0.07	0.00	0.00	1.00
Experience symptoms during pregnancy	0.66	0.65	2.40	0.66	0.51
Parity	4.15	4.07	1.30	0.32	0.75
Mistimed pregnancy	0.14	0.13	4.90	1.39	0.16
Unwanted pregnancy	0.17	0.18	-5.40	-1.31	0.19
Current smoker	0.05	0.05	-0.90	-0.25	0.80
Obese	0.11	0.09	5.20	1.42	0.16
Eat Balanced diet	0.23	0.23	-0.20	-0.04	0.97
Family history of disease	0.28	0.29	-1.70	-0.45	0.66
Poverty prevalence of the province	36.57	36.52	-0.10	-0.02	0.98

Governance index of the province	116.97	117.35	-1.90	-0.54	0.59
Public health expenditure of the province	145.77	146.30	-0.50	-0.14	0.89
Number of hospital bed per 1000 population	0.86	0.87	-3.80	-1.13	0.26

Note:

1. The values for member and non-member are expressed as either means (continuous variable) or proportion (binary variable).
2. We impose less than 10 percent as acceptable percentage bias
3. t- value and p-value use to compare the equality of two means

Table 2.4. Average treatment effects of health insurance on maternal health outcomes

Outcomes	Semi-parametric PSM (local linear regression)				IPW				Non-parametric			
	ATET	95CI		Effect size	ATET	95CI		Effect size	ATET	95CI		Effect size
Recommended prenatal care visit	0.07***	0.06	0.12	0.16	0.12*	0.08	0.17	0.27#	0.11*	0.08	0.14	0.25#
Facility-based delivery	0.06***	0.02	0.10	0.13	0.08*	0.04	0.12	0.17	0.05	0.02	0.07	0.10
Birth weight (in grams)	-29.88	-100.45	50.56	-0.03	-35.20	-129.56	69.83	-0.04	-7.44	-42.93	30.75	-0.01
Birth weight (binary)	0.01	-0.02	0.04	0.012	-0.00	-0.04	0.04	-0.01	0.00	-0.02	0.02	0.01
Postnatal visit	0.03	0.00	0.06	0.07	0.03*	0.00	0.06	0.08	0.05*	0.00	0.09	0.13

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

Note:

1. ATET means average treatment effect of the treated
2. Bootstrapped standard error from 999 replications taking into account the clustering effects of provincial level variables
3. Number sign (#) means clinically important estimates
4. Effect size is calculated using the formula: ATET/standard deviation. The difference of two groups is clinically importance if the effect size is $\geq$0.20.

Table 2.5. Average treatment effects of health insurance on maternal health outcomes, by sub-group

Subgroups	Semi-parametric PSM				IPW				Non-parametric			
	ATET	95 CI t-stat bootstrap		p-value	ATET	95 CI t-stat bootstrap		p-value	ATET	95 CI t-stat bootstrap		p-value
RURAL												
Recommended												
prenatal care visit	0.074*	0.041	0.110	0.00	0.108*	0.062	0.171	0.00	0.097*	0.064	0.130	0.00
Facility-based delivery	0.045	-0.004	0.090	0.06	0.065*	0.011	0.119	0.02	0.030*	0.014	0.046	0.00
Birthweight (in grams)	-28.058	-112.936	53.638	1.00	-27.395	-134.070	74.543	1.00	-19.835	-21.640	23.619	1.00
Birthweight (binary)	-0.005	-0.033	0.026	1.00	-0.013	-0.063	0.043	1.00	-0.001	-0.024	0.026	1.00
Postnatal care visit	0.022	-0.006	0.053	0.14	0.041*	0.004	0.085	0.05	0.041*	0.005	0.072	0.02
URBAN												
Recommended												
prenatal care visit	0.123*	0.042	0.200	0.00	0.125*	0.052	0.203	0.00	0.095*	0.045	0.136	0.00
Facility-based delivery	0.113*	0.045	0.180	0.00	0.107*	0.047	0.173	0.00	0.065*	0.040	0.150	0.02
Birthweight (in grams)	-55.510	-286.585	186.696	1.00	-39.017	-322.615	186.573	1.00	-25.995	-137.873	91.843	1.00
Birthweight (binary)	0.022	-0.037	0.090	0.51	0.013	-0.063	0.087	0.75	-0.001	-0.013	0.011	1.00
Postnatal care visit	0.048	-0.008	0.112	0.11	0.032	-0.024	0.090	0.28	0.034*	0.004	0.059	0.02
1st WEALTH QUINTILE												
Recommended												
prenatal care visit	0.097*	0.061	0.134	0.00	0.124*	0.077	0.186	0.00	0.096*	0.060	0.128	0.00
Facility-based delivery	0.046	-0.013	0.099	0.11	0.058	-0.004	0.125	0.08	0.035*	0.012	0.056	0.00
Birthweight (in grams)	-29.611	-143.845	84.024	1.293	-9.480	-146.014	156.720	1.00	-6.496	-150.969	148.712	1.00
Birthweight (binary)	-0.039	-0.086	0.005	1.022	-0.029	-0.073	0.032	1.00	-0.034	-0.114	0.059	1.00
Postnatal care visit	0.044*	0.006	0.083	0.024	0.051*	0.007	0.097	0.03	0.005*	0.002	0.009	0.04
2nd WEALTH QUINTILE												
Recommended												
prenatal care visit	0.053*	0.002	0.110	0.05	0.080*	0.024	0.154	0.02	0.022*	0.007	0.038	0.00
Facility-based delivery	0.070*	0.006	0.140	0.04	0.096*	0.035	0.166	0.00	0.037*	0.011	0.057	0.00
Birthweight (in grams)	-73.954	-199.834	83.396	1.00	-76.180	-243.855	59.113	1.00	-55.481	-286.057	163.289	1.00
Birthweight (binary)	0.024	-0.029	0.078	0.37	0.030	-0.029	0.090	0.32	0.007	-0.003	0.017	0.19
Postnatal care visit	-0.016	-0.058	0.024	1.00	0.002	-0.063	0.025	0.94	0.017	-0.026	0.057	0.43
UNIPAROUS												
Recommended												
prenatal care visit	0.043	-0.061	0.100	0.30	0.035	-0.040	0.124	0.40	0.045	-0.039	0.115	0.26
Facility-based delivery	0.097	0.026	0.164	0.01	0.056	-0.020	0.136	0.16	0.014	-0.001	0.028	0.06
Birthweight (in grams)	-4.247	-181.414	158.706	1.00	-44.511	-254.791	185.554	1.00	-0.054	-24.636	23.771	1.00
Birthweight (binary)	-0.019	-0.092	0.055	1.00	-0.019	-0.110	0.074	1.00	-0.013	-0.067	0.048	1.00
Postnatal care visit	0.040	-0.019	0.093	0.17	0.044	-0.019	0.115	0.20	0.032*	0.003	0.066	0.05
MULTIPAROUS												
Recommended												
prenatal care visit	0.103*	0.068	0.132	0.00	0.105*	0.069	0.160	0.00	0.085*	0.058	0.115	0.00
Facility-based delivery	0.074*	0.030	0.112	0.00	0.071*	0.024	0.118	0.00	0.053*	0.026	0.079	0.00
Birthweight (in grams)	-28.628	-117.335	61.353	1.00	-28.925	-146.429	83.965	1.00	-0.523	-46.301	40.878	1.00
Birthweight (binary)	0.000	-0.042	0.037	0.98	0.004	-0.040	0.055	0.88	0.008	-0.035	0.052	0.74
Postnatal care visit	0.028	-0.001	0.062	0.08	0.028	-0.008	0.067	0.14	0.037	-0.003	0.072	0.06
LOW EDUCATION												
Recommended												
prenatal care visit	0.123*	0.078	0.178	0.00	0.165*	0.102	0.255	0.00	0.122*	0.077	0.165	0.00
Facility-based delivery	0.091*	0.046	0.142	0.00	0.066	-0.014	0.131	0.08	0.063*	0.028	0.094	0.00
Birthweight (in grams)	43.363	-165.839	244.612	0.69	135.876	-40.355	356.272	0.18	66.532	-83.083	222.579	0.40
Birthweight (binary)	0.022	-0.039	0.076	0.47	0.031	-0.045	0.115	0.46	0.006	-0.026	0.036	0.74
Postnatal care visit	0.018	-0.037	0.064	0.50	0.016	-0.042	0.076	0.59	0.017	-0.005	0.041	0.15
HIGH EDUCATION												
Recommended												
prenatal care visit	0.062*	0.030	0.100	0.00	0.084*	0.044	0.135	0.00	0.047*	0.025	0.070	0.00
Facility-based delivery	0.045*	-0.003	0.095	0.07	0.068*	0.018	0.130	0.02	0.014*	0.003	0.023	0.00
Birthweight (in grams)	-72.126	-159.398	15.146	1.00	-86.149	-190.517	3.968	0.99	-19.587	-39.157	4.531	0.98
Birthweight (binary)	-0.018	-0.052	0.017	1.00	-0.013	-0.058	0.041	1.30	-0.012	-0.052	0.032	1.00
Postnatal care visit	0.025	-0.007	0.060	0.14	0.041*	0.001	0.090	0.05	0.016*	0.003	0.027	0.01

Note:

1. ATET means average treatment effect of the treated
2. Bootstrapped standard error from 999 replications taking into account the clustering effects of provincial level variables

Chapter 3: The impacts of subsidized health insurance expansion in Indonesia on healthcare use, health and healthcare expenditures

3.1. Introduction

Out-of-pocket health spending has adverse effects on healthcare access and use, and these effects can be catastrophic for the poor. According to the World Health Organization, in low and middle-income countries 400 million people do not have access to basic healthcare services, and 150 million people fall into extreme poverty every year because of healthcare-related spending. In response to these challenges, in recent years, governments around the world have channeled more resources into the health sector in an effort to achieve universal health coverage (UHC) (World Health Organization, 2010).

As a first step to achieve UHC, given their limited resources, a common strategy of governments in LMICs is the expansion of health insurance for the poor and vulnerable populations. While this falls short of the ultimate goal of UHC, which is to ensure health insurance for all citizens regardless of socio-economic status, it allocates resources to the population with the greatest needs (Giedion, Alfonso & Diaz, 2013).

Indonesia exemplifies this pattern. In 2005 the government introduced a public insurance program—Askeskin—targeted at the poor. In 2007, the Indonesian government renamed the program—to Jamkesmas—and expanded its coverage to include both the poor and near-poor (Harimurti, Pigazzini, Pambudi & Tandon, 2013; Mahendradhata, Trisnantoro, Listyadewi, Harimurti & Prawira, 2017). These initiatives played a central role in increasing the national insurance coverage rate from 20% in 2000 to 50% in 2014.

The Indonesian government invested heavily in the Jamkesmas program, and while the increase in the share of the population covered suggests that it was a success, the large investment warrants a rigorous impact evaluation, which is the purpose of our study. It is to the best of our knowledge the first to examine the impact of the introduction and expansion of Indonesia's subsidized health insurance from 2004 to 2014. In addition to its targeted approach, which is shared with many low and middle-income countries, Indonesia is an interesting case to examine because of its decentralized healthcare system. While targeting criteria are developed nationally, their interpretation and implementation occur at the local level. This introduces variation across local governments and admits a larger role for subjective and political considerations in its implementation. Finally, because enrolment is not mandatory—again, a feature shared with many other low and middle-income countries' programs—enrolment in Jamkesmas is subject to selection problems that can compromise both its effectiveness and the ability to assess it.

In this study, we use a 15-year panel dataset (waves in 2000, 2007 and 2014) to examine the impact of Jamkesmas on healthcare use, health outcomes, and catastrophic healthcare expenditures. The long follow-up period allows us to account for its long-term effects, especially on slow-moving conditions such as chronic illness and associated risk factors. Importantly, our data include detailed measures of the use of healthcare and health status, including anthropometric, biochemical and self-reported measures. Using these different measures allow us to examine the impact of health insurance from

different viewpoints regarding patient health status, which is important given a multi-dimensional concept of health.

3.2. Impact of health insurance in low and middle-income countries

General systematic reviews on the impact of insurance coverage on healthcare demand and on health status are available elsewhere (Chollet, 2006; Ringel, Hosek, Vollaard & Mahnovski, 2002; Zweifel & Manning, 2000). Here, we only focus on studies conducted in low and middle-income countries.

Despite the growing number of empirical studies on the impact of health insurance in low and middle-income countries, the impacts of health insurance programs remain inconclusive (Giedion, Alfonso & Diaz, 2013; Lagarde & Palmer, 2011; Spaan et al., 2012). As we describe below, the reasons for this are numerous, but a fundamental problem is that weak study designs undermine the quality of the evidence and what we can conclude (Giedion, Alfonso & Diaz, 2013).

These weak designs are rooted in a number of factors. First, because most health insurance programs in low and middle-income countries are not mandatory, and therefore prone to selection bias, a key challenge to evaluation is endogenous participation. Second, while a few randomized controlled trials have been implemented, they often suffer from limited external validity. Generalizability is further challenged by the fact that the design of health insurance programs in low and middle-income countries reflect contextual differences, particularly in terms of target population,

services covered, funding mechanisms, and the structure of the healthcare system (i.e., the role of public and private sectors in service delivery and financing). Third, most studies are confounded by changes in the delivery system such as the introduction of supply-side reforms in parallel with health insurance expansion, which is one of the reasons for variation in the results across studies. Finally, variation across studies in the (often limited) data available and in the health-related outcomes that can be studied, further make it challenging to draw general lessons regarding the impact of health insurance programs.

3.2.1. Impact on healthcare use

In light of the above, it is hard to make a general statement regarding the effect of health insurance on healthcare use because the impact varies considerably across different measures of healthcare use, population groups and context. For instance, the impact can differ for general measures compared to specific measures of healthcare use. General measures include consumption of non-specific healthcare services or goods, such as healthcare facility visits or hospital admissions. Specific measures include consumption of well-defined goods and services such as immunization, pap smear, and hypertensive drugs. Health insurance introduced in Gansu Province, China, for example, increased immunization rates but had no significant impact on inpatient or outpatient care visits (Wagstaff & Yu, 2007). Johar (2009) shows that an Indonesian health insurance program increased the consumption of contraceptives, but had no significant

impact on the use of preventive services. In explaining the results, Johar (2009) notes that demand for some healthcare services and goods might be highly price inelastic. Hence, consumption remains the same with or without health insurance. Second, supply-side issues can sometimes explain these differences. Health insurance has a greater impact on healthcare use under service-specific "vertical programs" focused in services such as immunization, tuberculosis treatment, family planning, and maternal and healthcare services because they are often better able to respond to demand created by health insurance.

Health insurance does not always increase overall healthcare use because it can increase the use of some services, but decrease the use of other services. The introduction of health insurance could increase the consumption of outpatient care, while reducing inpatient care (or vice versa). In Thailand, the insurance benefit of UC Program Scheme was designed to increase outpatient care and decrease inpatient care as a strategy to contain cost (Limwattananon et al., 2015; Panpiemras, Puttitanun, Samphantharak & Thampanishvong, 2011). In contrast, health insurance programs in Colombia and Ecuador were more focused on inpatient care benefits, which led to higher hospitalization rates and lower outpatient care visits (Trujillo, 2003; Waters, 1999). Introduction of health insurance can also decrease the use of non-formal healthcare services (Wang, Yip, Zhang & Hsiao, 2009) and differentially change the use of public and private healthcare facilities (Thornton et al., 2010).

Lastly, the impact of health insurance also varies across socio-economic groups. Low-income individuals, for example, are generally more sensitive to a reduction in the price of healthcare because of health insurance. But the ultimate impact can depend on the design of insurance programs and the availability of services among different groups in society. One of the major factors that determine the impact among poor is the level of copayment. Cost-sharing and low maximum coverage limits can make healthcare unaffordable despite the availability of health insurance. Further, in some settings, informal payments to health workers and other non-medical costs (e.g. transportation costs) keep healthcare unaffordable even for poor with health insurance (Wagstaff, Lindelow, Jun, Ling & Juncheng, 2009).

In summary, the expansion of insurance appears to affect use, but the precise ways it does so depends importantly on the nature of the health insurance provided – the services covered, rates of cost-sharing –and the nature of the delivery system.

3.2.2. Impact on health outcomes

In most jurisdictions, the ultimate goal of health insurance is to improve health. Increased healthcare utilization and reduced out-of-pocket expenditures are the intermediate goals. However, studies of the impact of health insurance on health outcomes in low and middle-income countries are quite limited. This is due in part to limited availability of appropriate outcome measures (Giedion, Alfonso & Diaz, 2013).

The available studies show mixed findings. Here, we identify two general issues that make it challenging to draw a definitive conclusion.

First, studies that demonstrate significant impacts of health insurance programs on health outcomes are often confounded by healthcare delivery reforms. Wagstaff & Yu (2007) show that a health insurance program in China reduced the number of sick days among the poor, but in addition to expanding health insurance, the government simultaneously infused large capital investments for hospital infrastructure and introduced reforms to improve the efficiency and quality of healthcare services. Quimbo, Peabody, Shimkhada, Florentino & Solon (2011) show that subsidized health insurance decreased the likelihood of Filipino children having infections and muscle wasting, however, the intervention also included an information and education campaign for mothers receiving the health insurance cards. Gertler, Giovagnoli & Martinez (2014) show that the expansion of Plan Nacer, which extended health insurance to Argentinian women, reduced the probability of extremely low birthweight and infant mortality, but the program also introduced pay-for-performance programs to local governments.

Second, studies suffer from methodological limitations. To observe the impact of Health insurance, the outcome measure of choice should be relevant. Some outcome measures remain unaffected even after the introduction of health insurance programs. Cuevas & Parker (2010) do not find an impact of health insurance on obesity. They argue that obesity, although an important factor of health is “notoriously difficult” to

overcome no matter how much attention is received. Also, health is multi-dimensional in concept. Health insurance could have a different impact on subjective health and objective health outcomes. In practice, self-rated health is commonly used to measure health status because it is easier to collect in population surveys, while objective measures of health are seldom collected because they require clinical measurement and testing. The timing of measurement of health outcomes also appears to be crucial. The impact of health insurance on chronic conditions and behavior may take some time to have detectable changes. In some empirical studies, researchers have noted short follow up as a potential reason for the lack of an observable impact of health insurance on health outcomes (Chen et al., 2007; Quimbo, Peabody, Shimkhada, Florentino & Solon (2011). For example, King et al. (2009) examine the impact of Mexico's health insurance program for the poor (Seguro Popular) on health outcomes using a community experiment. The program shows effects on healthcare utilization, but not on health outcomes. The authors argue that the lack of detectable impact on health outcomes is possibly due to the short duration of treatment (10 months), and longer assessment periods are needed to ascertain the long-term effects of the program.

3.3. Indonesia: general information

Indonesia is a nation of islands, with a population of 250 million, making it the fourth most populous country in the world. The World Bank classifies Indonesia as a low middle-income country. Like many countries in Asia, Indonesia has experienced rapid

economic growth in the last 15 years. The average annual economic GDP growth rate (in constant prices) from 2000 to 2015 was 5.8%, well above the global average of 2.8%. The GDP per capita income (in constant prices) increased from 2,143 USD in 2000 to 3,974 USD in 2015 (World Bank, 2017). Despite the rapid economic growth, poverty remains a major challenge. Eleven percent of the population (28 million people) are still considered poor, and a large portion of the population, known as near-poor, is vulnerable to falling into poverty as their income is just above the national poverty line. In 2012, the World Bank estimated that 40% of the population is considered poor or near-poor (Aji, 2015; World Bank, 2012).

In recent years, Indonesia has made remarkable progress in improving health outcomes. The infant mortality rate (IMR), one of the most sensitive measures of general health status, decreased from 41 infant deaths per 1000 livebirths in 2000 to 21 infant deaths per 1000 livebirths in 2015 (World Bank, 2017), meeting Indonesia's Millennium Development Goal, which was to reduce IMR from 68 in 1990 to 23 by 2015 (Association of Southeast Asian Nations, 2017). Despite the improvement in health outcomes, Indonesia still faces geographic and income-related health inequalities. For instance, the IMR among the poorest wealth quintile is 52 compared to 17 among the richest wealth quintile (Statistics Indonesia, 2013).

3.3.1. Indonesia: healthcare delivery system

Healthcare services in Indonesia are delivered through a mixed public and private system, though the public system dominates. Public healthcare provision is decentralized with districts having responsibility for the delivery of healthcare services. Indonesia has four administrative levels: (1) provinces, (2) cities, (3) districts and (4) villages. Nationally, there are 34 provinces, 97 cities, 6,500 districts and 75,000 villages (Heywood & Choi, 2010).

At the forefront of the district-level delivery system are 9,700 government primary care facilities called Puskesmas. Each facility serves around 30,000 individuals and provides basic primary care, public health services, and in some cases basic inpatient care services. Puskesmas also supervise a wider network of primary care services in villages such as auxiliary clinics, health posts, private clinics and village midwives. Officially, Puskesmas serve as gatekeepers to higher-level health facilities. However, in practice, patients can directly go to a higher-level facility without a referral from a Puskesmas. Throughout the study period, the number of beds in Puskesmas started to increase from about 20,000 in 2000 to 36,000 in 2014. After decentralization which happened in 2000, district governments build more Puskesmas, and many existing Puskesmas started to add inpatient beds (Harimurti, Pigazzini, Pambudi & Tandon, 2013). Private clinics deliver care alongside the Puskesmas. Although the number of private clinics is not tracked by the government, around 70 percent of physicians working in Puskesmas also have their own private practice (Harimurti, Pigazzini,

Pambudi & Tandon, 2013; Mahendradhata, Trisnantoro, Listyadewi, Harimurti & Prawira, 2017).

Inpatient care is provided by public and private hospitals. Indonesia has 1,632 secondary hospitals, of which 50% are public, and 372 tertiary hospitals providing high-level and specialized care, 80% of which are public. Almost all public hospitals are controlled by district governments. Most hospitals, particularly the privately-owned ones, are located in cities, and access to inpatient care is a major problem in many rural areas. In the last 15 years, the number of hospitals has increased and the associated number of inpatient beds per 1000 population increased from 0.97 in 2000 to 1.26 in 2014 (Appendix 2.1). The growth was partly because of private sector investments that increased the number of beds in private hospitals. The use of private and public hospitals varies by income group, with the rich tending to use private hospitals and the poor tending to use public facilities (Harimurti, Pigazzini, Pambudi & Tandon, 2013; Mahendradhata, Trisnantoro, Listyadewi, Harimurti & Prawira, 2017; Mahendradhata, Trisnantoro, Listyadewi, Harimurti & Prawira, 2017). Indonesia comprises 17,000 islands, making it hard for those living on remote islands to access healthcare services, especially hospitals.

3.3.2. Indonesia: healthcare financing system

From 2000 to 2014, the average annual growth rate in healthcare expenditure per capita (in constant prices) in Indonesia was 9.5% (91 USD in 2000 to 299 in 2014).

Over the same period, the share of health expenditure to GDP increased from 2% in 2000 to 2.8%, although this level remains relatively low compared to countries in Asia (World Bank, 2016; Mahendradhata, Trisnantoro, Listyadewi, Harimurti & Prawira, 2017). The low share is attributed to low public spending. The share of public spending to total healthcare expenditure remained relatively stable: 36% in 2000 and 38% in 2014. The majority of private spending (70%) was out-of-pocket payments (Mahendradhata, Trisnantoro, Listyadewi, Harimurti & Prawira, 2017); Panpiemras et al., 2011; Rokx, Schieber, Harimurti, Tandon & Somanathan, 2009) (Appendix 3.2).

In Indonesia, the flow of financing is complex and overlapping. District governments directly finance public health services, capital outlays for public healthcare facilities and salaries of healthcare workers in clinics. However, district governments receive grants from the provincial and national governments to augment their public health programs. Public health insurance, which included a number of distinct programs, is financed by a mixture of national and subnational governments.

The public health insurance system includes a set of distinct health insurance programs. Each program has its own management and source of financing, and attempts to cover specific population groups. Jamsotek and Askes are longstanding mandatory health insurance schemes of the national government that cover the private and public formal sector employees. Jamkesmas is a health insurance program of the national government that covers the poor and near-poor informal workers. In 2007, some local governments also introduced a health insurance program called Jamkesda, which covers

poor households that are not captured by Jamkesmas program due to mistargeting, and, in some districts, it supplements Jamkesmas. The introduction of Jamkesda in parallel with Jamkesmas is regarded as politically motivated. Jamkesda has provided some local governments the opportunity to use "free healthcare services" as a popular campaign tagline (Dwicaksono, Nurman & Prasetya, 2012). In 2011, the national government also introduced Jampersal, a health insurance program for poor mothers not covered by Jamkesmas, again because of mistargeting. Because Jamkesmas failed to cover a significant number of poor mothers, Jampersal is an effort to reduce maternal and infant deaths through a scheme solely devoted to identifying and enrolling poor mothers, and covering only maternal and child-related services (Achadi, Achadi, Pambudi & Marzoeki, 2014).

In addition to public health insurance programs, there are private sources of financing such as private health insurance and savings-related insurance. However, only a small portion of the population is covered by private health insurance plans (usually the rich). Table 3.1 shows the different coverage rates by income tercile of different health insurance programs in Indonesia for the period 2000 to 2014. Pro-poor health insurance programs such as Jamkesmas, Jamkesda, and Jampersal are seemingly mistargeted since a meaningful portion of the rich population is covered by these targeted health insurance programs.

3.3.3. Description of Jamkesmas

Jamkesmas is the primary government health insurance program targeted at poor (those below the poverty line) and near-poor (those just above the poverty line and at risk of falling into poverty) informal workers. Originally introduced as Askeksin in 2005 and targeted at only the poor, in 2007, it was renamed as Jamkesmas and was expanded to cover the near-poor as well. Although the expansion started in 2007, large enrollment increases only occurred in the succeeding years. In 2011, the Indonesian government estimated 76.4 million (out of 240 million) individuals were considered poor or near-poor and were eligible beneficiaries of Jamkesmas. Harimurti, Pigazzini, Pambudi & Tandon (2013) estimated that 40% of the poor and near-poor were covered by the program in 2012.While the national government facilitates the identification of eligible beneficiaries, the districts determine eligibility and enroll beneficiaries. In 2004 and 2011, Statistics Indonesia (BPS) conducted a national poverty survey. It provided the number of poor and near-poor for each district. Districts then validated the data from Statistics Indonesia using their own methods. As a consequence, the specific definition of poor and near-poor used for means testing and local government eligibility criteria varied by district. If the number of poor and near-poor was greater than the BPS district allocation numbers, these individuals were encouraged to enroll in other local government health insurance programs such as Jamkesda (Harimurti, Pigazzini, Pambudi & Tandon, 2013).

The Jamkesmas insurance premium is fully subsidized by the government, but enrolment is not mandatory. Beneficiaries hold a Jamkesmas insurance card making

them eligible to receive services under the program. Some individuals opt not to be enrolled because of stigma as bearers of Jamkesmas cards, since having the card signals the socio-economic status of the individual. Others do not enroll because of the administrative and bureaucratic hurdles in claiming benefits. One of the issues with enrollment is the discretion of the enroller. In practice, the enroller has flexibility, and the targeting criteria are partially subjective (Harimurti, Pigazzini, Pambudi & Tandon, 2013; Simmonds & Hort, 2013; Suryahadi, Febriany & Yumna, 2014). One-fifth (21%) of all Jamkesmas holders belonged to the top three economic deciles (Harimurti, Pigazzini, Pambudi & Tandon, 2013). We estimate from the 2014 Indonesia Family Life Survey (IFLS) approximately 25% of the richest income decile was enrolled in Jamkesmas, and approximately 45% of the poorest income decile was enrolled in Jamkesmas, indicating low uptake among the poor and evidence of mistargeting (Appendix 3.3).

The Ministry of Health at the national level defines the benefits package, which is meant to be comprehensive. The benefits include outpatient and inpatient care in public healthcare facilities and enlisted private healthcare facilities. On paper, all inpatient and outpatient care services are covered except for the following: general check-ups, cosmetic services, traditional medicines, fertility programs and dental services. Generic versions of prescription drugs are also included as long they are on the formulary. The MOH reimburses primary care facilities using fee-for-service and reimburses private and public hospitals using case rates. The program does not require cost-sharing at the point of service. However, in practice, informal payments exist and are rampant. They can

take different forms such as payments to health providers to cut waiting time or to acquire additional services in healthcare facilities. They also include direct payments by patients to health providers for certain drugs or medical services that are not in healthcare facilities. The actual amount of informal payments is hard to estimate (Ministry of Health, 2014).

3.4. Conceptual framework

Levy & Meltzer (2001) provide a useful conceptualization of the inter-relationships of health insurance, healthcare utilization and health status, reproduced below as Figure 3.1. Health depends not only on healthcare, but also on many factors such as health behaviors, observable characteristics such as age, sex, education, income, and unobservable characteristics such as genetic endowment and beliefs. In the case of Jamkesmas, where participation is non-random, some of these factors (e.g. income and education) are also likely correlated with health insurance coverage. The health status of an individual also affects the consumption of healthcare; individuals who are unhealthy are far more likely to seek care. In this framework, factors that affect health insurance, healthcare and health can be observed (e.g., education, income or sex) or unobserved (e.g., genetic endowment, belief system).

The relationship between healthcare and health in Figure 3.1 does not fully differentiate the concept of disease, health and function. It is useful however, to distinguish the difference between the two concepts: Evans & Stoddart (1990) define

"disease" as an abnormal physiologic function, and "health and function" as the experience of the disease by an individual. In the early stages, many diseases (e.g., elevated blood pressure or insufficient hemoglobin) are asymptomatic and have yet to be translated to detectable changes in health and function (e.g., self-rated health, unproductive work days). Our outcome measures include indicators of both disease and health and function.

3.5. Data

We use the longitudinal individual component of the Indonesian Family Life Survey (IFLS) conducted by the RAND Corporation. IFLS is an on-going longitudinal socio-economic and health survey. Some provinces were not surveyed because of limited resources and it was unsafe for interviewers to go to some provinces. The survey represents 13 of the 34 provinces, and 83% of the population. The survey collects data on individual respondents, their families, their households, and the communities in which they live. The first wave was administered in 1993 to 7,224 households (Strauss, Witoelar & Bondan, 2016), and succeeding waves were conducted in 1997, 2000, 2007 and 2014. IFLS is a dynamic panel. New family or household members are interviewed and tracked in the succeeding waves. Household or family members who appear in a previous cohort, but who move to another place or household were tracked and interviewed.

We use the 2000, 2007 and 2014 cycles of IFLS in the analysis. We link 30,815 adults (15 years old and above) in the 2000 wave with the 2007 wave. Defining non-response to include baseline respondents who could not be located during the follow-up survey, who died, or who were found but completely declined to participate, the non-response rate between 2000 and 2007 was 25% (n= 7,693), of whom 6% (n= 1,930) were reported to have died. We delete non-response between 2000 and 2007 (n=7,693), then linked the remaining individuals to the 2014 wave. The non-response rate between 2007 and 2014 was 22% (n=5,019), of whom 7% (n=1,696) were reported to have died. Finally, we delete non-response between 2007 and 2014 (n=5,019). The overall attrition is 41% (7,693+5,091=12,717). At this stage, respondents who did not respond to a subset of specific questions are still included (see Appendix 3.4 for details).

Table 3.2 shows the baseline characteristics (the year 2000) of respondents in the sample. Excluding those who died, those lost to follow-up in either 2007 or 2014 are more likely to be rich, a university graduate, male, and living in urban areas (see Appendix 3.5 for the complete results of the logistic regression model). We found no significant association between enrolment in Jamkesmas and mortality (see Appendix 3.6 for the complete results of the regression model).

3.6. Dependent Variables

We use various measures of healthcare use, health outcomes and out-of-pocket healthcare expenditures to examine the impact of Jamkesmas.

3.6.1. Healthcare use

Measures of healthcare use include use of inpatient care, number of inpatient days, use of outpatient care, and number of outpatient care visits. We also examine non-formal healthcare use: self-medication and traditional medicine. The inpatient care variable is a dummy variable equal to 1 if an individual was admitted to a hospital in the 12 months prior to the survey, and equal to 0 otherwise. The number of inpatient days (conditional on having been admitted) during the most recent admission is a count variable. The outpatient care variable is a dummy variable equal to 1 if an individual visited an outpatient health facility in the 4 weeks prior to the survey, and equal to 0 otherwise. The number of times visited a healthcare facility for outpatient care (conditional on having at least one visit) in the 4 weeks prior to the survey is a count variable. We focus only on needed care (treatment to illness and injury and consultation) and exclude visits for massage and cosmetic services. The self-medication variable is a dummy variable equal to 1 if an individual engaged in self-medication using a modern medicine in the 6 weeks prior to the survey, and is equal to 0 otherwise. The traditional medicine variable is a dummy variable equal to 1 if an individual used herbal medicine or visited a traditional healer in the 6 weeks prior to the survey, and is equal to 0 otherwise.

3.6.2. Health outcomes

As noted, following Evans & Stoddart (1990), we differentiate disease, health, and function. The measures of disease were based on the anthropometric, biochemical and clinical components of the survey for which healthcare workers collected blood samples and performed anthropometric and clinical testing. The measures of disease include systolic blood pressure (mmHg), hemoglobin (mg/dl), lung capacity (liter/min) and Body Mass Index (kg/m^2). Variables are specified both as continuous (in the conventional units) and as categorical variables. High blood pressure is equal to 1 if systolic blood pressure is more than 120 mmHg, and is otherwise 0. The variable for anemia is equal to 1 if hemoglobin is less than 12 mg per dl and is otherwise 0. BMI is usually classified into four categories: underweight (<18.5), normal (18.5 – 24.9), overweight (25.0 – 29.9) and obese (>30). In this study, we re-categorize the variable into a dummy equal to 1 if BMI is underweight and equal to 0 otherwise. We choose to model underweight because it is more prevalent than obesity among the poor in Indonesia. Also, we re-categorize BMI into a dummy to avoid complexity in modeling ordinal dependent variable with fixed effects.

We select blood pressure, anemia, lung capacity and underweight as measures of disease because they are known to affect long-term health and function. High blood pressure is a major risk factor for ischemic heart disease and stroke, which are associated with chronic disability and mortality. Anemia is a condition in which there are not enough red blood cells to carry oxygen to tissues. Several infectious and chronic conditions can cause anemia. Persistent anemia can lead to physical weakness and

cognitive impairment due to lack of iron. Lung capacity as measured by Peak Expiratory Flow (PEF) indicates obstructions in the respiratory pathway caused by chronic and acute conditions such as Chronic Obstructive Pulmonary Disease (COPD), asthma, respiratory infection, and malnutrition. A poor cardio-pulmonary function can severely affect physical performance and activity. Underweight could severely affect physical function and mental health (e.g., depression).

We use two measures of health and function: self-rated health and number of missed days of primary daily activities in a month because of illness. For the former, individuals subjectively assess their health using four ordinal categories (i.e., healthy, somewhat healthy, somewhat unhealthy and unhealthy). Like BMI, we re-categorize self-rated health into a dummy equal to 1 if 'healthy' and 'somewhat healthy', otherwise 0, again to reduce the complexity in modeling an ordinal variable with fixed effects. For the latter, individuals should report the number of days missed because of illness in the past month (range: 0 to 30 days). Our data do not contain questions to determine their daily activities, but it should pertain to a wide range of activities including school attendance or employment (e.g., farming, fishing, construction, household keeping).

3.6.3. Healthcare expenditures and financial protection

The survey includes information on out-of-pocket spending incurred during the last hospital admission and last outpatient care visit. Therefore, our measure of healthcare expenditure is the actual out-of-pocket spending (adjusted to 2010 prices)

incurred during the most recent hospital admission in the last 12 months prior to the survey, and the most recent outpatient care visit in the 4 weeks prior to the survey. For the measure of financial protection, we follow the World Bank and World Health Organization's definition of catastrophic healthcare expenditure. We create a dummy variable equal to 1 if the out-of-pocket healthcare expenditures during the last admission exceeded 10% of household expenditure per capita per year[3], equal to 0 otherwise.

3.7. Empirical strategy

3.7.1. Modelling healthcare use and healthcare expenditures

In modeling healthcare use and out-of-pocket healthcare expenditures, we use a two-part model within a generalized linear model framework. A two-part model allows us to model the two processes of healthcare use and healthcare spending. The first part of a two-part model predicts whether or not an individual used healthcare or reported a healthcare expenditure due to the last outpatient care or admission. The response variable for the first part is binary. The second part of a two-part model predicts the intensity of healthcare use and the actual expenditures conditional on healthcare use. Modeling the second part is challenging because observations are not normally distributed. Intensity and expenditure variables usually have restricted range and are

3 Household expenditure is the sum of food and non-food expenditures in a given year. In IFLS, depending on the expenditure item, the recall period varies from week to year. RAND Corporation annualized all the expenditures, but not seasonally-adjusted.

highly skewed, which makes OLS estimation biased and efficient. One can address the skewed distribution using generalized linear models (GLM) (Manning, Basu & Mullahy, 2005; Manning & Mullahy, 2001), and we use these (GLM) with pooled data to predict the intensity of healthcare use and out-of-pocket healthcare expenditures. Within the GLM framework, we need to specify the mean and variance functions. Following Jones, (2010) and Buntin & Zaslavsky (2003), we specify log link function in modeling for the expected mean, which is the commonly chosen link function in healthcare utilization and expenditure applications. In specifying the variance function, we use Modified Park's test, and gamma distribution seems to be the most appropriate function (Appendix 3.8).

We use the following specification for Parts 1 and 2:

Part 1: linear probability model

$$E(Y_{it}|X) = \beta_0 + \beta_1 Jamkesmas_{it} + \beta_2 OtherInsurance_{it} + \beta_3 YearsMember_{it} + \beta_4(YearsMember_{it} x\ YearsMember_{it}) + Ind_i + District_i + \beta_5 X_{it} \quad \textit{(Equation 1)}$$

Part 2: GLM log link function

$$log\left(E(Y_i|X)\right) = \alpha_0 + \alpha_1 Jamkesmas_i + \alpha_2 OtherInsurance_i + \alpha_3 YearsMember_i + \alpha_4(YearsMember_i x\ YearsMember_i + District_i + \alpha_5 X_i \quad \textit{(Equation 2)}$$

In part 1, we use a panel fixed-effects (FE) model to estimate the marginal effects of Jamkesmas on positive use of healthcare utilization and positive out-of-pocket

healthcare expenditures. Y_{it} is the dichotomous outcome of interest for individual i *(i =1…n*) at time t ($t = 1, 2, 3$). We model the following outcome of interests: visited an outpatient healthcare facility in the last 4 weeks, admitted in a hospital in the last 12 months, and incurred positive out-of-pocket healthcare expenditures due to outpatient care or inpatient care. $Jamkesmas_{it}$ is a dummy variable that indicates whether *i* individual at time *t* is enrolled in Jamkesmas. Because individuals could be enrolled in multiple insurance programs, $OtherInsurance_{it}$ indicates membership in public or private health insurance other than Jamkesmas. $YearsMember_{it}$ is the number of years an individual has been enrolled in Jamkesmas. Ind_i is the individual FE. $District_i$ is the district FE. We include individual FE to control for unobserved individual heterogeneity. To produce an unbiased estimate, the identification assumption in a FE model is that there is no correlation between the error and Jamkesmas because all the relevant unobservables are "absorbed" by the FE. We include the following time-varying covariates (X_{it})*:* age, marital status, education, log per capita household expenditure, employment, urbanity and survey cycle. For part 2, in addition to these variables, we include the following health outcomes in the model: high blood pressure, lung capacity, anemia, abnormal BMI, and self-rated health status.

We use linear probability models (OLS) in estimating the marginal effects because it is convenient and computationally tractable. Also, the results of linear probability model are easier to interpret, which is one key advantage of linear probability models over logit probability models. One disadvantage of linear probability

models, however, is they impose heteroscedasticity in the case of a dummy variable. We address this problem by using heteroscedasticity-consistent robust standard error estimates. For comparison, we run logit probability models, and we observe similar results (Appendix 3.7).

In parts 1 and 2, we run five models for each outcome of interest to see the changes in marginal effects as we include covariates in the model. In the first model, we only control for socio-demographic covariates. In the second model, we control health-related variables including risky behaviors (e.g. smoking) in addition to socio-demographic variables. In the third model, we use the same set of covariates in the second model, but we also include duration (in years) of membership in Jamkesmas up to second-degree polynomials. We highlight the results of the third model because in this model we have potentially controlled not only for socio-demographic characteristics, but also health variables, and possible temporal effects of Jamkesmas membership. The fourth and fifth models are similar to the third model, but we stratify the sample by poor (first tercile) and non-poor (second and third income tercile). Income group is based on household consumption per capita at baseline.

We model the use of non-formal healthcare, self-medication, and use of traditional medicine, for which we have only a measure of whether there was any use (no intensity of use). We specify the model using equation 1.

3.7.2. Modelling health outcomes

Modelling health outcomes

We use a panel FE OLS model to examine the impact of *Jamkesmas* on the following health outcomes: systolic blood pressure (continuous), lung capacity (continuous), anemia (binary), hypertension (binary) and underweight (binary). For the number of missed primary daily activities in the last month, a count variable, we use a negative binomial FE model. In specifying the model, we include the following time-varying covariates: years of membership in Jamkesmas, age, marital status, education, log per capita household expenditure, employment, urbanity, survey cycle, and comorbidities. We also include district fixed effects. We run five models for each outcome of interest to see how the incremental inclusion of additional covariates changes the estimated impact of *Jamkesmas* on health outcomes.

3.8. Results

Table 3.2 presents the characteristics of the respondents at baseline. Of the 18, 103, fifty-four percent are males, approximately 40% had grade school as the highest level of attainment, 30% were formal sector workers, 70% were married, and 65% were smokers. The distribution of respondents living in urban and rural areas was approximately the same. Table 3.3 presents the distribution of dependent variable: healthcare use, health outcomes and out-of-pocket healthcare expenditures of respondents by survey wave. Among healthcare utilization variables, we observe a monotonic upward trend over time only for inpatient care. The percentage of

respondents who had inpatient care increased from 2.0% in 2000 to 5.0% in 2014. Although the percentage of respondents who had inpatient care increased, the average inpatient days during the last admission remained the same. Unlike inpatient care, outpatient care visits decreased over the period. The percentage of respondents with outpatient care visits decreased from 11% in 2000 to 6.0% in 2007, then slightly increased to 8.0% in 2014. However, we observe no change in the average number of outpatient care visits, conditional on having at least one visit.

We observe a SES-gradient in the share of respondents with inpatient and outpatient care. The rich are more likely to have outpatient and inpatient care than the poor, a consistent pattern in all three survey periods. However, there is no noticeable SES-gradient in the number of inpatient days conditional on having been admitted or the number of visits to a healthcare facility for outpatient care conditional on having at least one visit. Nor is there a consistent SES-gradient for non-formal healthcare use in three survey periods.

The prevalence of hypertension shows an upward trend, while the prevalence of underweight shows a downward trend. The prevalence of hypertension increased from 49.0% in 2000 to 73.0% in 2014, while the prevalence of underweight decreased from 17.3% in 2000 to 9.8% in 2014. Self-rated health shows an interesting pattern. The percentage of respondents who rated themselves 'healthy' (category 1) increased from 8.2% in 2000 to 16.6% in 2014. This is a large increase. At the same time, the share of respondents who considered themselves 'somewhat healthy' decreased (category 2),

and the share of respondents who considered themselves 'somewhat unhealthy' and 'unhealthy' increased. The survey question on self-rated health did not change in the three surveys waves so we investigated this movement of responses across the four categories. Among those who reported to be 'somewhat healthy' in 2007 (n=2,198), 8% moved up to 'healthy', 39% remained 'somewhat healthy', 69% moved down to 'somewhat unhealthy,' and no one moved down to 'unhealthy' category in 2014. Stratifying by age group, among those who reported to be 'somewhat healthy' in 2007 and shifted to 'healthy' in 2014 were more likely from younger age groups, and those who shifted from 'somewhat healthy' in 2007 to 'somewhat unhealthy' were from older age groups (see Appendix 3.9 for the transition matrix by age group). The prevalence of underweight was higher among the poor, and the prevalence of obesity was higher among the rich, a consistent pattern in all survey waves

The average out-of-pocket healthcare expenditures (in 2010 prices) during last visit increase over time. In contrast, out-of-pocket expenditures due to inpatient care during last admission did not follow a monotonic trend. It increased from 2000 to 2007, then decreased in 2014. The rich have higher out-of-pocket healthcare expenditures compared to the poor, and the income gradient was consistent in all survey periods. The share of respondents with catastrophic healthcare expenditures was consistent over time, but the rich tend to have a higher share, a consistent pattern found in developing countries.

Table 3.4 shows the descriptive statistics of dependent variables by Jamkesmas membership for 2007 or 2014 as well as information from 2000 before the introduction of *Jamkesmas*, and Table 3.5 does the same for the independent control variables. The first and second columns of Tables 3.4 and 3.5 show the descriptive statistics of all dependent and independent variables at baseline (2000) by future Jamkesmas membership status in 2007 or 2014. The distribution of dependent variables at baseline shows small differences between future Jamkesmas and non-Jamkesmas members. However, over time, the difference between members and non-members widened for use of outpatient care, use of inpatient care and use of self-medication.

There is some indication that Jamkesmas members were less healthy. At baseline, future Jamkesmas and non-Jamkesmas members have lower lung capacity, were underweight and had lower self-rated health compared to non-members. However, the differences were small and not clinically important. We did not observe any large changes in the difference between members and non-members over time in any of the health outcomes except for the number of missed days of primary daily activities because of illness. The average OOP healthcare expenditures due to outpatient care and inpatient care were slightly different for future Jamkesmas and non-Jamkesmas members, a difference that widened over time. However, we did not observe large changes in the difference between catastrophic healthcare expenditure.

In summary, we did not observe a meaningful difference in the mean values of the dependent variables by future Jamkesmas and non-Jamkesmas membership.

Table 3.5 shows the descriptive statistics for the independent variables by Jamkesmas membership and survey period. At baseline, future Jamkesmas members were more likely to have lower education, be poor and self-employed. Jamkesmas targets poor and near-poor workers in the informal sector so systematic differences in terms of education, income group and employment between Jamkesmas members and non-members are expected. However, the difference in the distribution by Jamkesmas membership widened over time in some independent variables such as employment and income, but the difference for other variables remained relatively the same.

Regression results: outpatient and inpatient care

Table 3.6 shows the marginal effects of Jamkesmas on healthcare use from our two-part model. Focusing first on outpatient care, we find an association between *Jamkesmas* with higher likelihood of having an outpatient care even after controlling for covariates including years of membership (Model 3; $\beta_1 = 0.023$). If we stratify the model by income group, the marginal effects are not statistically significant (Models 4 and 5; $\beta_1's$). Also, the duration of Jamkesmas membership is not associated with the likelihood of having an outpatient care (Model 1-5; β_3, β_4). The results for the part-2 GLM model indicate that although we observe higher likelihood of having an outpatient care, Jamkesmas is not associated with the frequency of outpatient care among those with at least one visit after controlling for years of membership (Model 3; α_1). Although,

we find statistically significant marginal effects if we exclude years of membership as one of the covariates (Models 1 and 2; a_3, a_4).

Jamkesmas is associated with higher likelihood of having an inpatient care. The marginal effects are statistically significant in Models 1 to 3, and we observe a large marginal effect in Model 3 (β_1=0.032). Interestingly, we observe heterogeneity of marginal effects between poor and non-poor. We find large and statistically significant marginal effects among the non-poor (Model 4; β_1=0.042), but insignificant among the poor. The duration of Jamkesmas membership is not associated with the likelihood of inpatient care (Model 1-5; β_3, β_4). The results for the part-2 GLM model suggests that Jamkesmas is not associated with duration of inpatient days (Model 3; a_1).

Jamkesmas is not associated with the use of self-medication and traditional medicine after controlling for covariates including years of membership (Model 3; β_3). However, we find positive marginal effects on self-medication if we exclude years of membership as one of the covariates (Model 1-2; β_3, β_4). We find no impact on the use traditional medicine in all models.

Regression results: health outcomes

Tables 3.7a and 3.7b show the marginal effects of *Jamkesmas* on our measures of health outcomes. In Models 1 and 2 (β_1), the marginal effects of Jamkesmas on systolic blood pressure and lung capacity (continuous) are significant, though the statistical significance disappears in Model 3 (β_1). We did not observe any significant

impact for hypertension (binary), anemia (binary), underweight (binary), and self-rated health (binary) in any model. To validate our estimates for underweight, we also ran a pooled ordinal logit using BMI with four categories, and found no statistically significant marginal effects (data not shown). The marginal effects for the duration of *Jamkesmas* membership are not statistically significant for any of the health outcome measures in all models (β_3, β_4).

The marginal effects of Jamkemas on the number of missed days of primary daily activities are statistically significant in Models 1 to 3, with Model 3 having the largest marginal effects (($\beta_1, =$0.204). When we stratify the model by income, we observe large marginal effects among the poor ($\beta_3, =$0.312 days). and a non-statistically significant effect among the non-poor (Model 5).

Regression results: OOP and financial protection

Table 3.8 shows the marginal effects of Jamkesmas on OOP and catastrophic healthcare expenditures. Jamkesmas is associated with lower OOP incurred during the last outpatient care and inpatient care in Models 1 and 2, but the effect decreases in magnitude and becomes statistically non-significant when we include the full set of covariates in Model 3. We observe a similar pattern for OOP incurred during the last admission. The marginal effects are statistically significant in Models 1 and 2, but not significant in Model 3, with decreasing marginal effects as we include more covariates. When we stratify the model by income group, the marginal effects of Jamkesmas on

OOP incurred during outpatient or inpatient care are larger among the poor. We find no evidence that Jamkesmas is associated with lower catastrophic healthcare expenditures.

3.9. Discussion

In this study, we investigated the impact of the expansion of Jamkesmas, a public insurance program targeted at the poor and non-poor in Indonesia, on healthcare utilization, health outcomes, and out-of-pocket healthcare expenditures. Jamkesmas is the largest subsidized health insurance program in Indonesia. Although the program targets the poor and near-poor population, we observed leakage, with a significant portion of the Jamkesmas members being non-poor. Also, the program suffered from low uptake. In 2014, only about 50% of the poorest decile were enrolled in the program. Mistargeting is a problem shared by many subsidized health insurance programs in low and middle-income countries. This problem opens important policy questions about whether Jamkesmas is meeting its pro-poor objective.

One challenge in examining the causal impact of Jamkesmas is selection. As discussed earlier, enrollment is voluntary and subject to some discretion by program staff, resulting in non-random participation. Jamkesmas participation may be associated with individual and district level-characteristics. However, the problem of selection in this case does not appear to be large, at least on observables. The typical selection problem in voluntary health insurance participation is that members are systematically

different from non-members. In the case of Jamkesmas, although the differences between members and non-members for some health outcomes are statistically significant, the differences are small and clinically unimportant. We only observed large differences in income, education, and employment, which is expected given the targeted nature of the program. This still leaves the possibility of selection on unobservables. To the extent that such selection was based on invariant unobserved effects, our use of fixed-effects models where possible can correct for such a problem.

During the period of our study, Indonesia experienced a significant supply-side reform. As noted in our literature review, the number of government clinics (Puskesmas) started to increase after decentralization in 2000. The increase in supply-side that occurred in the last 15 years could have affected healthcare use with or without health insurance. However, the impact of supply-side reforms may be considered random as it affects both treatment and comparison group hence it should not bias our estimates.

Our findings suggest that Jamkesmas is associated with a higher probability of having outpatient care. Our study also explored the intensity of healthcare use, which is often not examined in empirical studies in low and middle-income countries because such information is seldom collected. We found that Jamkesmas increases the frequency of outpatient care. It is also associated with a higher probability of having inpatient care, with a larger impact among the non-poor, but no significant impact on the number of inpatient days during the most recent inpatient visit. This makes Jamkesmas a subsidized

health insurance program in a low and middle-income country with a positive impact on healthcare use, and in particular a positive impact on both inpatient and outpatient care.

The positive impact of Jamkesmas on outpatient care is promising. The goal of a health system is to expand outpatient care, particularly preventive, rather than inpatient care and especially to population groups who are at more risk of serious conditions. However, the positive impact of Jamkemas on inpatient care among the non-poor, and the lack of impact among the poor is striking. If the benefits of an insurance program are not accruing for the intended beneficiaries, this may be evidence of poor targeting. This finding points to the seemingly pro-rich effects of a pro-poor program like Jamkesmas when there is weak targeting and aspects of the delivery system favor the rich. It is possible that this finding is a reflection of the differential access to inpatient care of poor and non-poor other than health insurance.

In general, Jamkesmas is not associated with improvements in any health outcomes even after controlling for temporal effects. The median duration of membership is approximately 2 years, and longer duration may be needed to detect changes, especially for chronic conditions.

There are several possible explanations for why Jamkemas improved healthcare use but did not produce improvements in health. First, health insurance can increase healthcare use, but healthcare services may not be a major determinant of health status (Chen et al., 2007; Smith, 1999). The social determinants of health framework suggests that health is determined not only by healthcare but by physical, environmental and

other socio-economic conditions (Smith, 1999; Evans & Stoddart, 1990). Second, the lack of observable impact might be a reflection of the poor quality of healthcare services. In low-resource settings, quantity is often prioritized over quality. Third, the increase in healthcare use might be attributed to an increase in the use of marginally effective services with small associated health benefits (Chen et al., 2007).

Although we found no evidence of an impact on health outcomes, our findings show a significantly higher number of missed days of daily activities reported by Jamkemas members, and the marginal effects are more pronounced among the poor. Initially, we hypothesized that health insurance would reduce the number of reported missed days of daily primary activity last month. However, our findings say otherwise. Because 'daily primary activity' is a broad concept, it is hard to make a general conclusion. In the case of informal workers who have health insurance, members who are sick may have now have access to healthcare providers who will advise them to stop working and rest to aid recovery. To our knowledge, no study has used this outcome before hence our findings provide a new insight, which is worth exploring in future research especially in other contexts.

Jamkesmas is associated with lower out-of-pocket healthcare expenditures, and the poor seem to have benefitted more. However, we did not find evidence that Jamkesmas is associated with lower catastrophic healthcare expenditures, meaning, although OOP significantly decreased, it was not large enough to make a significant reduction in the contribution of OOP relative to one's total expenditure or income. This

finding is also observed in other empirical studies especially in programs with unregulated copayments (Wagstaff, Lindelow, Jun, Ling & Juncheng, 2009).

There are numbers of limitations in the expenditure data of IFLS that might affect the validity of our results. First, we only evaluated the OOP health expenditure during the last admission in the past 12 months hence we might have not fully evaluated the effects of health insurance on catastrophic health expenditures. The total OOP health expenditures of respondents incurred the whole year with multiple inpatient visits are not captured. Second, we used annualized household expenditure in estimating catastrophic health expenditures. Household expenditure is the sum of food and non-food expenditures in a given year. In IFLS, depending on the expenditure item, the recall period varies from week to year. The RAND Corporation annualized all the expenditures without seasonal adjustment, with the latter potentially introducing a type of measurement error. The long duration of recall for some items might also have underestimated household expenditures, and the lack of seasonal adjustment do not take into account temporal variation in health expenditures, which could also affect the validity of estimated household health expenditures.

3.10. Conclusion

In conclusion, despite the evidence of mistargeting, Jamkemas appear to have improved healthcare use and reduced out-of-pocket expenditures. The lack of impact on various health outcomes provides an important reminder for low and middle-income

countries that health insurance expansion alone may not improve health outcomes. The Indonesian government should complement health insurance with other non-financial interventions. Affordability is just one dimension of healthcare access, but other factors such as geographical, cultural (e.g. stigma), and education and awareness can affect healthcare use, which are critical determinants of access among the poor. Lastly, the Indonesian government should explore complement health expansion with population-based interventions and other non-healthcare interventions that are known to affect health status.

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Table 3.1. Coverage rate, by health insurance by income group (tercile) and year

	Poor			Middle			Rich		
Insurance	**2000**	**2007**	**2014**	**2000**	**2007**	**2014**	**2000**	**2007**	**2014**
Jamkesmas/Askesin		18.7%	39.0%		10.7%	28.1%		5.3%	22.3%
Askes	2.4%	2.2%	4.3%	6.5%	7.7%	9.0%	14.0%	17.7%	19.5%
Jamsostek	1.9%	2.2%	2.4%	3.5%	5.5%	4.7%	5.3%	7.2%	6.4%
Employer provided benefits (private)	1.4%	0.5%	0.9%	2.8%	1.6%	2.3%	4.0%	2.2%	3.5%
Private health insurance	0.1%	0.2%	0.2%	0.1%	0.6%	1.2%	0.9%	1.9%	3.9%
Savings-related insurance		0.0%	0.1%		0.2%	0.4%		0.3%	1.5%
Jamkesda			5.5%			7.0%			6.1%
Jampersal			0.2%			0.2%			0.1%
Uninsured	93.8%	76.4%	51.1%	87.9%	74.2%	52.3%	77.8%	66.2%	44.3%

Note: blank means not available

Source: Authors' estimates using Indonesia Family Life Survey (various rounds)

Table 3.2. Baseline characteristics of respondents

Variable	Category	Frequency	Percentage/mean	Range
Age		18,103	34.6	15-101
Sex	Male	9,824	54.3	0-1
	Female	8,279	45.7	0-1
Education	No education	1,632	9.1	0-1
	Grade school	7,650	42.5	0-1
	Junior HS	3,068	17.0	0-1
	Senior HS	2,469	13.7	0-1
	Vocational	2,462	13.7	0-1
	University	722	4.0	0-1
Employment	Self-employed	4,940	28.78	0-1
	Government	811	4.73	0-1
	Private	4,336	25.27	0-1
	Unpaid worker	4,866	28.35	0-1
	Unemployed	2,108	12.28	0-1
	Retired	101	0.59	0-1
Marital status	Single	4,287	24.1	0-1
	Married	12,611	70.9	0-1
	Separated	101	0.6	0-1
	Widow	796	4.5	0-1
Urbanity	Rural	8,741	48.3	0-1
	Urban	9,362	51.7	0-1
Income group*	Poor	6871	38.2	0-1
	Middle	6312	35.1	0-1
	Rich	4825	26.8	0-1
Tobacco	Not smoker	5,395	32.0	0-1
	Former smoker	357	2.1	0-1
	Current smoker	11,113	65.9	0-1

Note: *Distribution not equal because of systemic differences in attrition

Table 3.3. Descriptive statistics of dependent variables, by survey year (n=18,103)

Dependent variables	2000				2007				2014			
	Poor	Middle	Rich	Total	Poor	Middle	Rich	Total	Poor	Middle	Rich	Total
Healthcare utilization												
Outpatient care	8.7%	11.9%	14.2%	11.0%	5.5%	6.2%	7.6%	6.0%	6.4%	8.1%	9.6%	8.0%
Number of outpatient visits*	1.4	1.4	1.5	1.4	1.4	1.4	1.4	1.4	1.8	1.8	2.0	1.9
Inpatient care	1.4%	2.0%	2.7%	2.0%	1.8%	2.7%	3.6%	3.0%	4.0%	4.3%	6.3%	5.0%
Number of inpatient days (during last admission) *	5.7	4.4	4.9	4.9	4.3	5.2	4.7	4.8	4.4	4.6	5.2	4.8
Traditional medicine	13.1%	14.4%	14.4%	14.0%	13.6%	15.3%	14.2%	14.0%	13.5%	15.3%	14.2%	14.0%
Self-medication	53.1%	57.1%	55.9%	55.2%	49.9%	51.5%	50.1%	50.1%	53.4%	53.1%	50.7%	52.6%
Disease												
Systolic BP (mmHg)	121.8	121.6	120.5	121.4	129.2	129.6	129.7	129.5	136.1	134.2	133.8	134.8
High blood pressure (>120 mmHg)	49.9%	49.6%	47.0%	49.0%	65.1%	65.8%	66.5%	66.0%	74.0%	71.4%	71.8%	73.0%
Anemia (<13mg/dl)	49.0%	45.3%	42.8%	46.0%	40.6%	38.0%	36.0%	39.0%	45.1%	43.6%	39.5%	44.0%
Lung capacity (L)	320.9	332.4	339.5	329.9	308.7	320.8	333.3	319.6	319.7	341.2	356.2	337.2
BMI (underweight)	20.7%	16.6%	13.6%	17.3%	14.9%	11.7%	8.1%	12.0%	13.7%	9.0%	5.5%	9.8%
Normal	68.1%	67.2%	63.2%	66.5%	64.1%	59.8%	54.9%	60.5%	56.4%	53.0%	46.8%	52.6%
Overweight	9.5%	13.7%	19.2%	13.6%	15.7%	22.8%	27.0%	21.4%	23.1%	28.4%	34.4%	28.0%
Obese	1.8%	2.5%	4.0%	2.6%	5.3%	5.8%	9.9%	6.2%	6.8%	9.6%	13.3%	9.6%
Health and function												
Self-rated health (healthy)	8.0%	7.7%	9.1%	8.2%	9.1%	10.0%	10.6%	9.8%	16.4%	16.5%	16.9%	16.6%
Somewhat healthy	81.5%	82.0%	79.8%	81.2%	77.4%	75.3%	75.4%	76.1%	54.5%	57.8%	57.9%	56.6%
Somewhat unhealthy	10.4%	10.1%	11.0%	10.5%	13.3%	14.4%	13.8%	13.8%	26.0%	23.6%	23.4%	24.5%
Unhealthy	0.1%	0.1%	0.1%	0.1%	0.3%	0.3%	0.2%	0.3%	3.1%	2.1%	1.9%	2.4%
Healthy (Healthy + somewhat healthy)	83.4%	84.0%	83.9%	83.0%	80.1%	80.0%	79.9%	79.0%	67.5%	71.0%	71.0%	68.0%
Number of missed days in a month	1.1	1.1	1.1	1.1	1.6	1.5	1.7	1.6	3.0	2.8	2.6	2.8
OOP Health expenditure/financial protection												
Inpatient expenditures (1000 Rupiah in 2010 prices)	1,488	1,290	2,261	1,695	1,234	1,677	2,515	1,860	916	1,302	1,388	1,200
Outpatient expenditures (1000 Rupiah in 2010 prices)	25	28	58	37	29	33	79	47	37	48	76	54
Catastrophic health expenditures	1.3%	1.5%	1.9%	1.5%	1.4%	1.9%	2.0%	1.7%	1.5%	1.5%	1.6%	1.5%

Note: * non-users are excluded in the mean

Table 3.4. Descriptive statistics of dependent variables, by survey year and Jamkesmas membership

Dependent variables	2000		2007		2014	
	Non-member	Future member (2007 or 2014)	Non-member	Member	Non-member	Member
Healthcare utilization						
Outpatient care	11.7%	11.8%	6.0%	7.0%*	8.0%	9.0%*
Number of outpatient visits♦	1.4	1.4	1.4	1.7	1.9	2.0
Inpatient care	1.9%	1.8%	3.0%	3.0%	4.0%	6.0%*
Number of hospital days ♦	5.2	4.3	4.9	4.9	4.8	4.6
Traditional medicine	14.2%	14.0%	14.0%	14.0%	14.0%	14.0%
Self-medication	56%	57.8%*	51%	54.8%***	52%	56.8%**
Health outcomes						
Disease						
Systolic BP (mmHg)	122.1	122.0	129.1	130.3*	135.1	134.2*
High blood pressure (>120 mmHg)	48.6%	48.3%	63.0%	65.0%	71.0%	71.0%
Anemia (<13mg/dl)	45.1%	47.8%**	38.0%	38.0%	42.0%	46.0%**
Lung capacity (L)	333.2	322.6**	323.2	306.5***	339.5	332.3*
BMI (underweight)	18.9%	16.4%**	11.1%	15.5%**	9.2%	11.3%**
Normal	66.0%	66.7%	60.1%	61.2%	51.9%	53.9%**
Overweight	12.7%	14.2%**	21.9%	17.9%**	28.9%	26.1%**
Obese	2.4%	2.8%	7.0%	5.3%**	9.9%	8.7%**
Health and function						
Self-rated health (healthy)	8.5%	8.2%	10.0%	9.1%	16.8%	16.1%
Somewhat healthy	81.9%	80.0**	76.3%	74.15%**	57.5%	54.5%**
Somewhat unhealthy	9.4%	11.0**	13.4%	16.3%*	23.5%	26.7%**
Unhealthy	0.1%	0.1%	0.2%	0.4%***	2.3%	2.7%*
Healthy (Healthy + somewhat healthy)	88.3%	85.5%	86.0%	83.0%***	74.0%	71.0%**
Number of missed days in a month	1.09	1.18	1.55	1.86***	2.71	3.06**
Health expenditure/financial protection						
Inpatient expenditures (2010 prices) ♦	1,562,917	1,410,302***	2,087,282	948,844***	1,318,716	786,440***
Outpatient expenditures (2010 prices) ♦	36,021	27,408***	46,756	24,239***	56,820	27,877***
Catastrophic expenditure	1.3%	1.1%	1.6%	1.4%	1.6%	1.7%

Note: Standard errors in parentheses. t-test are heteroskedastic clustered standard errors (at the level of household)

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

♦ non-users are excluded in the mean

Table 3.5. Descriptive statistics of independent variables, by survey year and Jamkesmas membership

Dependent variables	2000		2007		2014	
	Non-member	Future member (2007 or 2014)	Non-member	Member	Non-member	Member
Age (mean)	35.4	35.5	42.5	44.5**	50.1	49.4
Urban	47.1%	46.8%	57.5%	51.5%****	55.5%	58.1**
Education						
No education	8.2%	10.7**	8.8%	13.1%***	9.3%	10.3%
Grade school	42.3%	53.0%***	42.8%	62.0%***	42.1%	50.6***
Junior HS	16.8%	16.6%	15.9%	12.8%***	15.0%	15.9%
Senior HS	13.7%	8.8%***	12.6%	5.8%***	13.5%	10.0%***
Vocational	14.9%	9.0%***	14.1%	5.7%***	12.4%	9.3%***
University	4.1%	1.9%***	5.9%	0.8%***	7.7%	4.1%***
Employment						
Self-employed	30.6%	30.1%	39.9%	49.2%***	43.2%	46.8%***
Government	6.6%	1.8%***	6.2%	0.8%***	5.7%	2.4%***
Private	23.6%	30.8%***	20.5%	16.0%***	19.2%	22.9%***
Unpaid worker	28.1%	27.8%	28.3%	29.1%	24.0%	21.8%**
Unemployed	10.7%	9.2%**	2.9%	2.6%	2.7%	2.2%
Retired	0.6%	0.3%**	2.2%	2.2%	5.2%	3.9%**
Marital status						
Single	21.7%	19.3%**	9.5%	8.7%	3.8%	3.1%
Married	73.7%	75.5%*	82.5%	82.2%	82.6%	83.7%
Separated	0.6%	0.6%	0.6%	0.8%	0.6%	0.7%
Widow	4.1%	4.6%	7.4%	8.4%*	13.0%	12.6%
Income						
Poor	35.8%	50.0%***	36.6%	59.1%***	36.1%	50.5%***
Middle	36.7%	31.3%	35.7%	30.0%***	34.9%	30.8%***
Rich	27.5%	18.8%***	27.8%	11.0%***	29.0%	18.8%***
Smoking						
Not smoker	32.2%	34.3%**	34.0%	37.3%***	32.5%	33.3%
Former smoker	2.2%	2.2%	2.9%	2.0%*	6.8%	6.6%
Current smoker	65.6%	63.5%**	63.0%	60.6%**	60.8%	60.1%
Insurance-related						
members of other insurance	15.6%	8.3%	16.7%	2.0%	25.1%	10.2%
Years of membership in Jamkesmas	-	-	0	2.3	0	3.8

Note: Standard errors in parentheses. Note: t-test are heteroskedastic clustered standard errors (at the level of household

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

Table 3.6. Marginal effects of Jamkesmas on healthcare use

Dependent variable	Models	First stage (FE-OLS) use/no-use	Marginal effects (pooled GLM) Number of nights/visits
Outpatient care	Model 1: Socio-demographics ($\beta_1; \alpha_1$)	0.0113*	0.371***
Models1-3 (n=13,157)		(0.005)	(0.094)
	Model 2: Socio-demographics + health variables		
Model 4 (n=5,067)	($\beta_1; \alpha_1$)	0.009	0.397 ***
Model 5 (n=8,160)		(0.005)	(0.096)
	Model 3: Model 2 plus years of membership		
	($\beta_1; \alpha_1$)	0.0231*	0.220
Part 2		(0.012)	(0.147)
Models1-3 (n=3,156)	Years of membership ($\beta_3; \alpha_3$)	-0.007	0.109
Model 4 (n=909)		(0.007)	(0.088)
Model 5 (n=2,247)	Years of membership^2 ($\beta_4; \alpha_4$)	0.000	-.0100
		(0.001)	(0.009)
	Model 4: Model 3 (poor) ($\beta_1; \alpha_1$)	0.024	0.332
		(0.017)	(0.238)
	Years of membership ($\beta_3; \alpha_3$)	-0.006	0.181
		(0.010)	(0.134)
	Years of membership^2 ($\beta_4; \alpha_4$)	0.000	(-0.017)
		(0.001)	0.013
	Model 5: Model 4 (non-poor) ($\beta_1; \alpha_1$)	0.025	0.272
		(0.015)	(0.187)
	Years of membership ($\beta_3; \alpha_3$)	-0.006	0.022
		(0.009)	(0.118)
	Years of membership^2 ($\beta_4; \alpha_4$)	0.000	-0.001
		(0.001)	(0.014)
Inpatient care	Model 1: Socio-demographics ($\beta_1; \alpha_1$)	0.0181***	0.565
Part 1		(0.004)	(0.378)
	Model 2: Socio-demographics + health variables		
Models1-3 (n=13,972)	($\beta_1; \alpha_1$)	0.0179***	0.556
Model 4 (n=5,376)		(0.004)	(0.337)
	Model 3: Model 2 plus years of membership		
Model 5 (n=8,690)	($\beta_1; \alpha_1$)	0.0316***	0.947
		(0.009)	(0.726)
Part 2	Years of membership ($\beta_3; \alpha_3$)	-0.007	-0.351
Models1-3 (n=1,224)		(0.005)	(0.449)
Model 4 (n=346)	Years of membership^2 ($\beta_4; \alpha_4$)	0.000	0.046
Model 5 (n=877)		(0.001)	(0.053)
	Model 4: Model 3 (poor) ($\beta_1; \alpha_1$)	0.017	0.210
		(0.012)	(0.784)
	Years of membership ($\beta_3; \alpha_3$)	-0.003	-0.429
		(0.007)	(0.430)
	Years of membership^2 ($\beta_4; \alpha_4$)	0.000	0.084
		(0.001)	(0.047)
	Model 5: Model 4 (non-poor) $\beta_1; \alpha_1$)	0.0417**	0.828
		(0.014)	(1.114)
	Years of membership ($\beta_3; \alpha_3$)	-0.008	-0.005
		(0.008)	(1.084)
	Years of membership^2 ($\beta_4; \alpha_4$)	0.000	-0.008
		(0.001)	(0.209)
Traditional medicine	Model 1: Socio-demographics (β_1)	-0.006	

		(0.009)
	Model 2: Socio-demographics + health variables	
Models1-3 (n=13,840)	(β_1)	-0.009
Model 4 (n=5,284)		(0.010)
Model 5 (n=8,613)	Model 3: Model 2 plus years of membership (β_1)	-0.008
		(0.019)
	Years of membership (β_3)	-0.001
		(0.001)
	Years of membership^2 (β_4)	0.000
		(0.000)
	Model 4: Model 3 (poor) (β_1)	-0.034
		(0.028)
	Years of membership (β_3)	-0.002
		(0.002)
	Years of membership^2 (β_4)	0.000
		(0.000)
	Model 5: Model 4 (non-poor) $\beta_1; \alpha_1$)	0.009
		(0.025)
	Years of membership (β_3)	0.000
		(0.002)
	Years of membership^2 (β_4)	0.000
		(0.000)
Self-medication	Model 1: Socio-demographics (β_1)	0.0261*
		(0.011)
	Model 2: Socio-demographics + health variables	
Models1-3 (n=13,840)	(β_1)	0.0226*
Model 4 (n=5,284)		(0.011)
Model 5 (n=8,613)	Model 3: Model 2 plus years of membership (β_1)	-0.012
		(0.022)
	Years of membership (β_3)	-0.002
		(0.002)
	Years of membership^2 (β_4)	0.000
		(0.000)
	Model 4: Model 3 (poor) (β_1)	0.004
		(0.034)
	Years of membership (β_3)	-0.001
		(0.002)
	Years of membership^2 (β_4)	0.000
		(0.000)
	Model 5: Model 4 (non-poor) β_1)	-0.021
		(0.028)
	Years of membership (β_3)	-0.001
		(0.002)
	Years of membership^2 (β_4)	0.000
		(0.000)

Note: Standard errors in parentheses. Heteroskedastic clustered standard errors
Model 1: Other insurance, age, age2, marital status, education, urbanity, cycle
Model 2: Model 1 including: general health, log consumption per capita, BMI, lung capacity, anemia, diagnosed with chronic condition, tobacco smoking
Model 3: Model 2 + years of membership in Jamkesmas
Model 4: Model 3 + years of membership in Jamkesmas conditional of being poor at baseline (2000)
Model 5: Model 3 + years of membership in Jamkesmas conditional of being non-poor at baseline (2000)
* p<0.05, ** p<0.01, *** p<0.001

Table 3.7a. Marginal effects of Jamkesmas on health outcomes (disease)

Model	Marginal effects				
	Systolic BP (FE-OLS)	Hypertension (FE-OLS)	Lung capacity (FE-OLS)	Anemia (FE-OLS)	Underweight (FE-OLS)
Model 1: Socio-demographics (β_1)	-0.710**	-0.005	2.232*	0.007	0.005
	(0.261)	(0.007)	(1.096)	(0.008)	(0.004)
Model 2: Socio-demographics + health variables (β_1)	-0.610*	-0.004	2.667*	0.006	0.005
	(0.263)	(0.008)	(1.130)	(0.008)	(0.003)
Model 3: Model 2 plus years of membership (β_1)	-0.006	0.032	4.611	0.034	0.016
	(0.565)	(0.017)	(2.535)	(0.019)	(0.010)
Years of membership (β_3)	-0.187	-0.0266*	-1.424	-0.016	-0.005
	(0.327)	(0.011)	(1.542)	(0.012)	(0.006)
Years of membership^2 (β_4)	-0.033	0.003	0.252	0.003	0.000
	(0.038)	(0.001)	(0.188)	(0.002)	(0.001)
Model 4: Model 3 (poor) (β_1)	0.299	0.050	1.621	0.031	0.009
	(0.876)	(0.028)	(3.775)	(0.030)	(0.017)
Years of membership (β_3)	0.101	-0.024	-0.254	-0.016	0.004
	(0.477)	(0.017)	(2.158)	(0.018)	(0.009)
Years of membership^2 (β_4)	-0.035	0.003	0.212	0.002	-0.001
	(0.054)	(0.002)	(0.250)	(0.002)	(0.001)
Model 5: Model 4 (non-poor) β_1)	-0.047	0.026	6.499	0.032	0.025
	(0.740)	(0.022)	(3.404)	(0.025)	(0.013)
Years of membership (β_3)	-0.452	-0.0304*	-2.048	-0.011	-0.015
	(0.456)	(0.015)	(2.209)	(0.017)	(0.009)
Years of membership^2 (β_4)	-0.040	0.002	0.207	0.002	0.001
	(0.055)	(0.002)	(0.281)	(0.002)	(0.001)
Models 1-3 (n)	14,402	14,402	14,052	14,052	14,052
Model 4 (n)	5,477	5,477	5,348	5,348	5,348
Model 5 (n)	8,925	8,925	8,704	8,704	8,704

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

Table 3.7b. Marginal effects of Jamkesmas on health outcomes (health and function)

	Marginal effects	
Models	**Self-rated health (fixed-effects OLS)**	**Missed days (fixed-effects negative binomial)**
Model 1: Socio-demographics (β_1)	-0.0238	0.107***
	(0.013)	(0.029)
Model 2: Socio-demographics + health variables (β_1)	-0.021	0.0960**
	(0.013)	(0.031)
Model 3: Model 2 plus years of membership (β_1)	-0.047	0.204**
	(0.027)	(0.068)
Years of membership (β_3)	0.016	-0.066
	(0.016)	(0.041)
Years of membership^2 (β_4)	-0.001	0.007
	(0.002)	(0.005)
Model 4: Model 3 (poor) (β_1)	-0.039	0.312**
	(0.039)	(0.107)
Years of membership (β_3)	0.025	-0.106
	(0.021)	(0.061)
Years of membership^2 (β_4)	-0.002	0.008
	(0.002)	(0.007)
Model 5: Model 4 (non-poor) ($\beta_1; \alpha_1$)	-0.046	0.145
	(0.037)	(0.088)
Years of membership (β_3)	0.003	-0.046
	(0.025)	(0.057)
Years of membership^2 (β_4)	-0.001	0.006
	(0.003)	(0.007)
Models 1-3 (n)	14,402	8181
Model 4 (n)	5,477	3010
Model 5 (n)	8,925	5071

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

Note:
Standard errors in parentheses. Heteroskedastic clustered standard errors (at the level of household)
Model 1: Other insurance, age, age2, marital status, education, urbanity, cycle
Model 2: Model 1 including: general health, log consumption per capita, BMI, lung capacity, anemia, diagnosed with chronic condition, tobacco smoking
Model 3: Model 2 + years of membership in Jamkesmas
Model 4: Model 3 + years of membership in Jamkesmas conditional of being poor at baseline (2000)
Model 5: Model 3 + years of membership in Jamkesmas conditional of being non-poor at baseline (2000)

Table 3.8. Marginal effects of Jamkesmas on out-of-pocket healthcare expenditures and catastrophic health expenditures

	Marginal effects		
Models	**OOP expenditures-outpatient (pooled GLM)**	**OOP expenditures-inpatient (pooled GLM)**	**Catastrophic expenditure (fixed-effects OLS)**
Model 1: Socio-demographics	-14,063***	-827,463***	0.00518*
	(3,904)	(206,762)	(0.003)
Model 2: Socio-demographics + health variables	-10,881**	-789,590***	0.004
	(3,532)	(216,827)	(0.003)
Model 3: Model 2 + years of membership	-8,814	-431,779	0.008
	(7,739)	(433,929)	(0.007)
Years of membership	2,153	-249,038	-0.002
	(4,790)	(368,219)	(0.003)
Years of membership^2	891	-23,312	0.000
	(659)	(62,764)	(0.000)
Model 4: Model 3 (poor)	-10,091	-290,640	0.006
	(8,146)	(1,213,668)	(0.008)
Years of membership	3,740	-235,078	-0.002
	(5,680)	(838,285)	(0.004)
Years of membership^2	-857	-43,738	0.000
	(882)	(113,718)	(0.000)
Model 5: Model 4 (non-poor)	-6,937	-77,090	0.009
	(9,396)	(545,582)	(0.010)
Years of membership	-1,315	-1,210,393	-0.003
	(5,410)	(625,044)	(0.005)
Years of membership^2	-402	235,294	0.000
	(698)	(148,592)	((0.001)
Models 1-3 (n)	1224	1145	14172
Model 4 (n)	346	332	5382
Model 5 (n)	877	825	8778

Note: Standard errors in parentheses. Heteroskedastic clustered standard errors (at the level of household)

Model 1: Other insurance, age, age2, marital status, education, urbanity, cycle

Model 2: Model 1 including: general health, log consumption per capita, BMI, lung capacity, anemia, diagnosed with chronic condition, tobacco smoking

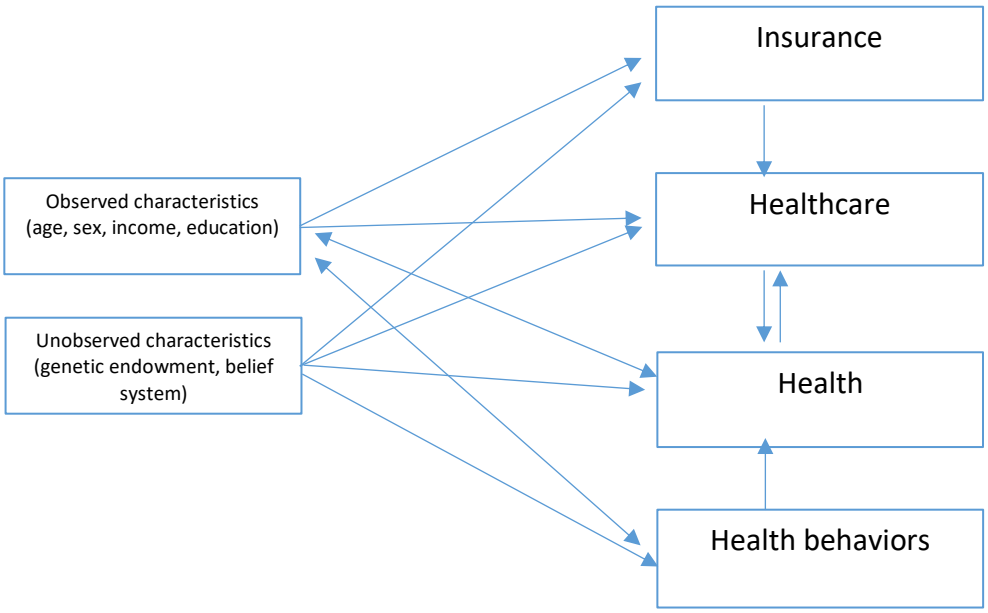
Model 3: Model 2 + years of membership in Jamkesmas

Model 4: Model 3 + years of membership in Jamkesmas conditional of being poor at baseline (2000)

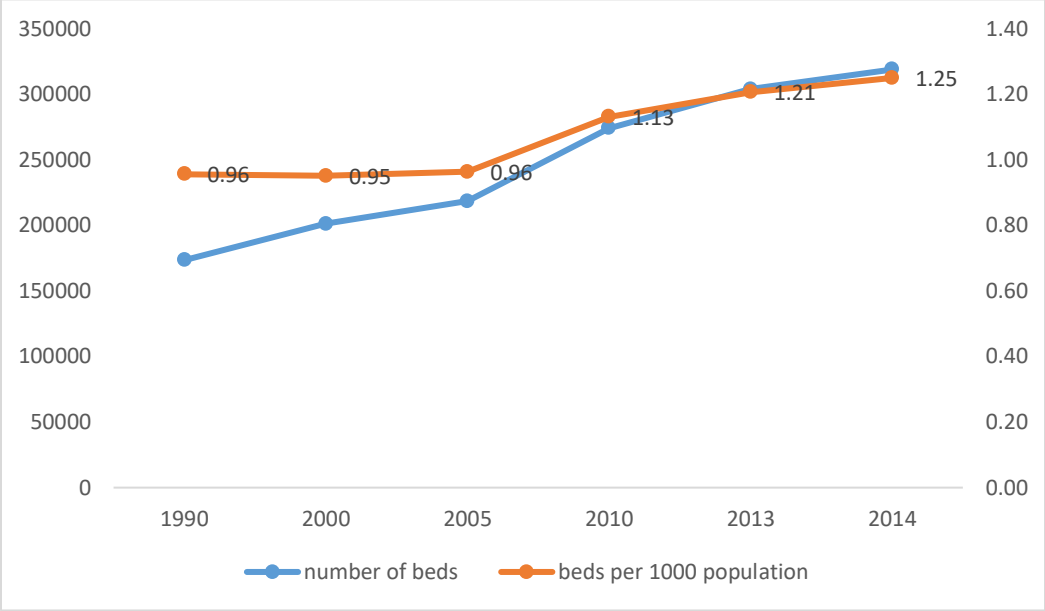
Model 5: Model 3 + years of membership in Jamkesmas conditional of being non-poor at baseline (2000)

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

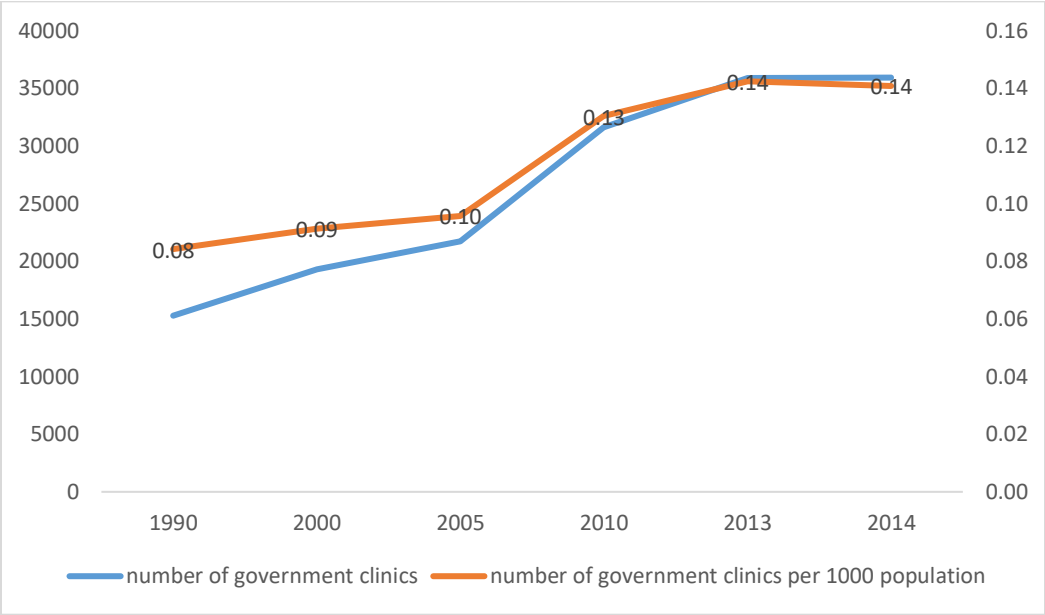
Figure 3.1. Relationships among insurance, healthcare and health (Levy & Meltzer, 2001, page 4)



Appendix 3.1.a. Number of beds (public and private), Indonesia, 1990-2014

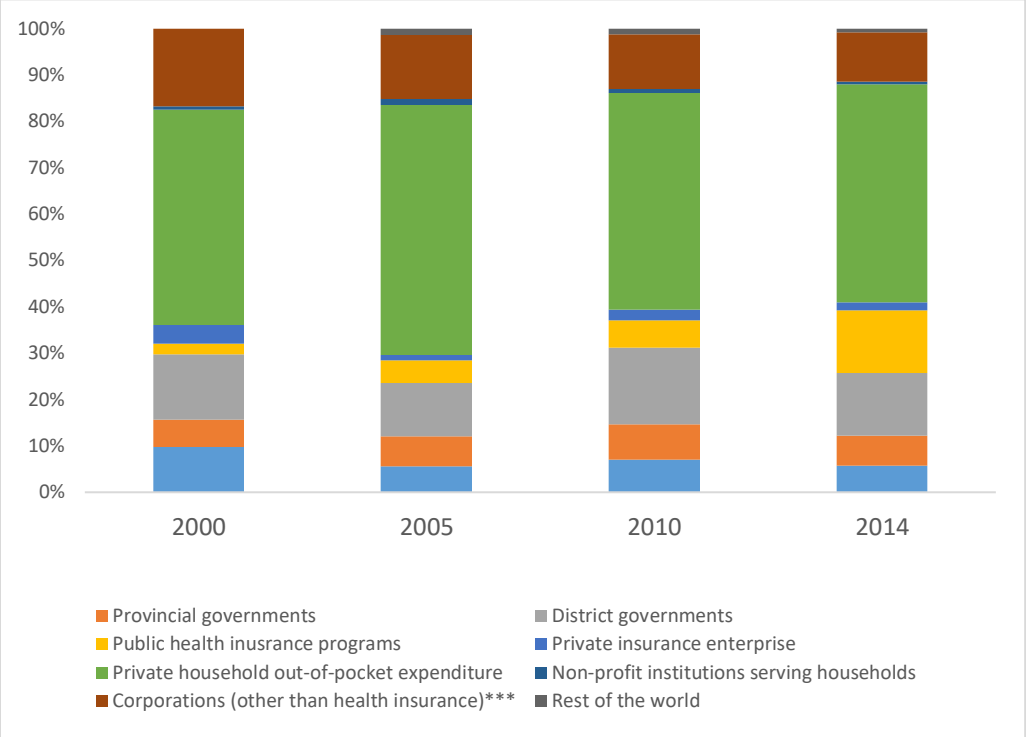


Appendix 3.1.b. Number of government clinic (Puskesmas) beds, Indonesia, 1990-2014



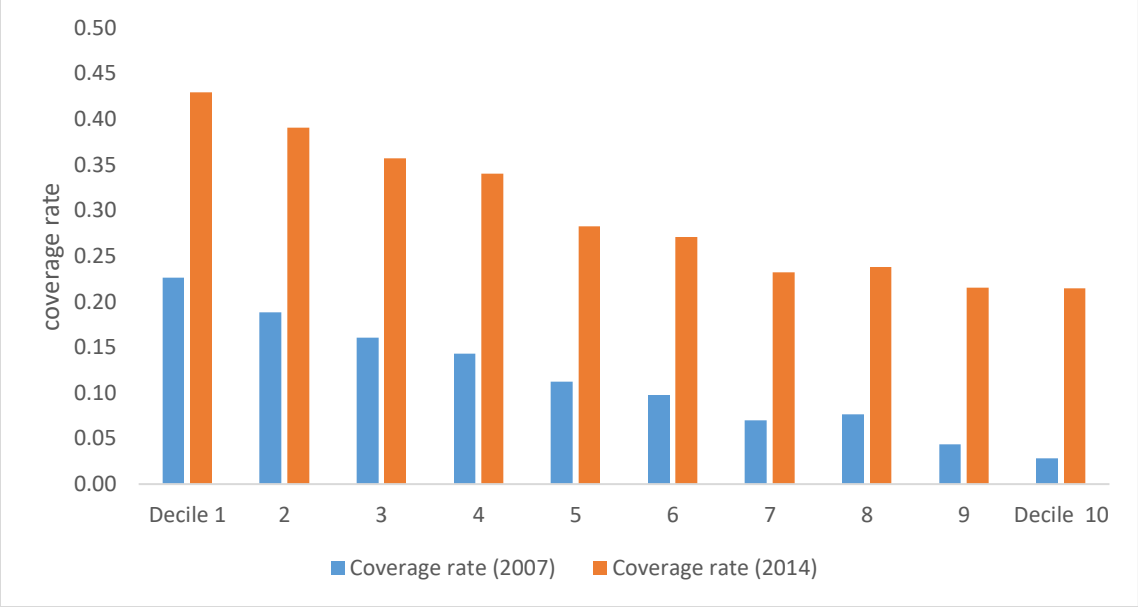
Source: Number of hospital beds and government clinic bed: Mahendradhata et al (2017); population based from World Bank (2017).

Appendix 3.2. Sources of health financing, Indonesia, 2000-2014



Source: Indonesia National Health Accounts (2017)

Appendix 3.3. Jamkesmas membership by income group (decile), Indonesia, 2007 and 2014



Source: Authors' estimates using Indonesia Family Life Survey (various rounds)

Appendix 3.4. Attrition of respondents

Year		Frequency	Share
2000	START	30,815	
2007	Cannot be found/full-decline	5,763	19%
	Died	1,930	6%
	Total	7,693	25%
	SAMPLE	23,122	75%
2014	Cannot be found/full-decline	3,323	14%
	Died	1,696	7%
	Total	5,019	22%
	GRAND SAMPLE	18,103	59%
Attrition			41%

We used logistic regression to determine the association of non-response with baseline characteristics (i.e., outcome: 1-non-response in 2007 or 2014; 0 – with response in 2007 and 2014. Deceased are excluded in the analysis).

Appendix 3.5. Association of non-response and baseline characteristics (2000)

Covariates	OR	SE	p-value	95 CI	
Age	0.903	0.006	0.000	0.891	0.914
age*age	1.001	0.000	0.000	1.001	1.001
Education (ref: No education)					
Grade school	0.933	0.065	0.316	0.814	1.069
Junior HS	1.031	0.080	0.692	0.885	1.201
Senior HS	1.039	0.084	0.640	0.886	1.218
Vocational	1.083	0.088	0.326	0.924	1.270
University graduate	1.812	0.175	0.000	1.499	2.190
Marital status (ref: single)					
Married	0.697	0.035	0.000	0.631	0.770
Separated	1.297	0.248	0.174	0.892	1.887
Widowed	0.963	0.092	0.692	0.798	1.162
Rural	0.661	0.023	0.000	0.618	0.706
Income group (ref: poor)					
Middle	1.067	0.042	0.098	0.988	1.152
Rich	1.644	0.067	0.000	1.517	1.781
Employment (ref: self-employed)					
Government	0.987	0.088	0.882	0.828	1.176
Private	1.392	0.068	0.000	1.264	1.533
Unpaid worker	1.525	0.078	0.000	1.380	1.685
Unemployed	2.079	0.124	0.000	1.849	2.338
Retired	2.064	0.346	0.000	1.486	2.866
Female	0.842	0.030	0.000	0.785	0.902

N= 23,195; R2: 0.0920

We used logistic regression to determine the association of Jamkesmas membership and mortality (i.e., outcome: 1-dead in 2014; 0-alive; covariates in 2007).

Appendix 3.6. Association of Jamkesmas membership (2007) and future mortality (2014)

	OR	SE	p-value		95 CI	
Jamkesmas	0.987	0.099	-0.130	0.895	0.811	1.201
Other insurance	1.043	0.122	0.360	0.718	0.829	1.313
Age	1.085	0.003	25.410	0.000	1.078	1.091
Female	0.634	0.057	-5.070	0.000	0.532	0.756
Rural	0.797	0.060	-3.030	0.002	0.688	0.923
Income group						
Middle	0.943	0.077	-0.730	0.468	0.804	1.105
Rich	0.908	0.087	-1.010	0.313	0.752	1.095
Marital status (ref: Single)						
Married	0.521	0.093	-3.670	0.000	0.368	0.739
Separated	0.304	0.171	-2.120	0.034	0.101	0.915
Widow	0.486	0.100	-3.490	0.000	0.324	0.728
Education (ref: No education)						
Grade school	1.065	0.106	0.640	0.525	0.877	1.294
Junior HS	1.154	0.165	1.010	0.314	0.873	1.527
Senior HS	0.734	0.133	-1.710	0.088	0.515	1.047
Vocational	0.702	0.123	-2.020	0.044	0.498	0.990
University	0.926	0.218	-0.330	0.745	0.584	1.469
Employment (ref: self-employed)						
Government	1.180	0.242	0.810	0.420	0.789	1.765
Private	1.217	0.154	1.550	0.120	0.950	1.559
Unpaid worker	1.387	0.142	3.200	0.001	1.135	1.694
Unemployed	2.332	0.356	5.550	0.000	1.729	3.144
Retired	2.186	0.262	6.530	0.000	1.729	2.765
Healthy	0.564	0.044	-7.280	0.000	0.483	0.658

N= 16,861; R2:0.22

Appendix 3.7. Association of Jamkesmas and healthcare use using logit probability model (odds ratio)

Dependent variable	Models	First stage (FE-Logit)
Outpatient care	Model 1: Socio-demographics	1.29**
		-0.13
	Model 2: Socio-demographics + health variables	1.26*
		-0.13
	Model 3: Model 2 + years of membership	1.45
		-0.33
	Model 4: Model 3 (poor)	1.91
		-0.74
	Model 5: Model 4 (non-poor)	1.33
		-0.39
Inpatient care	Model 1: Socio-demographics	2.00***
		-0.22
	Model 2: Socio-demographics + health variables	2.10***
		-0.26
	Model 3: Model 2 + years of membership	1.92*
		-0.49
	Model 4: Model 3 (poor)	2.69
		-1.38
	Model 5: Model 4 (non-poor)	1.47
		-0.5
Traditional medicine	Model 1: Socio-demographics	0.92
		-0.05
	Model 2: Socio-demographics + health variables	0.9
		-0.05
	Model 3: Model 2 + years of membership	0.9
		-0.11
	Model 4: Model 3 (poor)	0.84
		-0.17
	Model 5: Model 4 (non-poor)	0.95
		-0.15
Self-medication	Model 1: Socio-demographics	1.09*
		-0.05
	Model 2: Socio-demographics + health variables	1.07*
		-0.05
	Model 3: Model 2 + years of membership	0.95
		-0.1
	Model 4: Model 3 (poor)	1.04
		-0.16
	Model 5: Model 4 (non-poor)	0.91
		-0.12

Appendix 3.8. Modified Park's Test

	Number of visits (outpatient)		Inpatient days (inpatient)	
	chi	**p value**	**chi**	**p value**
Gaussian	637.83	0.000	7418.55	0.000
Poisson	166.54	0.000	1967.18	0.000
Gamma	0.31	0.579	6.63	0.010
Inverse Gaussian	139.13	0.000	1536.90	0.000

The table below shows the distribution of self-rated health categories in 2014 by self-rated health and age group in 2007. We did not produce a transition matrix for 2000 and 2007 because the distribution is stable in both years.

Appendix 3.9. Distribution of self-related health categories in 2014, by self-rated health and age group in 2007

Age	N	Healthy in 2007			
		healthy (2014)	somewhat healthy (2014)	somewhat unhealthy (2014)	unhealthy (2014)
21-30	482	29%	59%	11%	1%
31-40	473	29%	56%	14%	1%
41-50	371	23%	58%	18%	1%
51-60	161	20%	50%	29%	1%
61-70	58	16%	50%	28%	7%
71-80	14	21%	50%	21%	7%
81-90	4	25%	50%	25%	0%
Age	**N**	**Somewhat healthy in 2007**			
		healthy (2014)	**somewhat healthy (2014)**	**somewhat unhealthy (2014)**	**unhealthy (2014)**
21-30	3140	18%	65%	16%	1%
31-40	3366	18%	62%	19%	1%
41-50	2764	18%	57%	23%	2%
51-60	1663	14%	54%	30%	2%
61-70	880	11%	54%	30%	5%
71-80	265	11%	44%	38%	7%
81-90	38	11%	32%	47%	11%
Age	**N**	**Somewhat unhealthy (2007)**			
		healthy (2014)	**somewhat healthy (2014)**	**somewhat unhealthy (2014)**	**unhealthy (2014)**
21-30	398	13%	57%	27%	3%
31-40	505	11%	48%	37%	4%
41-50	535	9%	39%	47%	4%
51-60	383	5%	38%	51%	7%
61-70	249	7%	30%	57%	7%
71-80	114	5%	32%	54%	10%
81-90	14	7%	29%	64%	0%
Age	**N**	**Unhealthy (2007)**			
		healthy (2014)	**somewhat healthy (2014)**	**somewhat unhealthy (2014)**	**unhealthy (2014)**
21-30	4	0%	50%	50%	0%
31-40	13	23%	31%	15%	31%
41-50	8	25%	13%	63%	0%
51-60	9	11%	22%	33%	33%
61-70	4	0%	25%	75%	0%
71-80	3	0%	0%	33%	67%

Chapter 4: The age-related trajectories of health-related quality of life among persons with diabetes: evidence based on 16 years of Canadian longitudinal data

4.1. Introduction

In developed countries, mortality rates attributed to cardio-vascular diseases (CVD) had declined in the last 50 years. However, the rising prevalence of diabetes and obesity coupled with ageing population may offset this gain as more people are at risk of CVD (Organization for Economic Cooperation and Development, 2015). In OECD countries, approximately 7% of adult population had diabetes in 2011, and the prevalence is expected to increase to 11% by 2030 (Organization for Economic Co-operation and Development, 2015). In Canada, diabetes is one of the leading causes of morbidity. In 2015, approximately 9% of adults had diabetes, and the prevalence is expected to increase to 12 percent by 2025 (Canadian Diabetes Association, 2016). Diabetes when not controlled can lead to symptomatic health complications, which could affect well-being and economic productivity (Minor & Macewan, 2016; Rodríguez-Sánchez & Cantarero-Prieto, 2017). Diabetes can eventually lead to death. In 2015, one in ten deaths in Canadian adults was attributed to diabetes complications (Canadian Diabetes Association, 2016).

The complications associated with diabetes affect different dimensions of health-related quality of life (HRQL) such as social function, cognitive function, role function, physical function and general perception of health. Several studies show the negative association between diabetes and HRQL (Akinci, Yildirim & Go, 2008; Maddigan, Feeny, & Johnson, 2005; Maddigan, Feeny, Majumdar, Farris & Johnson, 2006; Ragnarson &

Apelqvist, 2000; Wu et al., 2002; Wexler, 2006). However most of these studies rely on cross-sectional analyses to examine descriptive association (Chiu & Wray, 2010).

The growing literature in epidemiology on life course models suggests that health status changes over time in response to shocks and exposures, recovery, and resilience. The transition of health status over time is influenced by physical, socio-economic, psychosocial, cultural and healthcare factor (Ben-Shlomo & Kuh, 2002; Evans & Stoddart, 1990; Halfon & Hochstein, 2002).

Based on the life course model, we estimate the level and rate of deterioration of HRQL among adults with diabetes over the lifespan. Such research is important in designing clinical and policy interventions for slowing down the deterioration of HRQL. With good glycemic control, adults with diabetes can potentially "compress morbidity" by delaying the burden of their condition, and achieve a level of HRQL similar to adults without diabetes (Fries, 1982).

There are limited studies on age-related trajectories focused on population with type-2 diabetes. Available studies compare the HRQL scores of persons with and with diabetes by age group using cross-sectional data. Such studies offer a crude depiction of the changes of HRQL over the life course. However, the observed difference is potentially biased because of differential survival and attrition between population with and without diabetes. We found a study conducted in the United States that examines the trajectory of HRQL among persons with type 1 and 2 diabetes using an 8-year longitudinal data. Chui & Wray (2010) find that persons with diabetes had experienced

lower Activities of Daily Living (ADL) scores and a faster rate of deterioration than persons without diabetes (Chiu & Wray, 2010). In Canada, we have not found a study that examines the deterioration of HRQL among person with diabetes within a life course framework.

In this study, we estimate the age-related trajectories of Health Utilities Index 3 (HUI3) from mid- to late-adulthood among Canadians with type-2 diabetes, and compare the trajectories with persons without diabetes. We examine if these age-related trajectories vary by sex, income and education. HUI3 is a multi-attribute utility measure use of health status and HRQL(Horsman, Furlong, Feeny & Torrance, 2003). To estimate the age-related trajectories, we use linear mixed model on and a data from 9-wave (16 years) cohort sequential longitudinal dataset.

4.2. Methods

4.2.1. Data

We use the longitudinal data from the Statistics Canada's National Population Health Survey (NPHS). The target population of the survey was community-dwelling Canadian residents of all ages from 10 provinces. Indian Reserves, Canadian Forces Bases, long-term care institutions, and some remote areas of Ontario and Quebec were excluded from the NPHS. The baseline survey was conducted in 1994/95, and the last follow-up survey was conducted in 2010/11. The longitudinal data is composed of 9 cycles in which the same individuals were surveyed every two years. The NPHS recorded all

deaths and non-responses after the baseline. For respondents who moved to long-term care facilities, their responses were administered through the facility survey component of the NPHS, and all information was retained in the longitudinal data (Tambay & Catlin, 1995).

4.2.2. Inclusion and exclusion criteria

The NPHS has 17,276 unique respondents in the baseline survey (year 1994/1995). Because diabetes is rare among the young population (only 0.5% of below 40 population have diabetes), we only include respondents 40 years old or above at baseline year, which leaves 7,992 respondents. We exclude persons with diabetes who were diagnosed before the age of 20 years to avoid potentially including persons with type-1 diabetes. In our study, we run two models that differed with respect to sample size. For the first model (diabetes as binary variable; 1- with diabetes; 0- without diabetes), we reshape the data from a person level (n=7,992) to time-person period (n=68,215). Because of missing values (for HUI3 or covariates), we further exclude 10,153 time-period person observation. We have 58,062 time-person period observations in our final sample size. For the second model (diabetes as 4-category variable; 0-without diabetes; 1-with diabetes lifestyle; 2-with diabetes oral medication; 3-with diabetes insulin), our baseline year is Cycle 3 (1998/1999) because Statistics Canada did not collect information about treatment type in Cycles 1 and 2. From the original sample size of 7,992, we exclude all respondents who died in Cycles 2 and 3, which leaves 7,402

respondents. In both models, respondents who died or who were moved to long-term care facilities are included in our analyses. Appendix 4.1a shows the attrition rates by cycle.

4.2.3. Dependent variable and covariates

Our outcome of interest is HUI3, a multi-attribute and utility-based measure of HRQL. HUI3 captures eight attributes, namely: vision, hearing, speech, ambulation, dexterity, emotion, cognition, and pain and discomfort. Each attribute has 5 or 6 levels. The HUI3 score is a continuous variable. It ranges from 1.00 (perfect health) to -0.36 (worst health). As defined in the HUI3 system, the overall HUI3 score for dead is 0.0 (Feeny et al., 2002).

We categorize respondents as diabetic if they answered, "yes" to the survey question, "Do you have any of the following long-term conditions [Diabetes] that have been diagnosed by a health professional?" We also construct another variable by diabetes treatment following the recommendation of the Canadian Diabetes Association for categorizing diabetes in population surveys. We identify the treatment type based on the following question, "Do you take any other treatment or medication for your diabetes? If Yes, what type of treatment?" We categorize treatment type into three: lifestyle change (diet and exercise) only; oral medication (with or without lifestyle change); and insulin (with or without lifestyle change and oral medication). Both diabetes variables are time-varying.

We control for time-invariant and time-varying covariates, and use the social determinants framework to identify covariates to be included in the model (Evans & Stoddart, 1990; Marmot, 2005). For time- invariant variables, we include racial background (1-white or 0-non-white), education (0-non high school or 1-graduated from high school). We also include birth cohort to control for differences across age- groups who experience an initial event such as birth in the same time period (Yang & Land, 2013). We categorize the respondents into 6 cohorts using the age at baseline year: 40-50, 51-60, 61-70, 71-80, 81-90, and 91-up. For time varying variables, we include the following: age terms (median-centered); rural residence (0-No or 1-Yes); income quintile (0-lowest; 4-highest); smoking (0-No or 1-Yes); physical activity (0-low, 1-medium or 2-high); Body Mass Index (0-normal and underweight, 1-overweight or 2-obese); has a regular doctor (0-No or 1-Yes); institutionalized (0-No or 1-Yes); stroke (0-No or 1-Yes); heart disease (0-No or 1-Yes); and depression (0-No or 1-Yes); and number of other chronic conditions (0-none, 1-one chronic conditions, 2- two chronic conditions or 3-three or more chronic conditions). We separate stroke, heart disease and depression from the other chronic conditions because they are prevalent chronic conditions among patients with diabetes, and have different mechanisms through which they affect HRQL. We also include mortality as one of the covariates (1-dead or 0-alive) because HUI3 scores, age and other covariates we use in the model predict mortality (Asakawa et al., 2012; Yang & Land, 2013). See Appendix 4.1b for the treatment of missing observations.

4.2.4. Statistical model

We use a linear mixed model (LMM) to estimate the age-related trajectories of HUI3 among diabetics and non-diabetics. LMM has the ability to incorporate repeated and correlated measures, model irregularly spaced measurement occasions, and to include time-variant and invariant predictors. Linear mixed models incorporate fixed and random effects simultaneously in one single regression equation (Asakawa et al., 2012; Singer & Willett, 2003; Stephen & Bryk, 2002; Yang & Land, 2013).

Our model specification is demonstrated by a two-level equation. The level-1 equation (eq.1) is a repeated observation model. Each individual's HUI3 trajectory is a function of age and time-varying covariates (including diabetes variable).

$$Y_{ij} = \alpha_{0j} + \beta_{1j}\mathrm{Age}_{ij} + \beta_{2j}\mathrm{Diabetes}_{ij} + \beta_{pj}X_{pij} + \varepsilon_{ij} \quad \text{(eq.1)}$$

where Y_{ij} is the HUI3 scores for individual j at cycle i, for j=1… N and i=1….9 (i.e. number of cycles). Age_{ij} is the mean-centered age of the individual j at cycle i. $\mathrm{Diabetes}_{ij}$ is the diabetes status for individual j at cycle i. We interact age and the diabetes variable to estimate the rate of deterioration. X_{pij} is the time-variant covariates, for p=1...P (i.e., P is the number of time-variant covariates). α_{0j} is the level-1 intercept or the average HUI3 when all covariates are at zero, and age is equal to the median age of the population; β_{1j} is the coefficient for the time predictor (age) or the average growth rate

of HUI3 for every year age of individual j; β_{2j} is the coefficient for diabetes variable or the average growth rate of HUI3 of individual j with diabetes; β_{pj} are the coefficients for other time-varying covariates; and ε_{ij} is the level-1 error term or intra-individual error term.

The individual growth parameters depend on individual-level characteristics. The level-2 model specifies time-invariant covariates associated with each individual. The intercept and slopes of randomly varying covariates in our level-1 equation are function of time-invariant covariates (equation 2).

$$a_{0j} = \gamma_{00} + \sigma_{01}Z_1 + \sigma_{0q}Z_q + \zeta_{0j} \qquad \text{(equation 2)}$$

$$\beta_{pj} = \gamma_{p0} + \sigma_{p1}Z_1 + \sigma_{pq}Z_q + \zeta_{pj}$$

where intercept a_{0j} and slopes β_{pj} in level-1 are functions of the following level-2 parameters: intercepts, $\gamma_{00,}$ and γ_{p0}; time-invariant covariates, Z and their respective slopes σ; and intra-individual error terms ζ. Hence if we combined the equations 1 and 2, Y_{ij} is a function of fixed and random effects arising from intra- and inter-individual error terms; p is the number of time- varying covariates; and q is the number of time-invariant covariates.

To account for the complex sampling design of the NPHS, we use population weights that represent Canadian population in the first survey cycle. We determine the statistical significance of the fixed effect estimates using two-tailed test. We consider

differences in mean HUI3 overall scores of 0.03 or more as clinically important (Horsman et al., 2003).

4.3. Results

Table 4.1 shows the distribution of respondents by socio-demographic characteristics, risk factors and comorbidities at baseline. The average HUI3 score was 0.81 (SD: 0.228). The prevalence of diabetes was 6.8%. In Cycle 3 (1998/1999), the prevalence of the diabetes is 9.1%. We can categorize respondents with diabetes by treatment. Four (4) percent are on lifestyle change only (through diet and exercise); 52% on oral medication; and 20% on insulin therapy. Twenty-four (24) percent respondents with diabetes did not state a specific treatment. Appendix 4.2 shows the bivariate relationship between HUI3 scores and covariates at baseline. The median HUI3 scores is lower among individuals with diabetes than individuals without diabetes (with diabetes: 0.66 v. without diabetes: 0.82; $p<0.001$). There are also significant differences in scores across treatments. Individuals with diabetes on insulin therapy have significantly lower HUI3 scores compared to those who were on lifestyle or on oral medication (no diabetes: 0.74 v. lifestyle change: 0.71 v. oral medication: 0.66 v. insulin: 0.55; $p<0.001$). Mean HUI3 score is significantly higher among males, high school graduates, married, or those in higher socio-economic status. The mean HUI3 score of is lower among respondents who are smokers and physically inactive. In terms of co-morbidities, mean HUI3 score is significantly lower among respondents with depression, heart disease and

stroke. The number of other chronic conditions is negatively correlated with HUI3 scores.

4.3.1. Diabetes by sex

Figure 4.1 shows the unconditional age-related trajectories of persons with and without diabetes by sex. Table 4.2 are the coefficients of the conditional models disaggregated by sex (Appendix 4.3.a for the estimates with standard errors). Controlling for time-varying and time-invariant socio-demographic, risk factor, co-morbidity and mortality covariates, the diabetes term is statistically significant and clinically important among females (-0.04; $p < 0.001$), but not among males significant (-0.02; $p > 0.05$). The diabetes term interacted with age is not significant both for males and females. The coefficients of covariates in the model follow the same pattern as observed in literature. High education, higher socio-economic status or being white is associated with higher HUI3 scores. Risk factors such as smoking, physical inactivity or obesity are associated with lower HUI3. Having a regular physician is not associated with HUI3 scores. Depression, heart disease and stroke are also associated with lower HUI3 scores. There is also a clear dose-response relationship between number of other chronic conditions and HUI3 scores. The higher the number of other chronic conditions, the lower the HUI3 scores. For females, the significant change of coefficients for diabetes terms when the dead variable is included (from -0. 06 to -0.04) reflects the importance of including mortality in the model to correct the otherwise biased trajectory (Asakawa et al., 2012;

Yang & Land, 2013). There is also an improvement in the goodness of fit after controlling for mortality.

4.3.2. Diabetes by education and income

Table 4.3 shows the conditional models disaggregated by income and educational attainment. For this particular analysis, we re-categorize income quintiles into two categories. We consider income quintiles 1 and 2 as low-income, and quintiles 3, 4 and 5 as non-low-income. After controlling for socio-demographic characteristics, risk factors, chronic conditions and mortality covariates in the model, the coefficients of the diabetes and interaction terms are not statistically significant in both groups of educational attainment. On the other hand, there is a statistically significant and clinically important difference between adults with diabetes and without diabetes among low-income population (-0.04; $p<0.001$), but the diabetes–time interaction term is not significant. For educational attainment, there is no significant difference between adults with diabetes and without diabetes among high school and non-high school graduates.

4.3.3. Diabetes using treatment type

We also run a conditional model using the diabetes treatment type (No diabetes, Diabetes – lifestyle change only; Diabetes – oral medication; and Diabetes –insulin). We created a dummy for each category including respondents who have diabetes but

information on intervention is missing (Diabetes-missing). We included the Diabetes-missing in the model to control for possible systematic selection of respondents who did not report their treatment type. Because of sample size limitation, we decided not to run separate regression models by sex, income and education. After controlling for time-varying and non-varying socio-demographic, risk factor and comorbidity covariates, the coefficients of Diabetes- lifestyle change and Diabetes – oral medication are statistically not significant. Diabetes – insulin is statistically significant and clinically important (-0.04; $p<0.05$). None of the diabetes terms interacted with age is statistically significant (see Appendix 4.3.b).

4.4. Discussion

We estimate the age-related trajectories of Canadian adults with diabetes and compared the trajectories to those without diabetes. Our result suggests that after controlling for time-varying and –invariant covariates, the level of HUI3 among female or low-income individuals with diabetes are significantly lower than their counterparts without diabetes over the life course. The coefficients in females (-0.04) and low-income individuals with diabetes (-0.04) are also clinically important (>0.03 is considered as clinically important) (Horsman et al., 2003). If we compare the effects associated with other chronic condtions, diabetes poses a serious threat in the reduction of HRQL scores. The effect asociated with diabetes is more or less similar to that of depression (-

0.05), and to that of chronic heart disease (i.e. our estimate is -0.07, and in another study is -0.05) (Garster, Palta, Sweitzer, Kaplan & Fryback, 2009).

There is a lack of consensus on the association of diabetes on HRQL in the literature. Diabetes, in general, has a small to moderate impact on HRQL after controlling for confounders (Hiltunen, Keinanen-Kiukaaniemi, Laara & Kivela, 1996; Wändell, 2005). Wandell (2005) concluded that the HRQL scores of adults with diabetes is similar to those without diabetes after controlling for stroke and depression. However, our findings suggest that even after controlling for stroke and depression, we still observed a statistically significant and clinically important difference. What drives the reduced HUI3 scores among females? The complications associated with diabetes might be more debilitating among females, which may not occur with a similar gravity among males. Wexler (2006) also identified that female sex an independent correlate of HRQL among persons with diabetes, and argued that the association can be explained, in part, by the severity of complications experience by females. Unfortunately, we do not have information on the severity complications in the dataset to examine this. To have a sense of the severity of other chronic conditions affecting females, we determined the number of chronic conditions among females with diabetes and compared it to men with diabetes. Females with diabetes have more chronic conditions than males with diabetes. We also unpack the eight attributes of HUI3 among adults with diabetes. We found that female without diabetes have higher prevalence of impaired cognition and mobility, and pain than their male counterparts (see Appendix 4.4).

Although HUI3 scores are lower among female adults with diabetes compared to those without diabetes over time, we found no evidence of significant difference in the rate of deterioration. This is a departure from the findings by Chiu & Wray (2010) in the US wherein they found lower levels of Activities of Daily Living (ADL) scores, and significantly higher rate of deterioration among adults with diabetes even after controlling for other chronic conditions (Chiu & Wray, 2010). Further investigation whether the contextual and healthcare system differences might explain the faster rate in the US and the lack of evidence of deterioration among adults with diabetes in Canada. The difference in the performance of ADL and HUI3 could also affect the comparison.

Our sub-group analyses also show that there is difference in HRQL between individuals with diabetes and without diabetes, but it only occurs in the low-income population. Although this gap persists over time, there is not enough evidence to support that the rate of deterioration is different between low income individuals with diabetes and non-low income individuals without diabetes. Our findings support the previous work of Ross and colleagues. They found that the age-related decline in HRQL do not appear to be different across income groups. This may be a reflection of a more inclusive social policies such as universal health program and old age benefits in Canada relative to the US and some other OECD countries (Ross et al., 2011).

If we categorize diabetes by treatment, only the coefficient of Diabetes-insulin is statistically significant and clinically important difference. After controlling for

confounders, we do not have airtight evidence that individuals with diabetes under lifestyle change or oral medication have lower HUI3 scores compared to persons without diabetes. There is no consistent evidence on the association between treatment type and HRQL. A study shows that oral treatment, whether combined with insulin or not, was found to be predictive of worse outcome than diet treatment only. However, Wandell (2005) find increasing impairment on HRQL by diet treatment, oral treatment, and insulin treatment, this association disappeared when adjusting for confounders (Wändell, Brorsson & Åberg, 1998). The UK Diabetes Prospective Study Group (1999) did not confirm that insulin therapy had a greater effect on HRQL than other therapies. Studies suggest how insulin therapy could potentially affect HRQL. Insulin therapy might induce negative attitude particularly among chronic users. Technical concerns, anxiety about the pain, proper use and difficulties of taking injections, and hypoglycemic symptoms could affect HRQL (Hunt, Valenzuela & Pugh, 1997).

The gap in HRQL scores of individuals with and without diabetes that persists over the life course highlights the importance of incorporating life-course perspective in diabetes care. The adverse complications of diabetes start at midlife hence primary prevention such as health promotion programs should start at an early age (Chiu & Wray, 2010). The statistically significant and clinically important difference in HRQL between individuals with and without diabetes, which was only detected among females and low-income individuals, also highlights the need to adopt interventions that address the biological, social and environmental factors such that persons with diabetes have

persistently lower HRQL over the lifespan, a pattern that was not detected among their male or high-income individuals with diabetes. For countries with aging population, diabetes prevention should be directed towards morbidity compression and HRQL improvement. The study provides evidence that persons with diabetes have the ability the compress morbidity, and sustain a rate of deterioration similar to non-diabetic individuals possibly through a more inclusive and universal social policies (Fries, 1982).

There are number of limitations to our analyses. First, because we rely on self-reported diabetes status, undiagnosed individuals might have been misclassified. However, this might only constitute relatively small number of respondents because Canada provides universal health coverage. Second, we might have misclassified type 1, type 2 and gestational diabetes. We addressed this by excluding respondents who were diagnosed with diabetes before the age of 20, but this algorithm has not been validated. There is no way we can also isolate the those with gestational diabetes. Third, covariates use in the study are also based on self-report. In particular, risk factors (e.g. smoking and physical activity) and chronic conditions might not be highly accurate because of possible over-reporting and underreporting. The dataset does not also include information on the severity of chronic conditions, which limits our assessments as to why there is differential effects on HRQL between males and females. In the case of missing observation, we used Last Observation Carry Forward (LOCF) method, which might not be not be the best method for imputing missing observation of time-varying covariates. Lastly, we used LMM in estimating age-related trajectories, which follows

the assumption of normal distribution. However, HUI3 is not normally distributed, hence we might have produced erroneous standard errors. We conducted a sensitivity analysis by running separate models using arcsine-transformed HUI3. However, the results of untransformed and transformed shows similar patterns. In future studies, researchers might want to employ other methods such as Generalized Linear Models to address the skewed HUI3 distribution.

In conclusion, HRQL declines with age at approximately the same rate among individuals with diabetes and without diabetes. The HRQL burden of diabetes is higher for females than for males and higher for individuals with low-income with diabetes than high-income individuals with diabetes. These results underscore the importance of primary prevention as well as chronic-care management.

4.5. Reference

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Table 4.1. Descriptive statistics at baseline (n=7,978; weighted)

Variable	Category	Mean or Percent
Diabetes	Yes	9.1
	No	90.9
Diabetes by treatment type [a]	No	90.9
	Lifestyle	0.4
	Oral medication	4.7
	Insulin	1.8
	no reported (but diabetic)	2.2
HUI3 (Mean)		0.812
Age (Mean)		61.7
Sex	Male	41.6
	Female	58.4
High school graduate	No	58.7
	Yes	41.3
Rural	No	48.2
	Yes	51.8
Income	Poorest	11.3
	Poor	27.1
	Middle	11.9
	Rich	18.9
	Richest	30.8
Married	No	53.1
	Yes	46.9
Physical activity	Low	69.9
	Medium	18.2
	High	11.9
Body Mass Index [b]	Underweight	2.4
	Normal	42.6
	Overweight	39.7
	Obese	15.4
Smoker	No	72.9
	Yes	27.1
Regular doctor	No	7.8
	Yes	92.2
Stroke	No	98.4
	Yes	1.6
Heart disease	No	89.2
	Yes	10.8
Depression	No	90.6
	Yes	9.4

Number of chronic conditions [c]	None	48.1
	1	32.4
	2	14.2
	3 or more	5.2

Note:

[a] Baseline is Cycle 3 because no treatment type in Cycles 1 and 2.[b] Body Mass Index–underweight is separated in this descriptive statistics, but combined with normal weight in the regression model due to sample size [c] Excluding stroke, heart disease and depression

Table 4.2. Fixed effects coefficients and fit indices of growth models of HUI3 Trajectories, by sex (n=7,978; weighted)

Variables	Female		Male	
	Model 1	Model 2	Model 1	Model 2
Fixed effects				
Age X Age (centered)[a]	-1.8 X 10^{-4}*	0.00	-3.7 X 10^{-4}***	-1.1 X 10^{-4}*
Age X Age X Age (centered)	-2.8 X 10^{-5}***	-7.3 X 10^{-6}***	-2.7 X 10^{-5}***	-5.9 X 10^{-6}*
Cohort 2 (Ref: Cohort 1) [b]	0.00	0.02	-0.02	-0.01
Cohort 3	0.00	0.03	0.02	-0.02
Cohort 4	0.16	0.02	0.353**	-0.04
Cohort 5	0.26	-0.32*	0.37	-0.48**
Cohort 6	0.43	-1.88***	-1.29	-1.17*
Diabetes	-0.06**	-0.04**	-0.02	-0.01
Diabetes X age (centered)	0.00	0.00	0.00	0.00
White	0.25***	0.07***	0.27***	0.05***
High school graduate	0.07***	0.05***	0.07***	0.02**
Rural	0.04***	-0.01	0.06***	-0.01
Married	0.01	0.00	0.031*	0.02*
Low income (Ref: Lowest Income)	-0.01	0.00	0.07***	0.03*
Middle income	0.02	0.02	0.05*	0.01
High income	0.00	0.02*	0.08***	0.03*
Highest income	0.01	0.03**	0.09***	0.05***
Physical activity – Medium (Ref: Low)	0.05***	0.04***	0.03***	0.01**
Physical activity - High	0.04***	0.04***	0.05***	0.03***
Smoker	-0.02	-0.03***	-0.01	-0.01
BMI – Overweight (Ref: Underweight and normal)	0.03**	0.02**	0.05***	0.01*
BMI - Obese	0.02	0.00	0.04*	0.00
Regular doctor	-0.02	-0.01	-0.01	-0.01
Heart disease	-0.07***	-0.04***	-0.04*	-0.03***
Stroke	-0.15***	-0.10***	-0.16***	-0.09***
Depression	-0.05***	-0.05***	-0.08***	-0.08***
1 chronic condition (Ref: None) [c]	-0.04***	-0.04***	-0.04***	-0.03***
2 chronic condition	-0.08***	-0.06***	-0.08***	-0.06***
3 or more chronic condition	-0.16***	-0.12***	-0.13***	-0.12***
Institutionalized	-0.04	-0.42***	-0.02	-0.42***
Dead		-0.65***		-0.70***
Random Effects				
Inter-individual variance				
Age (slope)	7.0 X 10^{-5}	4.1 X 10^{-7}	1.8 X 10^{-5}	1.5 X 10^{-13}
Age X Age (slope)	1.2 X 10^{-7}	4.7 X 10^{-15}	9.6 X 10^{-8}	9.4 X 10^{-21}
Age X Age X Age (slope)	3.2 X 10^{-10}	1.06 X 10^{-11}	5.7 X 10^{-10}	1.23 X 10^{-11}
Intercept	0.03	0.01	0.03	0.01
Intra-individual variance	0.04	0.03	0.05	0.02

AIC [d]	90.2	47.8	91.6	51.6
BIC [d]	442.4	408.4	434.1	402.2

Note:

Model 1 – controlled for all covariates except mortality. Model 2- controlled for all covariates including mortality. Standard errors are not shown (see appendix 4.1). [a] Median-centered. Median is 52. Age (centered) is removed from the table because it is not significant in both models. [b] We also interacted age and cohort but not shown in the table. The coefficients are not significant. [c] Chronic conditions other than stroke, heart disease and depression. [d] Akaike information criterion (AIC) and Bayesian information criterion (AIC) are criteria to measure goodness of fit, and are used for model selection. Lower values of AIC and BIC are desirable.

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

Table 4.3. Fixed effects coefficients and fit indices of growth models of HUI3 Trajectories, by education attainment and income (n=7,978; weighted)

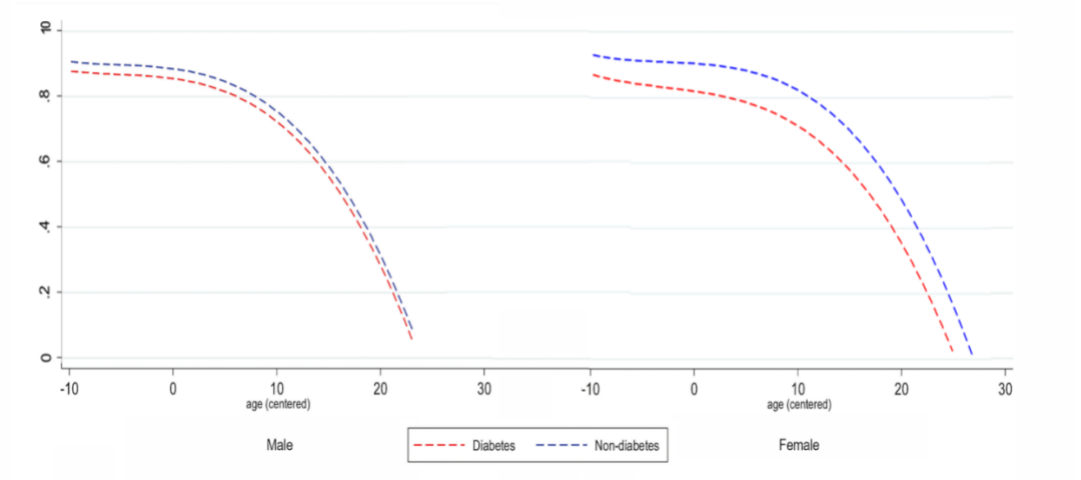
Variables	Non-high school		High school		Low-income		Non-low income	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Fixed effects								
Diabetes	-0.03	-0.03	-0.04	-0.02	-0.08**	-0.04**	-0.01	0.00
Diabetes X age	0.00	0.00	0.00	0.00	0.00	0.00	-0.003*	0.00
Random Effects (variance)								
Inter-individual								
Age (slope)	1.1×10^{-4}	1.9×10^{-21}	1.1×10^{-4}	7.9×10^{-6}	1.3×10^{-4}	2.4×10^{-17}	5.3×10^{-5}	7.9×10^{-6}
Age X Age (slope)	1.5×10^{-7}	2.2×10^{-23}	8.3×10^{-14}	1.9×10^{-23}	5.4×10^{-20}	4.0×10^{-19}	6.7×10^{-8}	1.1×10^{-23}
Age X Age X Age (slope)	2.2×10^{-10}	8.4×10^{-12}	6.9×10^{-10}	1.4×10^{-4}	1.1×10^{-10}	6.2×10^{-12}	3.1×10^{-10}	8.0×10^{-11}
Intercept	0.04	0.01	0.02	0.01	0.02	0.01	0.02	0.01
Intra-individual	0.05	0.03	0.03	0.02	0.05	0.03	0.03	0.02
AIC	102.6	42.5	77.7	45.7	93.0	43.4	69.9	37.1
BIC	449.9	356.8	425.6	401.8	405.9	324.3	390.9	366.4

Note:

Coefficients of the full models are not shown. Model 1 – controlled for all covariates except mortality. Model 2- controlled for all covariates including mortality.

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

Figure 4.1. Predicted HUI3, by sex



Appendix 4.1.a. Mortality rates, attrition rates

The tables below show the number of deaths (cumulative) and number of drop-outs (non-cumulative) per cycle. Drop-outs are respondents who were alive at the time of survey, but did not respond to the entire questionnaire. The share of deaths is higher among the group with diabetes

For subjects who died, we imputed missing values of all independent variables in the model using Last Observation Carried Forward (LOCF) method. In the event of death, the values of all independent variables for succeeding cycles will be constant (including age). Following the HUI3 scoring system, the HUI3 score is 0 if the respondent is dead. For subjects who are alive, but with missing covariates, we also use LOCF method. In the event that there is no initial value, we dropped them from the sample. Also, we did not impute missing values of HUI3. Missing HUI3 scores were also dropped from the sample.

Cumulative Mortality (%)

Cycle	Without diabetes	With diabetes
	Cumulative mortality (%)	Cumulative mortality (%)
Cycle 2	4%	12%
Cycle 3	9%	18%
Cycle 4	15%	25%
Cycle 5	21%	35%
Cycle 6	28%	39%
Cycle 7	34%	45%
Cycle 8	42%	54%
Cycle 9	46%	56%

Drop-out rates (%)

Cycle	Rate of non-response (non-cumulative)
Cycle 2	9%
Cycle 3	15%
Cycle 4	11%
Cycle 5	15%
Cycle 6	16%
Cycle 7	14%
Cycle 8	14%
Cycle 9	17%

Appendix 4.1.b. Analysis of missing treatment type

We checked if missing diabetes treatment type is associated with any socio-demographic variables. We coded missing treatment type as 1 otherwise 0, and ran a logistic regression (without diabetes are not included in the model). The table below shows the regression results. High educational attainment, living in rural, or being white is less likely to report their treatment type.

	Odds Ratio	SE	p value	95 CI	
age	1.00	0.02	0.85	0.97	1.04
High school graduate	0.29	0.13	0.00	0.12	0.67
Income quintile (ref: quintile 1)					
Income quintile 2	1.55	0.83	0.41	0.55	4.42
Income quintile 3	1.70	1.26	0.47	0.40	7.28
Income quintile 4	1.22	0.75	0.75	0.37	4.05
Income quintile 5	3.52	2.51	0.08	0.87	14.22
Rural	0.49	0.19	0.07	0.22	1.06
Married	1.01	0.41	0.97	0.46	2.25
Female	3.63	1.31	0.00	1.79	7.37
White	0.05	0.02	0.00	0.02	0.11

Appendix 4.2. Association of HUI3 and covariates at baseline (n=7,978; weighted)

Variable	Category	Mean (HUI3)	SD (HUI3)	p value
Age cohort	40-50 (reference)	0.86	0.21	
	51-60	0.82	0.23	0.000
	61-70	0.82	0.21	0.000
	71-80	0.78	0.26	0.000
	81-90	0.69	0.30	0.000
	91-up	0.56	0.34	0.000
Gender	Male	0.82	0.24	
	Female	0.80	0.24	0.000
High school graduate	No	0.78	0.26	
	Yes	0.86	0.20	0.000
Rural	No	0.82	0.23	
	Yes	0.80	0.25	0.020
Income	Lowest Income (reference)	0.73	0.28	
	Low Income	0.76	0.28	0.029
	Middle	0.79	0.24	0.000
	High Income	0.83	0.21	0.000
	Highest Income	0.87	0.19	0.000
Married	No	0.79	0.25	
	Yes	0.84	0.22	0.000
Physical activity	Low (reference)	0.78	0.25	
	Medium	0.86	0.19	0.000
	High	0.88	0.16	0.039
BMI	Underweight(reference)	0.66	0.32	
	Normal	0.81	0.24	0.000
	Overweight	0.83	0.22	0.000
	Obese	0.79	0.25	0.000
Smoker	No	0.81	0.24	
	Yes	0.79	0.25	0.004
Regular doctor	No	0.87	0.17	
	Yes	0.80	0.24	0.000
Stroke	No	0.81	0.24	
	Yes	0.56	0.35	0.000
Heart disease	No	0.83	0.23	0.000
	Yes	0.67	0.30	
Depression	No	0.82	0.22	0.000
	Yes	0.69	0.32	
Number of chronic conditions	None	0.87	0.18	
	1	0.79	0.24	0.000
	2	0.70	0.28	0.000
	3 or more	0.63	0.32	0.000
	No			

Diabetes		0.82	0.23	
	Yes	0.66	0.33	0.000
Diabetes (Cycle 3)	No (reference)	0.74	0.34	
	Lifestyle	0.71	0.34	0.003
	Oral medication	0.66	0.35	0.000
	Insulin	0.55	0.38	0.000
	no reported	0.38	0.44	

Note: We use Bonferroni's pairwise comparison to test whether there is significant difference between reference and a particular category

Appendix 4.3.a. Fixed effects coefficients and fit indices of growth models of HUI3 Trajectories, by sex (n=7,978; weighted)

Variables	Female		Male	
	Model 1	Model 2	Model 1	Model 2
Fixed effects				
Age (centered) [1]	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	(0.00)
Age X Age (centered)	-1.78X10-4*	0.00	-3.67X10-4***	-1.11X10-4*
	0.00	0.00	0.00	0.00
Age X Age X Age (centered)	-2.82X10-5***	-7.25X10-6***	-2.66X10-5***	-5.89X10-6*
	0.00	0.00	0.00	0.00
Cohort 2 (Ref: Cohort 1) [2]	0.00	0.02	-0.02	-0.01
	(0.02)	(0.01)	(0.02)	(0.01)
Cohort 3	0.00	0.03	0.02	-0.02
	(0.03)	(0.02)	(0.03)	(0.02)
Cohort 4	0.16	0.02	0.35**	-0.04
	(0.08)	(0.06)	(0.11)	(0.07)
Cohort 5	0.26	-0.32*	0.37	-0.48**
	(0.22)	(0.14)	(0.45)	(0.17)
Cohort 6	0.43	-1.88***	-1.29	-1.17*
	(0.70)	(0.52)	(0.94)	(0.49)
	(0.02)	(0.02)	(0.03)	(0.02)
Diabetes	-0.06**	-0.04**	-0.02	-0.01
	(0.02)	(0.02)	(0.02)	(0.01)
Diabetes X Age (centered)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
White	0.25***	0.07***	0.27***	0.05***
	(0.03)	(0.01)	(0.03)	(0.01)
High school graduate	0.07***	0.05***	0.07***	0.02**
	(0.01)	(0.01)	(0.01)	0.01
Rural	0.04***	-0.01	0.06***	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Married	0.01	0.00	0.031*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Low Income (Ref: Lowest Income)	-0.01	0.00	0.07***	0.03*
	(0.01)	(0.01)	(0.02)	(0.01)
Middle Income	0.02	0.02	0.05*	0.01
	(0.02)	(0.01)	(0.02)	(0.02)
High Income	0.00	0.02*	0.08***	0.03*
	(0.02)	(-0.01)	(-0.02)	(-0.01)
Highest Income	0.01	0.03**	0.09***	0.05***
	(0.02)	(0.01)	(0.02)	(0.01)
Physical activity – Medium (Ref: Low)	0.05***	0.04***	0.03***	0.01**
	(0.01)	(0.01)	(0.01)	(0.01)
Physical activity - High	0.04***	0.04***	0.05***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Smoker	-0.02	-0.03***	-0.01	-0.01
	(0.01)	(0.01)	(0.02)	(0.01)
BMI – overweight (Ref: Underweight and normal)	0.03**	0.02**	0.05***	0.01*
	(-0.01)	(-0.01)	(-0.01)	(-0.01)
BMI - Obese	0.02	0.00	0.04*	0.00
	(0.01)	(0.01)	(0.02)	(0.01)
Regular doctor	-0.02	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.02)	(0.01)
Heart disease	-0.07***	-0.04***	-0.04*	-0.03***

	(0.02)	(0.01)	(0.02)	(0.01)
Stroke	-0.15***	-0.10***	-0.16***	-0.09***
	(0.03)	(0.02)	(0.03)	(0.02)
Depression	-0.05***	-0.05***	-0.08***	-0.08***
	(0.01)	(0.01)	(0.02)	(0.01)
1 chronic condition (Ref: None) [3]	-0.04***	-0.04***	-0.04***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
2 chronic condition	-0.08***	-0.06***	-0.08***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
3 or more chronic condition	-0.16***	-0.12***	-0.13***	-0.12***
	(0.02)	(0.01)	(0.02)	(0.01)
Institutionalized	-0.04	-0.42***	-0.02	-0.42***
	(0.03)	(0.03)	(0.04)	(0.04)
Dead		-0.65***		-0.70***
		(0.01)		(0.01)
Random Effects				
Inter-individual variance				
Age (slope)	7.02X10-5	4.11X10-7	1.82X10-5	1.51X10-13
Age X Age (slope)	1.15X10-7	4.72X10-15	9.62X10-8	9.40X10-21
Age X Age X Age (slope)	3.21X10-10	1.06X10-11	5.76X10-10	1.23X10-11
Intercept	0.03	0.01	0.03	0.01
Intra-individual variance	0.04	0.03	0.05	0.02
AIC [4]	90.24	47.83	91.61	51.55
BIC [4]	442.40	408.40	434.10	402.20

Note:

Model 1 – controlled for all covariates except mortality. Model 2- controlled for all covariates including mortality. Coefficients and standard error is in parenthesis.

* p<0.05 *** p<0.001

[1]Median-entered. Median is 52

[2]We also interacted age and cohort but not shown in the table

[3] Chronic conditions other than stroke, heart disease and depression

[4]Akaike information criterion (AIC) and Bayesian information criterion (AIC) are criteria to measure goodness of fit, and use for model selection. Lower values of AIC and BIC are desirable.

Appendix 4.3.b. Fixed effects coefficients and fit indices of growth models of HUI3 Trajectories using diabetes with treatment type

Variables	Model 1	Model 2
Age X Age (centered)[1]	-0.0002*	-0.000
	(0.00)	(0.00)
Age X Age X Age (centered)	3.21x10-6***	8.51X10-6***
	(0.00)	(0.00)
Cohort 2[2]	-0.015	0.01
	(0.02)	(0.01)
Cohort 3	-0.12**	-0.02
	(0.04)	(0.02)
Cohort 4	-0.04	-0.08
	(0.12)	(0.07)
Cohort 5	-0.13	-0.53**
	(0.30)	(0.16)
Cohort 6	-1.06	-1.06**
	(1.43)	(0.35)
Diabetes -lifestyle change (Ref: No diabetes)	-0.06	-0.06
	(0.04)	(0.04)
Diabetes-oral medication	0.01	0.00
	(0.02)	(0.01)
Diabetes -insulin therapy	-0.07	-0.04*
	(0.04)	(0.02)
Diabetes - no therapy reported	-0.09**	-0.01
	(0.03)	(0.01)
Diabetes -lifestyle change X age	0.00	0.00
	(0.01)	(0.00)
Diabetes -oral medication X age	-0.00**	-0.00
	(0.00)	(0.00)
Diabetes -insulin therapy X age	0.00	0.00
	(0.00)	(0.00)
Diabetes - no therapy reported X age	0.00	0.00*
	(0.00)	(0.00)
female	0.07***	0.02**
	(0.01)	(0.01)
white	0.36***	0.065***
	(0.03)	(0.01)
High school graduate	0.07***	0.04***
	(0.01)	(0.01)
Rural	0.02*	-0.00
	(0.01)	(0.00)
Married	0.02*	0.01
	(0.01)	(0.01)
Low Income (Ref: Lowest Income)	0.03*	0.01
	(0.01)	(0.01)
Middle Income	0.03	0.02*
	(0.02)	(0.01)

High Income	0.02	0.02*
	(0.01)	(0.01)
Highest Income	0.04**	0.04***
	(0.01)	(0.01)
Physical activity – Medium (Ref: Low)	0.04***	0.03***
	(0.01)	(0.00)
Physical activity - High	0.04***	0.03***
	(0.01)	(0.01)
Smoker	-0.02	-0.02***
	(0.01)	(0.01)
BMI – overweight (Ref: Underweight and normal)	0.03***	0.01*
	(0.01)	(0.01)
BMI - Obese	0.02*	-0.01
	(0.01)	(0.01)
Regular doctor	-0.01	-0.01
	(0.01)	(0.01)
Heart disease	-0.06***	-0.03***
	(0.01)	(0.00)
Stroke	-0.14***	-0.10***
	(0.02)	(0.01)
Depression	-0.06***	-0.06***
	(0.01)	(0.01)
1 chronic condition (Ref: None)[3]	-0.04***	-0.03***
	(0.01)	(0.00)
2 chronic condition	-0.08***	-0.06***
	(0.01)	(0.01)
3 or more chronic condition	-0.16***	-0.12***
	(0.02)	(0.01)
Institutionalized	-0.03	-0.44***
	(0.02)	(0.03)
Dead		-0.67***
		(0.01)
AIC[4]	102.30	39.13
BIC[4]	528.50	474.00

Note: Model 1 – controlled for all covariates except mortality. Model 2- controlled for all covariates including mortality. Coefficients and standard error is in parenthesis

* p<0.05 *** p<0.001

[1]Median-entered. Median is 52

[2]We also interacted age and cohort but not shown in the table

[3] Chronic conditions other than stroke, heart disease and depression

[4]Akaike information criterion (AIC) and Bayesian information criterion (AIC) are criteria to measure goodness of fit, and use for model selection. Lower values of AIC and BIC are desirable.

Appendix 4.4. Unpacking HUI3

The table below shows the prevalence of severity of individual attributes by diabetes status. The proportion of population with severe problem is higher among persons with diabetes. The relatively higher prevalence of severe problem among persons with diabetes is noted on the following attributes: cognition (33.2%), pain (36.4%) and ambulation (23.1%).

Distribution of the severity of HUI3 attributes, by diabetes status (Cycle 1)

Severity	Vision		Hearing		Emotion		Cognition		Pain		Speech		Ambulation		Dexterity	
	ND	D	ND	D	ND	D	ND	D	ND	D	ND	D	ND	D	ND	D
No problem (%)	24	17	80	79	75	71	69	63	78	57	99	98	92	77	98	97
Moderate problem (%)	72	72	5	8	22	22	3	4	4	7						
Severe problem (%)	5	11	6	14	4	8	29	33	18	36	1	2	8	23	2	3

Note: ND (Without diabetes); D (With diabetes). Each attribute has 6 levels. However, we re-categorized them to three because of sample size limitation. We further merged the categories moderate and severe in Speech, Ambulation and Dexterity into two.

The table below shows the prevalence of impaired attributes among persons with diabetes disaggregated by gender. Note that impaired emotion, impaired cognition and pain might be driving the lower HUI3 scores among females.

Prevalence (%) of impaired HUI3 attributes among persons with diabetes, by cycle and gender

Attributes	Cycle 1		Cycle 2		Cycle 3		Cycle 4		Cycle 5		Cycle 6		Cycle 7		Cycle 8		Cycle 9	
	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F
Vision	82	82	77	91	84	85	79	84	79	86	76	89	76	89	76	87	80	85
Hearing	9	9	12	8	13	12	8	6	11	8	10	9	8	8	9	9	14	13
Mobility	12	16	16	18	15	20	17	19	17	24	15	27	12	26	19	28	15	26
Emotion	26	35	26	32	33	30	34	32	32	29	34	33	25	29	32	33	29	28
Cognition	35	41	31	35	35	43	36	34	34	34	34	36	38	34	34	41	35	35
Pain	37	51	28	39	30	36	29	30	32	40	26	37	22	31	32	33	30	28

Note: M (Male); F(Female). We excluded speech and dexterity due to sample size limitation.

The table below shows that female with diabetes, on average, experience more number of co-morbidities than males with diabetes. Further, the prevalence of chronic conditions that are highly related to mortality is higher among female with diabetes than male with diabetes.

Average number and prevalence of chronic condition among person with diabetes, by gender

	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5	Cycle 6	Cycle 7	Cycle 8	Cycle 9
Average number of chronic condition among persons with diabetes									
Male	1.3	1.8	1.7	1.8	1.8	1.8	2.1	2.0	2.2
Female	2.2	2.4	2.5	2.6	2.8	2.8	3.0	3.0	3.1
Chronic conditions related to mortality (%)									
Male	37	45	42	47	49	51	60	55	57
Female	54	53	58	61	62	65	68	67	69
Chronic conditions that may be related to mortality (%)									
Male	1	11	5	8	9	10	10	11	13
Female	8	15	16	17	18	20	21	22	22
Conditions not related to mortality (%)									
Male	45	57	48	52	53	55	56	54	58
Female	59	66	72	68	70	72	72	72	73

Note: Conditions related to mortality include high blood pressure, chronic bronchitis or emphysema. Conditions that may be related to mortality include Asthma, Alzheimer's disease or dementia. Conditions that not related to mortality include food allergies, allergies other than food allergies, arthritis or rheumatism, back problems excluding arthritis, migraine headaches, sinusitis, epilepsy, stomach or intestinal ulcers, urinary incontinence, cataracts, glaucoma, and other long-term condition.

Chapter 5: Conclusion

In Chapter 2, we examined the impact of the national health insurance program of the Philippines on maternal and health outcomes among poor Filipino mothers. In Chapter 3, we evaluated the impact of Jamkesmas, the largest subsidized health insurance Indonesia on wide-range of healthcare utilization, health outcomes, and healthcare expenditures. In Chapter 4, we characterized the age-related-trajectories of health-related quality of life of Canadians with diabetes.

In Chapter 2, we found that national health insurance program in the Philippines is associated with more prenatal care visits, greater likelihood of facility-based birth delivery, and more post-natal care, and the impact is most pronounced among the poorest women. However, we did not observe improvements in birthweight.

In Chapter 3, we found that Jamkesmas is associated with higher likelihood of outpatient care, but we did not observe heterogeneity across income groups. Among those who had outpatient care, Jamkesmas is also associated with higher number of outpatient care visits. Jamkesmas is also associated with higher likelihood of inpatient care, with larger impact among the rich. However, we did not observe a statistically significant impact on health outcomes even adjusting for temporal effects. We observed lower out-of-pocket healthcare expenditure but no impact on catastrophic healthcare expenditures.

Our findings in Chapters 2 and 3 provide an important insight that despite improvements in healthcare utilization and reduction in out-of-pocket healthcare expenditures, health insurance may not improve health outcomes. In Chapter 3, we also found heterogeneity in impact on inpatient care. We observed large and statistically significant impact among the rich, but no statistically significant impact among the poor. This is a potential indication that the poor might not have benefitted from the expansion of Jamkesmas. We observe mistargeting in the program, meaning a number of the rich population were covered, a problem also common in the Philippine national health insurance.

In Chapter 4, we found that the poor and women with diabetes experience a lower health-related quality of life trajectories, but there is no evidence that the rate of deterioration of their health-related quality of life is faster than for individuals without diabetes. Our finding differs from a trajectory study conducted in the United States, where significantly faster deterioration was observed among individuals with diabetes (Chiu & Wray, 2010). The study provides evidence that individuals with diabetes have the ability the 'compress morbidity' and sustain a rate of deterioration similar to healthy individuals.