Three Essays on Economic Analysis of Health Care:
Focusing on Efficiency, Equity, and Effectiveness

by

Yuichi Watanabe

A doctoral thesis submitted to the Graduate School of Economics, Waseda University
in fulfillment of the requirements for the degree of Doctor of Philosophy in Economics

December 2023

Doctoral Committee:

Haruko Noguchi, Ph.D., Chair

Toshihide Arimura, Ph.D.

Rei Goto, MD, Ph.D.

ABSTRACT

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Yuichi Watanabe

Health care is one of the major research fields in health economics. This thesis analyzes health care activities from an economic perspective, focusing on the efficiency of health care delivery, income-related inequalities in health care consumption, and the causal impacts of health checkups on health care. The first chapter evaluates the efficiency and productivity of surgical treatments across surgical specialties in a high-volume Japanese teaching hospital. The second chapter examines income-related inequalities in health care utilization and spending under universal coverage in a long-term perspective for the case of the Republic of Korea. The third chapter investigates the causal relationship between participation in health checkups and health care expenses and use under the Japanese healthcare system.

Chapter one evaluates the efficiency and productivity of surgical treatments across surgical specialties in a high-volume Japanese university hospital. Japan's healthcare expenditures, which are largely publicly funded, have been growing dramatically due to the rapid aging of the population as well as the innovation and diffusion of new medical technologies. The efficiency and productivity of healthcare providers is a critical issue to maintain or improve the existing quality of health care under the constraint of tight government financial resources. In particular, a large amount of hospital resources are utilized in surgical procedures in the inpatient care setting; annual costs for surgical treatments are estimated to be approximately USD 20 billion. Using unique longitudinal clinical data at the individual surgeon level, this chapter aims to estimate the technical efficiency of surgical treatments across surgical specialties in a high-volume Japanese teaching hospital by employing stochastic frontier analysis (SFA) with production frontier models. We simultaneously examine the impacts of potential determinants that are likely to affect inefficiency in operating rooms. Our empirical results show a relatively high average technical efficiency of surgical production, with modest disparity across surgical specialties. However,

there is room to reorganize and improve resource utilization in the operating rooms of surgical specialties that show lower technical efficiency. We also demonstrate that an increase in the number of operations performed by a surgeon significantly reduces operating room inefficiency, whereas the revision of the fee-for-service schedule for surgical treatments does not have a significant impact on inefficiency. In addition, we find higher technical efficiency among surgeons who perform multiple daily surgeries than those who perform a single operation in a day. We suggest that it is important for hospital management to retain efficient surgeons and physicians and provide efficient healthcare services given the competitive Japanese healthcare market.

Chapter two considers income-related inequality in health care under universal coverage from a long-run perspective in the case of the Republic of Korea. Many countries have sought to promote well-being for their entire populations through the implementation of universal health coverage (UHC). To identify the extent to which UHC has been attained, it is necessary to evaluate equity of access to use of needed care and the cost burden of health services for the country's entire population. Exploiting longitudinal data from a nationally representative health survey from 2008 to 2018, this chapter investigates how income-related inequalities in health care use and spending in Korea have varied over time and examines the extent to which need and non-need factors contribute those inequalities, using an in-depth decomposition analysis, allowing for heterogeneous responses across income groups. The empirical results show that overall health care utilization is disproportionately concentrated among the poor over both the short and long run. Income-group differences and household characteristics, such as marital status, make larger pro-poor contributions to inequality in inpatient care use, while chronic disease prevalence greatly pushes outpatient care utilization in a pro-poor direction. These considerations suggest that it is important for health care policy in Korea to focus on improvements in the health status and well-being of low-income groups, as poor people are likely to be in poorer health. The results regarding inpatient care expenses indicate a similar pattern of pro-poor bias, implying that higher spending on inpatient care may be a heavier financial burden for low-income people. Long-run inequality favors the better-off in terms of outpatient care expenses, where the contribution of income-group differences has the largest impact. People in high-income groups may spend most on costly services in outpatient care, including uninsured services, with the help of additional private health insurance.

Chapter three investigates the causal relationship between participation in health checkups and health care under the Japanese healthcare system. There exists a globally growing concern regarding the prevention and control of non-communicable diseases (NCDs), and Japan is no exception wherein lifestyle-related NCDs have a significant impact on public health. To prevent the prevalence of metabolic syndrome and control the rising healthcare costs, the Japanese government initiated a novel annual health checkup initiative, known as the Specific Health Checkups (SHC) and Specific Health Guidance (SHG), which targets individuals aged 40-74 years in April 2008. Utilizing distinctive longitudinal administrative data at the individual enrollee level for the periods between fiscal year (FY) 2011 and FY 2016, graciously provided by a local municipality in Japan, this chapter examines the causal impacts of taking the SHC on their health care expenditures and utilization for inpatient and outpatient care services. We employ an instrumental variable (IV) estimation that relies on regional variation in peer effects as a determinant in the individual's decision, allowing for a deeper investigation into the heterogenous impacts with specific demographic groups. Our IV estimation for the entire sample demonstrates little significant effects of the SHC participation on health care expenses and use in both the same and the subsequent FYs at the intensive margin, given that it proves to be a sufficiently strong instrument. We only find that it may have a small possibility of reducing inpatient care utilization in the following FY. However, our stratification analysis uncovers distinct patterns. Individuals under the age of 65 years may decrease their inpatient care utilization in in the subsequent FY, while the elderly over 65 years of age are inclined to raise their annual expenses for physician visits in the year following the SHC participation. Additionally, males tend to increase their annual expenditures for hospital admission soon after participating in the SHC. Conversely, females are more likely to reduce their use of hospitalization through the SHC participation. These findings emphasize the necessity of providing the SHC participants with tailor-made follow-up care, beyond the SHG, considering the heterogenous causal effects within different demographic groups.

ACKNOWLEDGMENTS

First and foremost, I would like to express my deepest gratitude to my supervisor, Professor Haruko Noguchi, for her continuous support and encouragement. My doctoral work at the Graduate School of Economics, Waseda University has always been behind the expected schedule. My research and this dissertation would not have been accomplished without her persistent help and encouragement. I would also like to extend my thanks to Professor Toshihide Arimura (Waseda University) and Dr. Rei Goto (Keio University) in my doctoral committee for their insightful comments and questions. Their comments and suggestions have helped improve my dissertation.

For the research described in chapter one, we would like to sincerely thank to Teikyo University Hospital, which allowed us to utilize the valuable data on surgical records. We also gratefully acknowledge the financial support from Waseda Institute of Social& Human Capital Studies (WISH) for travel expenses to present this paper at an international academic conference, and appreciate the Waseda Institute of Political Economy (WINPEC) for its financial support. Our special thanks go to Dr. Akira Kawamura (Waseda University) for providing valuable comments, and Dr. Hiroyuki Kawaguchi (Seijo University) for discussing our paper at the 13th Annual Conference of the Japan Health Economics Association (JHEA). Further, we would like to extend appreciation to those who participated in the 5th European Health Economics Association (EuHEA) PhD Student-Supervisor and Early Career Researcher Conference for their helpful comments and suggestions. This work was supported by the Japan Society for the Promotion of Science (JSPS) KAKENHI Grant Number 17K09247 to Dr. Yoshinori Nakata (Teikyo University).

For the study described in chapter two, I am sincerely grateful to Korea Institute for Health and Social Affairs, which provided me with valuable data on the Korea Health Panel Survey. I also express my gratitude to Dr. Toshiaki Aizawa (Hokkaido University) for discussing my paper at the 17th Annual Conference of the JHEA. Further, I would like to extend appreciation to Dr. Owen O'Donnell (Erasmus University Rotterdam) and Dr. Tom Van Ourti (Erasmus University Rotterdam) for providing valuable comments and suggestions at the Tinbergen Institute Summer School on Inequalities in Health and Healthcare. My special thanks go to Dr. Haruko Noguchi (Waseda University), Dr. Narimasa Kumagai (Seinan Gakuin University) and those who participated in the 15th International Health Economics Association (IHEA) World Congress for their helpful comments. This work was supported by the JSPS Grant-in-Aid for Early-Career Scientists (Grant Number 18K17341).

For the research presented in chapter three, we would like to sincerely express our appreciation to Mr. Nobuyuki Izumida (National Institute of Population and Social Security Research), who provided us with valuable data on the administrative records of a municipality in Japan as well as useful information on data characteristics and institutional background. We also extend our special thanks to those who participated in the 13th IHEA World Congress for their helpful comments. This work was supported by the JSPS KAKENHI Grant Numbers 15H03365 and 20K02230 to Mr. Nobuyuki Izumida.

Lastly, I am deeply thankful to my parents and brother for their long-standing support and care with affection.

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Introduction

Health care is one of the major research fields in health economics. People often demand health care services which are provided by health professionals. Many countries have sought to promote well-being for their entire populations by achieving universal health coverage (UHC) that ensures people's equal access to essential health care at an affordable cost. On the other hand, health care spending as a share of gross domestic product (GDP) has been growing rapidly in many countries including Japan due to the aging population and the development of new medical technologies. In recent years, preventive care such as health checkups and screening tests draws attention with the aim of improving population health as well as containing increases in health care expenditures.

This thesis analyzes health care activities from an economic perspective with a special focus on the efficiency of health care delivery, income-related inequalities in health care consumption, and the causal impacts of health checkups on health care. The first chapter addresses the supply side of heath care services, evaluating the efficiency and productivity of surgical treatments across surgical specialties in a high-volume Japanese teaching hospital. The second chapter focuses on the demand side of health care, examining income-related inequalities in health care utilization and spending under universal coverage in a long-term perspective for the case of the Republic of Korea. The third chapter considers the effects of preventive interventions on health care, investigating the causal relationship between participation in health checkups and health care expenses or use under the Japanese healthcare system.

Chapter one evaluates the efficiency and productivity of surgical treatments across surgical specialties in a high-volume Japanese university hospital. Japan's healthcare expenditures, which are largely publicly funded, have been growing dramatically due to the rapid aging of the population as well as the innovation and diffusion of new medical technologies regardless of the government's huge fiscal debt. The efficiency and productivity of healthcare providers is a critical issue to maintain or improve the existing quality of health care under the constraint of tight government financial resources. In particular, a large amount of hospital resources are utilized in surgical procedures in the inpatient care setting; annual costs for surgical treatments are estimated to be approximately USD 20 billion. Therefore, managing operating rooms efficiently should be one of hospitals' topmost concerns.

Using unique longitudinal clinical data at the individual surgeon level, this chapter aims to estimate the technical efficiency of surgical treatments across various surgical specialties in a high-volume Japanese teaching hospital by employing stochastic frontier analysis (SFA) with production frontier models. We simultaneously examine the impacts of potential determinants that are likely to affect inefficiency in operating rooms. In our longitudinal analysis, we explicitly adjust for patient characteristics and the level of technical difficulty of each surgical operation. To examine the robustness of our main analysis using the full sample, we also divide it into two subsamples: sample (A), consisting of principal surgeons who performed a single operation in a day and sample (B), composed of those who performed multiple operations in a day.

Our empirical results show a relatively high average technical efficiency of surgical production, with modest disparity across surgical specialties. However, there is room to reorganize and improve resource utilization in the operating rooms of surgical specialties that show lower technical efficiency. We also demonstrate that an increase in the number of operations performed by a surgeon significantly reduces operating room inefficiency, whereas the revision of the fee-for-service schedule for surgical treatments does not have a significant impact on inefficiency. It is reasonable to think that surgical volume which represents the surgical proficiency and technical capability of surgeons would be a determinant of technical efficiency in operating rooms. In addition, we find higher technical efficiency among surgeons who perform multiple daily surgeries under the strict time management than those who perform a single operation in a day. We suggest that it is important for hospital management to retain efficient surgeons and physicians and provide efficient healthcare services given the competitive Japanese healthcare market.

Chapter two considers income-related inequality in health care utilization and spending under universal coverage from a long-run perspective in the case of the Republic of Korea. Many countries seek to promote well-being for their entire populations through the implementation of UHC. Korea first introduced mandatory health insurance in 1977 and ultimately achieved UHC in 1989. However, health financing in Korea has been characterized by the shrinking role of government and a limited range of covered services, as well as a greater dependence on private spending which is partly covered by purchasing private health insurance. To identify the extent to which UHC has been attained, it is necessary to evaluate equity of access to use of needed care and the cost burden of health services for the country's entire population.

Exploiting longitudinal data from a nationally representative health survey from 2008 to 2018, this chapter investigates how income-related inequalities in health care use and spending in Korea have varied over time and examines the extent to which different factors contribute those inequalities by using an in-depth decomposition analysis, allowing for heterogeneity. I use short-run and long-run concentration indices as measures of the degree of inequality, with an index of health-related income mobility defined as the difference between two concentration indices. Moreover, I employ an extended decomposition method that allows for variation in individual responses to need and non-need determinants across income groups.

The empirical results show that overall health care utilization is disproportionately concentrated among the poor over both the short and long run. Income-group differences and household characteristics, such as marital status, make larger pro-poor contributions to inequality in inpatient care use, while chronic disease prevalence greatly pushes outpatient care utilization in a pro-poor direction. These considerations suggest that it is important for health care policy in Korea to focus on improvements in the health status and well-being of low-income groups, as poor people are likely to be in poorer health. The results regarding inpatient care expenses indicate a similar pattern of pro-poor bias, implying that higher spending on inpatient care may be a heavier financial burden for low-income people. Thus, additional financially supportive measures should be provided for them to mitigate their heavy burden of inpatient care spending and prevent them from suffering economic hardship. Long-run inequality favors the better-off in terms of outpatient care expenses, where the contribution of income-group differences has the largest impact. People in high-income groups may spend most on costly services in outpatient care, including uninsured services, with the help of additional private health insurance.

Chapter three investigates the causal relationship between participation in health checkups and health care expenditures or utilization under the Japanese healthcare system. There exists a growing concern on a global scale regarding the prevention and control of non-communicable diseases (NCDs), such as cardiovascular diseases, cancers, chronic respiratory diseases and diabetes. Japan, a high-income nation experiencing rapid population aging, is no exception wherein lifestyle-related NCDs have a significant impact on public health. To prevent the prevalence of metabolic syndrome, a precursor to NCDs, and to control the rising healthcare costs, the Japanese government initiated a novel annual health checkup initiative, known as the Specific Health Checkups (SHC) and Specific Health Guidance (SHG), which targets individuals aged 40-74 years in April 2008.

By utilizing distinctive longitudinal administrative data at the individual enrollee level for the periods between fiscal year (FY) 2011 and FY 2016, this chapter aims to examine the causal impacts of taking the SHC on their health care expenditures and utilization for inpatient and outpatient care services. Our complied dataset was graciously provided by a local municipality identified as 'city X' in Japan. We employ an instrumental variable (IV) estimation as an identification strategy that relies on regional variation in peer effects as a determinant in the individual's decision to account for the endogeneity issue with regards to participation in the SHC. We also conduct the age cohort, gender and income group stratification analysis, allowing for a deeper investigation into the heterogenous impacts.

Our IV estimation for the entire sample demonstrates little significant effects of the SHC participation on health care expenses and use in both the same and the subsequent FYs at the intensive margin, given that it proves to be a sufficiently strong instrument. We only find that it may have a small possibility of reducing inpatient care utilization in the following FY. This suggests that implementing the SHC in city X may not be cost-effective, as it does not lead to an overall reduction in health care expenditures and use. However, our stratification analysis uncovers distinct patterns. Individuals under the age of 65 years may decrease their inpatient care utilization in in the subsequent FY, while the elderly over 65 years of age are inclined to raise their annual expenses for physician visits in the year following the SHC participation. Additionally, males tend to increase their annual expenditures for hospital admission soon after participating in the SHC. Conversely, females are more likely to reduce their use of hospitalization through the SHC participation. These findings emphasize the necessity of providing the SHC participants with tailor-made follow-up care, beyond the SHG, considering the heterogenous causal effects within different demographic groups.

Chapter 1

How efficient are surgical treatments in Japan?

The case of a high-volume Japanese hospital[*]

1.1 Introduction

The Japanese healthcare system has provided universal healthcare insurance since 1961 (Ikegami et al., 2011). Under this system, the country's healthcare expenditures have been ballooning due to the rapidly aging population and also due to the innovation and diffusion of new medical technologies, a large proportion of which are publicly funded by central and local governments (MHLW, 2017a).[1] However, the sustainability of the current healthcare system has recently been called into question because of the Japanese government's huge fiscal debt. Because of the necessity of maintaining or even improving the existing quality of health care under the constraint of tight government financial resources, the efficiency and productivity of healthcare providers is a critical issue.

In FY 2015, approximately 36.8% (or USD 128.7 billion) of total healthcare expenditures were from inpatient care, which was primarily provided by hospitals (MHLW, 2017a).[2] According to the Statistics of Medical Care Activities in Public Health Insurance (SMCAPHI), produced by the Ministry of Health, Labour and Welfare (MHLW) every June since the 1970s,

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[*] This chapter is the outgrowth of the previously published article listed as follows: Watanabe, Y., Noguchi, H., Nakata, Y., (2020) How efficient are surgical treatments in Japan? The case of a high-volume Japanese hospital. *Health Care Management Science*. 23(3), 401–413 (https://doi.org/10.1007/s10729-020-09507-3). All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee, and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Formal consent from patients was not required. The Teikyo University Institutional Review Board has approved this study. Anonymity of the data has been strictly maintained by de-identification. The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this study. The authors also declare that they have no relevant or material financial interests that relate to the research described in this chapter.

[1] Out of total healthcare expenditures (about USD 350.0 billion) in FY 2015, public funding accounted for 38.9% (about USD 136.1 billion), insurance premiums were 48.8% (about USD 170.8 billion), and the rest, including patient funding, amounted to 12.3% (about USD 43.1 billion) (MHLW, 2017a). All expenditures are calculated as 100 Japanese yen = 0.826173 USD, which is the period average exchange rate for 2015.

[2] The Japanese Medical Service Law defines two types of medical facilities: hospitals and clinics. A "hospital" is a medical facility with 20 or more beds, while a "clinic" has less than 20 beds or no beds at all.

the average daily expenditure for inpatient care is about USD 263.6: the largest portion, \$100.5 (38.1%), is for hospitalization charges;[3] followed by \$78.1 (29.6%) for services provided by the Diagnosis Procedure Combination/Per-Diem Payment System (DPC/PDPS);[4] and \$41.2 (15.6%) for surgical treatments (MHLW, 2016). Although the surgical treatment portion may not seem very large, the total amount for surgical expenditures in Japan is considerable. We estimate these expenditures to be approximately USD 20 billion per year.[5] This shows that a large amount of hospital resources are utilized in surgical procedures, particularly in the inpatient setting; therefore, managing operating rooms efficiently should be one of hospitals' topmost concerns. The efficiency of operating rooms depends on each surgeon's productivity because the surgeon is the one primarily responsible for the sequence of procedures and for resource utilization. Surgeons oversee other medical professionals and manage the utilization of medical devices and materials. They are also responsible for total surgical time. A quick turnover could result in an improvement in operating room efficiency.

This chapter aims to evaluate the efficiency and productivity of surgeons across various surgical specialties and identify determinants of inefficiency in operating rooms. As we focus on the technical efficiency of one hospital's operating rooms rather than managerial efficiency across multiple hospitals, we are able to assess homogenous surgeon level with respect to educational background and surgical procedures in a constant external environment surrounding surgeons[6] (excluding policy reform). We apply stochastic frontier analysis (SFA) to our data, which were from a variety of surgical cases at a university hospital in Tokyo—one of Japan's largest hospitals— with more than 1,000 beds. According to MHLW (MHLW, 2015), in FY 2014, 93.7%

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[3] Hospitalization charges refer to admission and management fees for various types of inpatient care.

[4] DPC/PDPS refers to a flat-rate payment system for each hospital stay based on diagnosis group. To control rising costs, MHLW introduced DPC/PDPS as of April 2003 (Ishii, 2012). The ratio of hospital beds under DPC/PDPS increased gradually from 7.7% in FY 2003 to more than 50% in FY 2010, and it has remained at approximately 50–55% since (MHLW, 2015).

[5] Since SMCAPHI is based on only one month's medical records (every June), total spending for all surgical treatments for one year is unfortunately not available. Assuming the ratio of surgical fees per day (15.6%) is constant for all hospitalizations, we estimate the total amount of surgical spending by multiplying total inpatient care (about USD 128.7 billion) by 0.156.

[6] Medical equipment and ancillary services (e.g., nursing practices and availability of support personnel) in operating rooms are considered to comprise a significant resource environment. These factors are set to be identical across operating rooms and thus held constant in a single hospital setting. In addition, the operating rooms are shared across surgical specialties in the hospital of this study.

of surgical cases under general anesthesia were performed in hospitals with over 100 beds, while 55.8% of patients with malignant tumors underwent surgery in high-volume hospitals with 500 beds or more. Although this study focuses only on performance at a single university hospital, it is representative of high-volume, high-tech Japanese medical facilities. Therefore, the results may have significant implications for the efficiency and productivity of other high-volume medical facilities in Japan.

Many studies have been conducted to evaluate the efficiency of healthcare services delivery; this body of research has also been reviewed by other studies (Hollingsworth, 2003; Worthington, 2004; Hollingsworth, 2006; Chilingerian and Sherman, 2011). Most studies have focused primarily on the performance of healthcare organizations (e.g., hospitals and nursing homes), either by employing data envelopment analysis (DEA) or SFA. Some have also examined the efficiency of specific healthcare services (e.g., primary care and dental services). In the context of Japanese healthcare services, Kawaguchi et al. (2010) estimate the technical efficiency of hospitals using inpatient DPC panel data and a longitudinal SFA model. Besstremyannaya (2011) also examines the link between managerial performance and cost efficiency for a panel of Japanese general public hospitals using SFA with latent classes.

As Chilingerian and Sherman (2011) point out, a recent development in this field is the application of non-parametric DEA to individual physician-level data to evaluate the technical efficiency of each physician or surgeon in a clinical setting. Using surgical data compiled from a Japanese teaching hospital, Nakata et al. (2015a; 2015b) demonstrate that surgeons' operating room efficiency scores as measured by DEA differ significantly among surgical specialties. They also demonstrate that the surgical reimbursement system is a significant predictor of surgeons' efficiency in operating rooms (Nakata et al., 2017). However, some empirical studies using individual physician-level data have also begun to employ parametric SFA rather than DEA. For example, Koch and Slabbert (2012) estimate a stochastic frontier production function and use it to examine the technical efficiency of specialist surgeons in South Africa. Given the small sample size, their results show relatively low efficiency, averaging around 50%, suggesting problems such as sample selection bias and unobserved heterogeneity at the practice level. Heimeshoff et al. (2014) and Kwietniewski and Schreyögg (2018) use SFA to estimate the technical, cost, and profit efficiency of outpatient physicians' practices in Germany and identify factors that influence the efficiency of different physician specialist groups. They adequately control for degrees of practice specialization, differences in patient case-mixes, and environmental factors such as physician density. However, their results, showing an extremely high technical efficiency, averaging over 97% for each physician specialist group, are questionable from practical and clinical perspectives.

Researchers are increasingly focusing on the study of performance in the delivery of healthcare services. Very little is known, however, about clinical efficiency at the individual physician or surgeon level and about the factors that influence this efficiency. To the best of our knowledge, this is the first empirical study to estimate a production frontier and technical efficiency of operating rooms by applying SFA to individual, surgeon-level surgical cases. Because we create longitudinal data for each surgeon, we can incorporate time-invariant heterogeneity across surgeons into our analysis. This is highly beneficial, as it allows us to simultaneously estimate the impact of possible inefficiency determinants, such as surgeon technical capability and exogenous policy reform, which occurred in the study period. Moreover, we explicitly adjust for patient characteristics and the level of technical difficulty of each surgical operation.

The rest of this chapter is structured as follows: Section 1.2 describes the data used in this study and the summary statistics. Section 1.3 presents our empirical strategies, including specification of the production functions and derivation of the stochastic production frontier models. Section 1.4 outlines the estimation results and performs the robustness checks. Section 1.5 discusses the implications and limitations of this study.

1.2 Data

1.2.1 Description of data

This study uses compiled data extracted from surgical records in the electronic medical record system of Teikyo University Hospital in the Tokyo metropolitan area, which has a population of around 10 million people. The hospital has 1,078 beds, 13 surgical specialties, and a surgical volume of approximately 9,000 annual cases. A currently practicing physician extracted information on all surgical cases performed in the main operating rooms from April 1 through

September 30 for each year from 2014–2017. Clinical and claims information were recorded as follows: date of surgery; surgical specialty; name of the responsible surgeon;[7] number of assisting physicians; start and end time of the operation (yielding total surgical time);[8] patient's age and sex;[9] prognostic information on in-hospital mortality after surgery;[10] classification of "K codes"[11] corresponding with surgical fees; and whether or not there was overtime.[12] As standard case-mix indices do not exist in Japan, we also obtained additional information on the degree of technical difficulty required for each surgical operation corresponding to a certain K code from the reports of the Japanese Joint Committee of Social Insurance by the Multidisciplinary Group of Surgical Associations (Japanese Joint Committee of Social Insurance by the Multidisciplinary Group of Surgical Associations, 2015; 2017).[13]

Under the universal health insurance system in Japan, most healthcare providers are reimbursed on a fee-for-service basis. The fee schedule is uniformly determined by the national government. Therefore, the same fee schedule is enforced for all insurance plans and almost all healthcare providers. In this manner, the coverage and fees reimbursed to physicians and hospitals have been uniform across the nation since 1959 (Ikegami et al., 2011). The fee schedule is revised every two years by the Central Social Insurance Medical Council ("Chuikyo" in Japanese), and one revision took place in April of 2016, a year for which we were collecting data. The surgical

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[7] Surgeons in this study belong to one of the following 12 surgical specialties: thoracic surgery, cardiovascular surgery, neurosurgery, obstetrics and gynecology, ophthalmology, plastic surgery, orthopedics, general surgery, pediatric surgery, urology, emergency surgery, and otorhinolaryngology.

[8] An operation's start time occurs at skin incision and the end time occurs at skin closure. The operating rooms officially run from 8:30 to 17:00 on weekdays and 8:30 to 12:30 on Saturday.

[9] Patient's sex is defined as a dummy variable taking the value of 1 if sex is female, and the value of 0 if sex is male.

[10] Patient's prognostic information on in-hospital mortality refers to whether a patient dies within one month after surgery. It is considered a proxy for the severity of a patient's condition.

[11] In the fee schedule, K codes are attached to medical practices such as surgeries and treatments. They evaluate different types of surgical procedures and enable us to compute the total reimbursements for heterogeneous surgical procedures.

[12] Certain percentages are added to the surgical fee when a patient is admitted to the hospital outside of regular business hours (e.g., in the middle of the night or on holidays) and goes directly into surgery.

[13] The Japanese Joint Committee of Social Insurance by the Multidisciplinary Group of Surgical Associations, which is often called "Gaihoren" in Japanese, attempts to establish a fair scale of surgical fee reimbursement by revealing the original cost and markup methods. It reports the expected level of technical difficulty and the estimated costs for the number of attending staff and the duration of each surgical procedure. It then provides an approximate estimate for the final price (Hayashida and Imanaka, 2005).

fees for all surgeries are classified into over 1,000 K codes in the fee schedule, such as K000–K939, and each surgical procedure is assigned to one or a combination of K codes (Social Insurance Institute, 2014). The surgical fees are identical in principle, according to various types of surgical operations, regardless of the following factors: who performs the surgery (e.g., the same principle applies whether a senior surgeon or a surgical trainee performs the surgery, as long as the surgeon has medical licensure); how many surgeons and medical doctors are involved with the surgery; how long it takes to complete the surgery; and how severe the patient's condition is (Social Insurance Institute, 2014). However, higher surgical fees are assumed to be assigned to surgical operations with a higher degree of complexity and resource intensity and with higher costs incurred. Nevertheless, additional reimbursements for expensive surgical devices, such as those for automatic suturing and imaging navigation, are excluded from our data. Other fees for blood transfusions, medications, special insurance, medical materials, and anesthesia are also excluded. In this study, the fee for each surgical operation is defined as an output variable, described in detail in Section 1.3.1 Production functions.

Certain operations are excluded from our sample. First, surgical procedures that were not reimbursed under the current payment system are excluded. Second, surgical procedures performed under local anesthesia that was administered by surgeons, in the absence of anesthesiologists, are excluded to equalize resource utilization. Oral and dermatologic surgical procedures are also excluded because most of these cases are minor surgeries performed under local anesthesia, and those performed under general anesthesia do not represent the full scope of surgical operations. Third, surgical cases with incomplete records, for any reason, are excluded.

1.2.2 Summary statistics

Table 1.1 reports the summary statistics for selected variables used in our analysis. Our sample includes a total of 11,440 surgical cases in 12 specialties overseen by 263 different principal surgeons; the number of surgical operations performed by each surgeon over the six months of each fiscal year ranges from 1 to 117 cases among 596 surgeon-years. The average surgical fee for a surgical case is 38,900 points, which can be converted to monetary values by 1 point = 10 Japanese yen (i.e., approximately USD 3,214). Each procedure requires, on average, 140 minutes of surgical time[14] and three surgeons or assisting doctors. Almost all surgeries performed in this hospital require two or more surgeons and assisting physicians, including residents and trainees. The technical difficulty of each surgical operation is classified into seven grades, with the seventh grade being the highest level of difficulty. Approximately 12.8% of the surgical cases are performed outside of official operating hours, and about 8% have an additional charge for overtime.

Table 1.2 reports the summary statistics for surgical fees, surgical time, and the number of surgeons in charge by surgical specialties and fiscal year (from April to September). Cardiovascular surgery and neurosurgery have relatively higher surgical fees on average, but the standard deviations tend to be large. Cardiovascular surgery requires the most time and the greatest number of responsible surgeons among all the surgical specialties. General surgery and neurosurgery also tend to require longer than average surgical times. On the other hand, surgical specialties such as ophthalmology and plastic surgery have lower than average surgical fees with smaller standard deviations. Ophthalmology takes the least amount of time and requires the fewest physicians for each surgical case. These three variables do not change dramatically over the four fiscal years.

1.3 Empirical strategies

1.3.1 Production functions

In the production of physician services, output variables are generally defined as indices of the service volumes provided by an individual physician or surgeon with the utilization of capital and labor inputs,[15] although another suitable definition of physician output can be based on the physician's impact on patient health (Reinhardt, 1972; Thurston and Libby, 2002). Koch and Slabbert (2012), for example, regard the monthly number of patients treated and surgeries performed as output measures, while Heimeshoff et al. (2014) and Kwietniewski and Schreyögg

[14] Most cases that take less than five minutes of surgical time are minor surgeries performed on infants or young children under general anesthesia (e.g., removing a foreign body from the esophagus or removing a subcutaneous tumor).

[15] A physician's output can be measured in terms of office or patient visits, the number of patients treated, the days of hospital admission after surgery, and aggregate billings to patients or gross sales revenues (Reinhardt, 1972; Reinhardt, 1975; Thurston and Libby, 2002).

(2018) view the number of cases a physician treats per year as the output variable in a production function.

From the information we collected on surgical cases, including patient characteristics and the level of technical difficulty of operations, this study does not calculate aggregate numbers for surgical cases or patients treated by surgeons on a monthly or yearly basis. Instead, we define output as the total surgical fees for each surgery, while the inputs of capital and labor are defined as (1) the duration of each surgery and (2) the number of physicians in charge of each surgery, respectively. Based on the assumption that efficient surgeons maximize output while minimizing the utilization of inputs, we specify the standard Cobb-Douglas (CD) production function for a surgery as

$$Y = A_{CD} K^{\alpha_{CD}} L^{\beta_{CD}}, \tag{1}$$

where Y is the output, K is the capital input, L is the labor input, A is the total factor productivity, and α and β are the output elasticities of capital and labor, respectively. We also specify the flexible translogarithmic (T) form of the production function at the same time as

$$Y = \exp\left[\ln(A_T) + \alpha_T \ln(K) + \beta_T \ln(L) + \frac{1}{2}\gamma \alpha_T \beta_T [\ln(K) - \ln(L)]^2\right], \tag{2}$$

where $\gamma = 0$ corresponds to the Cobb-Douglas form of a production function.

Our definition of output and input variables and our assumption of output maximization are reasonable because surgeons choose from a wide range of surgical procedures, which have a range of fees. They strive to achieve the maximum surgical fee through an optimal combination of selected surgical procedures best suited to the patient's condition, plus effective capital and labor utilization. This output measure can be interpreted as the result of the total quantity weighted by the fee for each surgical procedure, rather than the expected hospital revenue from each surgical case. Since it is also assumed to be positively associated with the complexity and resource intensity of surgical operations as well as the factor costs of surgical production,[16] surgical

[16] Reinhardt (1972; 1975) justifies the use of patient billings as an output index by presupposing that the medical fees assigned to particular services are closely related to the relative factor costs of these

payments here adequately reflect the volume of output in a homogeneous way.

Empirical studies have often defined capital inputs in the production of physician services in terms of office or floor space, medical equipment, and a substitute for physician hours of practice (Reinhardt, 1972; Reinhardt, 1975; Thurston and Libby, 2002). We treat the duration of the surgery as a capital input, representing the rental and depreciation cost of operating rooms and medical equipment. The number of surgeons and assisting physicians is treated as a labor input, while we are unable to incorporate the number of assisting nurses and medical technicians working in operating rooms due to a lack of relevant information.

Another important assumption is that both production functions conform to the law of decreasing returns to scale, namely $\alpha_{CD} + \beta_{CD} < 1$ in equation (1) and $\alpha_T + \beta_T < 1$ in equation (2). It is natural to assume decreasing returns to scale here because the number of surgical procedures performed by each surgeon does not increase proportionately with inputs. Likewise, it is difficult to imagine that a surgeon would expect surgical fees to increase in direct proportion to (or more than) inputs when he or she utilizes more resources in the operating room.

1.3.2 Stochastic production frontier models

With the aim of estimating technical efficiency in operating rooms and identifying determinants of inefficiency, we employ SFA with production frontier models in which the residual is characterized by a composite error term of the classical idiosyncratic disturbance and inefficiency (Jacobs et al., 2006). By taking the logarithm of both the production functions specified in equations (1) and (2) and controlling for additional covariates that are likely to affect output, we derive the following empirical models in the repeated cross-sectional setting:

$$\ln(Y_i) = \beta_0^{CD} + \beta_K^{CD}\ln(K_i) + \beta_L^{CD}\ln(L_i) + \textstyle\sum_j \beta_j^{CD} X_{ji} + v_i^{CD} - u_i^{CD}, \tag{3}$$

$$\ln(Y_i) = \beta_0^T + \beta_K^T\ln(K_i) + \beta_L^T\ln(L_i) + \frac{1}{2}\beta_{KK}^T[\ln(K_i)]^2 + \frac{1}{2}\beta_{LL}^T[\ln(L_i)]^2$$

$$+ \beta_{KL}^T\ln(K_i)\ln(L_i) + \textstyle\sum_j \beta_j^T X_{ji} + v_i^T - u_i^T, \tag{4}$$

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services, which is supported by evidence that relative physician fees vary as a function of relative factor costs.

where $\boldsymbol{X}_i$ represents the vector of dummy variables for each individual surgical case i: official operating hours; day of the week (from Sunday to Saturday); week of the month; month of the year (from April to September); fiscal year; overtime addition; the level of technical difficulty; patient's age,[17] sex, and whether there was in-hospital mortality after surgery; surgical specialty; and principal surgeon. These covariates can be described as factors likely to account for heterogeneity in the inputs and influence the shape of the production technology.

We assume that the idiosyncratic error terms, $v_i^{CD,T}$, are independently and identically distributed ($i.i.d.$) as $N\left(0, \sigma_{v^{CD,T}}^2\right)$. The one-sided inefficiency terms, $u_i^{CD,T}$, are assumed to be following a non-negative truncated-normal distribution as $i.i.d.\, N^+\left(\mu_i^{CD,T}, \sigma_{u^{CD,T}}^2\right)$, being also distributed independently of $v_i^{CD,T}$. Furthermore, the conditional mean models for estimating the impacts of exogenous inefficiency determinants are derived as

$$\mu_i^{CD,T} = \delta_0^{CD,T} + \boldsymbol{Z}_i'\boldsymbol{\delta}_{CD,T},^{18} \tag{5}$$

where $\boldsymbol{Z}_i$ is a set of inefficiency determinants that are defined as (1) the surgical volume performed by principal surgeons during six months in each fiscal year as a proxy for their time-varying technical capability[19] and (2) the revision of the surgical reimbursement system as an exogenous policy reform.[20] They are assumed to directly affect the degree of technical inefficiency rather than be incorporated into a set of regressors $\boldsymbol{X}$ that influence the production

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[17] Patient's age is categorized into 10 groups with 10 years per group (e.g., 0–9, 10–19, 20–29, etc.), then these age groups are transformed into dummy variables. The reference group is determined as 0–9.

[18] If one assumes that the inefficiency terms follow a non-negative half-normal distribution (i.e., $u_i^{CD,T} \sim i.i.d.\, N^+\left(0, \sigma_{u^{CD,T}}^2\right)$), then the assumption of heteroskedastic inefficiency terms allows us to model linear variance functions of a set of exogenous inefficiency determinants instead as $\sigma_{u_i^{CD,T}}^2 = \exp\left(\psi_0^{CD,T} + \boldsymbol{Z}_i'\boldsymbol{\psi}_{CD,T}\right)$. As there is no a priori justification for the use of any particular distribution for the inefficiency terms (Rosko, 2004), the hypothesis of a half-normal distribution should be statistically tested against the assumptions of a truncated-normal distribution.

[19] Surgical volume is taken as the logarithm in the estimation. Other than that, we also considered the inclusion of surgeons' accumulated clinical experience, defined as the number of years since medical school graduation on the date of surgical procedure or their current academic rank. However, this information is only partly available to us; thus, the use of this variable would lead to a serious issue of selection bias.

[20] The revision of the surgical reimbursement system is simply a dummy variable taking the value of 1 during the period from April to September for the years 2016 and 2017, and the value of 0 during the period from April to September for the years 2014 and 2015.

structure. Nevertheless, the validity of the identified inefficiency factors should be statistically tested against the model without them or the one including them in the production functions. Then, we carry out simultaneous estimations of equations (3) and (5) in the Cobb-Douglas production function, and the corresponding equations of (4) and (5) in the translog form. Once the point estimates of the inefficiency terms are obtained, as defined in Kumbhakar and Lovell (2000), the technical efficiency of each surgical case can be estimated from

$$TE_i^{CD,T} = E\left[\exp\left(-u_i^{CD,T} | \left(v_i^{CD,T} - u_i^{CD,T}\right)\right)\right]. \tag{6}$$

Along with repeated cross-sectional models, we consider longitudinal models because our data includes date of surgery, start and end times, and names of responsible surgeons, so we can trace individual principal surgeons as a panel unit over time. Since some principal surgeons perform multiple surgical cases per day (five cases in a day at most), we divide a day into five time slots and set one slot as a time unit.[21] Technical efficiency in operating rooms for each principal surgeon is believed to vary across time periods, which is a necessary condition for our longitudinal analysis. Following Battese and Coelli (1995), we employ the maximum likelihood random-effects time-varying inefficiency effects models in a longitudinal setting.[22]

We define a similar specification here in the same types of production functions (3) and (4) by only replacing i with st, which indicates an individual principal surgeon s at time slot t. $\boldsymbol{X}_{st}$ represents the vector of the same dummy covariates as in the cross-sectional models, except the principal surgeon dummies for each st. The impact of a set of inefficiency determinants, $\boldsymbol{Z}_{st}$, can be simultaneously estimated in the conditional mean models with the same distributional assumptions made in the composed error terms (Battese and Coelli, 1995). The technical efficiency of surgical production for each principal surgeon at each time slot can also be estimated

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21 Surgeons performing fewer than five surgical cases in a day are assigned from the first time slot of the day. For example, a surgeon who performs three surgeries in a day is assigned to the first three slots of the day. Note that each time slot does not correspond to the actual time of day, rather it represents the sequence of surgical operations in a day.

22 One of the benefits of using panel data is being able to control for unobservable individual heterogeneity. It is tempting to employ the “true” fixed-effects or “true” random-effects models proposed by Greene (2005) instead, which disentangle time-varying inefficiency from unit-specific time-invariant unobserved heterogeneity. We discuss the application of these models later.

in the same manner defined in equation (6).

1.4 Estimation results

1.4.1 Main results

First, it is worth noting that the generalized log-likelihood ratio (LR) tests are used to examine the choice of functional forms. They indicate that the Cobb-Douglas forms are rejected in favor of the translog forms in both the cross-sectional and longitudinal settings (LR test statistic is 100.13 and 88.55, respectively). Thus, the translog models better fit the data and cannot be reduced to the Cobb-Douglas forms despite the results that the major parameters in the translog specification are not significantly different from zero, except for the squares of capital and the constants. The LR tests also reject the models assuming a half-normal distribution on the inefficiency terms in the repeated cross-sectional setting (LR test statistic is 368.36 and 381.84, respectively), implying that the distributional assumptions of truncated-normal models are more preferred. We conduct additional LR tests to evaluate the impacts of the identified inefficiency factors, which reject the hypothetical models without them or the one incorporating them as additional regressors, thereby supporting the inclusion of inefficiency determinants in the simultaneous estimation procedure.

Table 1.3 shows our estimation results for both the repeated cross-sectional and longitudinal models. They demonstrate that the output elasticities of capital (duration of surgical operation) and labor (number of surgeons and assisting physicians) in the Cobb-Douglas production functions are significant under the assumption of decreasing returns to scale (the sum of each elasticity ranging from 0.613 [= 0.483 + 0.130] to 0.688 [= 0.519 + 0.169]),[23] although the translog functional forms are preferred based on the LR tests. We also find here that the output elasticity of capital is much higher than that of labor. Average technical efficiency in the translog production functions is estimated as 0.755 in the cross-sectional model and 0.723 in the longitudinal model, showing relatively small variations over the four fiscal years (ranging from 0.752 to 0.759 in the former and from 0.721 to 0.726 in the latter) and modest disparity across

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[23] The Wald tests also reject the hypothesis of constant returns to scale, which assumes that the sum of the output elasticities of capital and labor turns out to be one.

surgical specialties.[24] Our results also demonstrate that an increase in surgical volume (as a proxy for a surgeon's time-varying technical capability) significantly reduces the inefficiency of surgical production, while the revision of the surgical reimbursement system does not necessarily affect the change in inefficiency.[25]

Figures 1.1 and 1.2 show the mean of technical efficiency for four fiscal years by surgical specialties, each of which is estimated from the cross-sectional and longitudinal translog production functions. Again, we do not find a remarkable gap between the highest and lowest specialties in terms of average technical efficiency: 0.070 in the former model and 0.084 in the latter, between the highest (cardiovascular surgery) and lowest (plastic surgery). Nevertheless, some specialties that have relatively higher surgical fees on average show higher technical efficiency (e.g., cardiovascular and thoracic surgery), whereas others demonstrate relatively lower technical efficiency (e.g., neurosurgery and general surgery). Cardiovascular surgery, however, exhibits the widest range between minimum and maximum efficiency values among all surgical specialties; meanwhile, thoracic surgery and neurosurgery have narrower ranges. In contrast, such surgical specialties as obstetrics & gynecology and orthopedics have lower surgical fees on average but show rather high technical efficiency. Further, plastic surgery, urology, and emergency surgery belong to the group of surgical specialties that exhibit the lowest technical efficiency, showing lower surgical fees on average as well.

1.4.2 Robustness checks

To examine the robustness of our main results, we divide the full sample into two subsamples: sample (A), consisting of principal surgeons who performed a single operation in a day and sample (B), composed of those who performed multiple operations in a day, and we apply the same longitudinal model to estimate both the Cobb-Douglas and translog production functions.

We conduct the generalized LR tests again to test the choice of functional forms in both subsamples. They reject the Cobb-Douglas form in favor of the translog form in sample (A) (LR

[24] We can reject the hypothesis that there is no significant difference in means among surgical specialties based on the one-way analysis-of-variance (ANOVA) and Kruskal-Wallis H tests.

[25] There were no major changes in the surgical fee schedule when the revision of the fee schedule was implemented in April 2016; most changes were focused on division of functions among healthcare facilities and nursing care. There were some minor changes, for example, reimbursement for an emergency Caesarean section increased 10.2% in April 2016.

test statistic is 22.76) but instead support the Cobb-Douglas form in sample (B) (LR test statistic is -9.87). Thus, the translog model better fits the data in sample (A), while it can be reduced to the Cobb-Douglas specification in sample (B). The LR tests are also used to examine the influence of the identified inefficiency factors in both subsamples, demonstrating the rejection of the hypothetical models without them or the one including them in a set of regressors.

Table 1.4 presents the estimation results for the two subsamples. Although the translog functional form is preferred especially in sample (A), based on the LR test, the results for the Cobb-Douglas models show that the output elasticities of capital (duration of surgery) and labor (number of surgeons) are significant under the assumption of decreasing returns to scale, as expected: the sum of each elasticity is 0.723 (= 0.564 + 0.159) in sample (A) and 0.620 (= 0.464 + 0.156) in sample (B),[26] and again, the elasticity of capital is higher than that of labor. Average technical efficiency is estimated as 0.702 in the translog model of sample (A) and relatively higher at 0.757 in the Cobb-Douglas model of sample (B). The results for both subsamples demonstrate that the increase in surgical volume performed by principal surgeons significantly reduces the inefficiency of surgical production and that the revision of the surgical reimbursement system does not significantly change inefficiency, as is the case in the previous full sample results.

Figure 1.3 shows the mean technical efficiency for four fiscal years by surgical specialties according to each subsample.[27] Similarly, cardiovascular and thoracic surgery, which have higher surgical fees on average, show higher technical efficiency. On the other hand, obstetrics & gynecology has surgical fees that are lower on average, but they also exhibit a rather high technical efficiency. We also find that the technical efficiency of ophthalmology becomes the lowest among sample (A) and that of neurosurgery remains lower than many other specialties in sample (B). The ranges between minimum and maximum technical efficiency values become narrower in sample (B) for some specialties.

1.5 Discussion

[26] The Wald tests reject the hypothesis of constant returns to scale again.
[27] We can also reject the hypothesis that there is no significant difference in means among surgical specialties based on the one-way ANOVA and Kruskal-Wallis H tests.

We estimate the production functions of surgical operations in a Japanese high-volume hospital by employing SFA with production frontier models. Our empirical findings are summarized and discussed as follows: First, capital's higher output elasticity compared to labor in the Cobb-Douglas specification indicates that the change in surgical time is more sensitive and responsive to a surgical fee increase rather than to a change in the number of physicians, the latter most likely being a costlier investment. While the translog functional forms are generally preferred based on the LR tests, we also demonstrated with robustness checks that the Cobb-Douglas model is supported for subsample (B), in which surgeons perform multiple operations daily. This implies that the restricted assumption of equal substitution between the duration of surgery and the number of surgeons is held only for sample (B).

The overall technical efficiency of operating rooms is higher than what was found in a previous study using individual surgeon-level data (e.g., approximately 0.5 in Koch and Slabbert, 2012),[28] although it is difficult to make direct comparisons between studies carried out in different settings. It is reasonable that we would find higher efficiency among surgeons who perform multiple daily surgeries, since these surgeons would be forced to exercise strict time management. Our results also demonstrate that a modest difference exists between surgical specialties in terms of average technical efficiency and a relatively high efficiency has been maintained over four fiscal years without large fluctuations. This might reveal one of the characteristics of Japanese high-volume teaching hospitals, in the sense that clinical management and resource utilization tend to be well organized.

We also clarified that the inefficiency of surgical production is most reduced by the increase in surgical volume performed by surgeons. Clinical practice guidelines often recommend that patients undergo operations at healthcare facilities where surgical volume is large enough to ensure clinical safety. The number of surgeries performed represents the time-varying surgical proficiency and technical capability of a surgeon as well as the clinical activity in his or her area of specialization. Thus, it is reasonable to think that this variable would be a determinant of

[28] While our estimates are lower than the results in Heimeshoff et al. (2014) and Kwietniewski and Schreyögg (2018), which show extremely high technical efficiency (over 0.97 on average), their results may not be appropriate for comparison; as indicated in Section 1.1, Introduction, the results of Heimeshoff et al. (2014) and Kwietniewski and Schreyögg (2018) are questionable from practical and clinical perspectives.

technical efficiency in operating rooms. On the other hand, at least during this study period, the revision of the surgical reimbursement system (as an exogenous policy reform) does not play a significant role in changing technical efficiency. In other words, the policy shock to surgical payments does not influence the efficient utilization of the inputs.

Again, we did not find a large disparity across surgical specialties with respect to average technical efficiency. Cardiovascular surgery achieves the highest technical efficiency with the highest average surgical fees despite having the largest investment in input factors. Also, specialties such as thoracic surgery, obstetrics & gynecology, and orthopedics show relatively higher technical efficiency while minimizing input factors, especially in terms of surgical time. In contrast, neurosurgery and general surgery are characterized by lower technical efficiency despite their higher average surgical fees, implying that using more time for operations reduces technical efficiency. Moreover, surgical specialties such as plastic surgery, urology, and emergency surgery also show the lowest technical efficiency, partly due to relatively longer operation time, despite lower surgical fees. Regarding the lower technical efficiency for neurosurgery within subsample (B), this might stem from the fact that the surgeons who perform multiple neurological surgeries in a day are often younger and less experienced surgeons who tend to require more time to complete surgeries than their more experienced colleagues. Based on these findings, we suggest that there is room to reorganize and improve resource utilization in the operating rooms of surgical specialties that show lower technical efficiency; that is to say, to attain higher surgical efficiency in higher specialties with average technical efficiency.

This study has some limitations. First, ideally we would employ a "true" fixed-effects or random-effects model to take advantage of the panel-data setting of our sample.[29] However, application of a "true" fixed-effects model to our sample yielded unrealistic results: our assumption of decreasing returns to scale was violated and the mean of technical efficiency was nearly 1.0.[30] The failure to feasibly estimate these models may be due to the incidental parameters

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[29] The former model includes unit-specific dummies as an additional set of explanatory variables to capture unobserved individual heterogeneity, and the latter model treats the unit-specific intercepts as random variables (Greene, 2005).

[30] The output elasticities of capital and labor were estimated to be over 1.0 in the "true" fixed-effects model with the assumption that the inefficiency term follows a non-negative truncated-normal or exponential distribution. Applying the "true" random-effects model to our sample did not result in successful convergence.

problem that arises when the number of parameters to be estimated increases with sample size (Greene, 2005; Kumbhakar et al., 2015). In contrast, the failure may be attributable to a lack of substantial variation among individuals in their levels of efficiency over time (Jacobs, 2006), implying that surgeons were operating at similar levels of technical efficiency during our study period. Meanwhile, the similar estimation results of our two models, as presented in Table 1.3, may also imply that the individual fixed-effects captured by their individual dummies are relatively small.

Secondly, although surgical volume as an inefficiency determinant was assumed to be exogenous, the number of cases surgeons perform per fiscal year might be endogenous and correlated with unobservable factors (e.g., heterogeneous surgical demand and human relationships among surgeons within the department or division) that are absorbed in the error terms. In future research, we will address the potential endogeneity issue in the stochastic frontier models by, for example, applying instrumental variable (IV) approaches, which are currently under development in the relevant research. Thirdly, further estimation of the cost functions would be preferable because the duality of the production function usually allows for cost frontier formation as well. However, we could not specify any cost functions to estimate cost efficiency due to the unavailability of detailed cost data (e.g., factor prices for surgeons, medical professionals, and medical equipment).

Lastly, our analysis focuses on estimating the surgical efficiency of a single high-volume teaching hospital in Tokyo, Japan. That hospital and its surgeons may not represent all Japanese hospitals and surgeons, suggesting our results may not have external validity for other hospitals in Japan. However, Teikyo University Hospital is currently approved as a special-functioning hospital in Japan, with the capability to provide advanced medical care, develop advanced medical technologies, and conduct advanced medical care training.[31] It is important for hospital management to retain efficient surgeons and physicians and provide efficient healthcare services

[31] There are several requirements for approval of special-functioning hospitals: providing medical care to patients who are referred by other hospitals or clinics; having 400 or more beds; strict staff deployment (e.g., there must be twice as many doctors as in ordinary hospitals); having medical facilities such as intensive care units, sterile rooms, and drug information management rooms; improvement of a medical safety management system; recognizing 16 specified clinical areas in principle; and so forth (MHLW, 2017b). There are 85 approved special functioning hospitals as of June 2017.

under the competitive market between Japanese hospitals. Efficient resource utilization and allocation within and outside the hospitals are likely to have a significant impact on society as a whole. We suggest that the relatively high levels of technical efficiency found in the operating rooms of this hospital may correspond with other special-functioning hospitals in Japan, which are similar in terms of facilities and physician numbers. The importance of efficiently operating teaching hospitals is also growing, as they are not only expected to produce skillful and efficient surgeons through advanced medical training, but they are also expected to help improve fee schedules so that they adequately reflect surgical efficiency and motivate other medical facilities to reorganize their clinical management and resource utilization for efficiency.

Table 1.1 Summary statistics for selected variables

	Mean	Std. Dev.	Min	Max	Obs.
Surgical fee	38,900	41,472	200	913,500	11,440
Surgical time	139.93	115.79	1	995	11,440
Surgeons & MDs	2.99	1.03	1	10	11,440
Principal surgeons	–	–	1	263	11,440
Surgical specialties	–	–	1	12	11,440
Technical difficulty	4.45	1.14	1	7	11,440
Official hours	0.13	0.33	0	1	11,440
Overtime addition	0.08	0.27	0	1	11,440
Patient's age	51.66	23.36	0	99	11,440
Patient's sex	0.48	0.50	0	1	11,440
In-hospital mortality	0.01	0.11	0	1	11,440
Surgical volume	19.19	20.46	1	117	596 (surgeon-years)

Table 1.2 Summary statistics for key variables by surgical specialties and fiscal year

	Obs.	**Surgical fee** Mean (Std. Dev.)	**Surgical time** Mean (Std. Dev.)	**Surgeons & MDs** Mean (Std. Dev.)
Cardiovascular surgery	988	96,686.7 (77,801.8)	237.7 (141.2)	3.69 (1.09)
Emergency surgery	1,163	29,909.5 (32,993.9)	133.1 (96.5)	2.80 (0.86)
Otorhinolaryngology	806	22,808.3 (21,960.7)	114.9 (80.5)	2.42 (0.72)
Obstetrics & Gynecology	1,391	27,610.9 (18,409.5)	95.1 (72.6)	3.08 (1.02)
Neurosurgery	547	78,239.3 (56,690.2)	194.2 (146.9)	2.66 (0.91)
Ophthalmology	408	15,150.9 (17,248.5)	44.0 (35.5)	2.30 (0.74)
Orthopedics	2,217	28,284.3 (19,617.6)	112.0 (72.6)	3.29 (1.06)
Pediatric surgery	239	24,884.6 (25,473.1)	61.8 (66.6)	2.95 (0.86)
Plastic surgery	560	19,815.6 (22,093.9)	115.0 (99.0)	2.63 (0.92)
General surgery	1,807	43,766.0 (31,000.6)	209.0 (140.3)	3.11 (1.04)
Thoracic surgery	470	59,739.8 (27,017.6)	107.0 (70.6)	2.68 (0.84)
Urology	844	26,093.2 (26,669.9)	126.4 (114.1)	2.70 (0.91)
2014	3,037	36,736.7 (38,956.9)	137.3 (111.9)	2.83 (0.99)
2015	2,775	39,154.8 (42,029.2)	137.8 (116.0)	3.02 (1.07)
2016	2,755	40,400.0 (42,101.4)	141.7 (114.6)	3.09 (1.03)
2017	2,873	39,502.4 (42,809.2)	143.0 (120.6)	3.02 (1.01)

Table 1.3 Estimation results for the repeated cross-sectional and longitudinal models

	Repeated cross-section		**Longitudinal (ML-RE)**	
	Cobb-Douglas	Translog	Cobb-Douglas	Translog
Constant	7.345***(0.190)	8.225***(0.323)	6.704***(0.124)	7.669***(0.281)
ln(K)	0.483***(0.020)	0.048 (0.106)	0.519***(0.023)	0.059 (0.118)
ln(L)	0.130***(0.026)	0.138 (0.161)	0.169***(0.033)	0.170 (0.165)
$(\ln K)^2$		0.051***(0.011)		0.054***(0.013)
$(\ln L)^2$		0.045 (0.044)		0.038 (0.056)
(lnK)(lnL)		-0.024 (0.029)		-0.019 (0.036)
Surgeon's dummy	Yes	Yes	No	No
		Inefficiency determinants		
Constant	-243.73***(42.6)	-247.90***(43.1)	-4.214***(1.048)	-1.284 (0.794)
Surgical volume	-33.48***(11.56)	-34.08***(11.69)	-1.741***(0.299)	-0.797***(0.212)
Revision	9.786 (20.40)	11.274 (20.24)	0.013 (0.596)	-0.087 (0.307)
Technical efficiency	0.758	0.755	0.734	0.723
σ_u^2	10.66***(0.304)	10.85***(0.319)	1.977***(0.074)	1.341***(0.163)
σ_v^2	0.356***(0.019)	0.349***(0.019)	0.396***(0.021)	0.386***(0.022)
λ	29.97***(0.314)	31.07***(0.330)	4.992***(0.088)	3.473***(0.172)
Log likelihood	-7570.84	-7520.77	-8731.06	-8686.78
Number of groups	–	–	263	263
Number of obs.	11,440	11,440	11,440	11,440

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors in parentheses are clustered at the individual surgeon level.

Table 1.4 Estimation results for robustness checks

	(A) Single surgery		**(B) Multiple surgeries**	
	Cobb-Douglas	Translog	Cobb-Douglas	Translog
Constant	6.391***(0.135)	7.245***(0.314)	7.146***(0.141)	8.243***(0.308)
ln(K)	0.564***(0.024)	0.219 (0.135)	0.464***(0.027)	-0.076 (0.136)
ln(L)	0.159***(0.036)	-0.014 (0.187)	0.156***(0.044)	0.221 (0.239)
$(\ln K)^2$		0.037**(0.015)		0.066***(0.017)
$(\ln L)^2$		0.035 (0.061)		0.025 (0.073)
(lnK)(lnL)		0.020 (0.038)		-0.027 (0.046)
Surgeon's dummy	No	No	No	No
		Inefficiency determinants		
Constant	-2.796 (2.260)	-0.584 (0.410)	-4.207 (3.368)	0.415 (0.486)
Surgical volume	-0.911*(0.477)	-0.446***(0.129)	-2.592***(0.816)	-0.344***(0.142)
Revision	-0.354 (0.467)	-0.145 (0.215)	1.681 (1.311)	0.168 (0.198)
Technical efficiency	0.721	0.702	0.757	0.726
σ_u^2	1.582***(0.419)	1.079***(0.107)	2.107***(0.105)	0.730***(0.073)
σ_v^2	0.415***(0.022)	0.402***(0.023)	0.368***(0.026)	0.367***(0.028)
λ	3.817***(0.425)	2.682***(0.121)	5.720***(0.123)	1.992***(0.097)
Log likelihood	-5287.07	-5275.68	-3320.37	-3325.31
Number of groups	262	262	141	141
Number of obs.	6,547	6,547	4,893	4,893

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors in parentheses are clustered at the individual surgeon level.

Figure 1.1 Technical efficiency by surgical specialties from main estimation

(Cross-section: Translog)

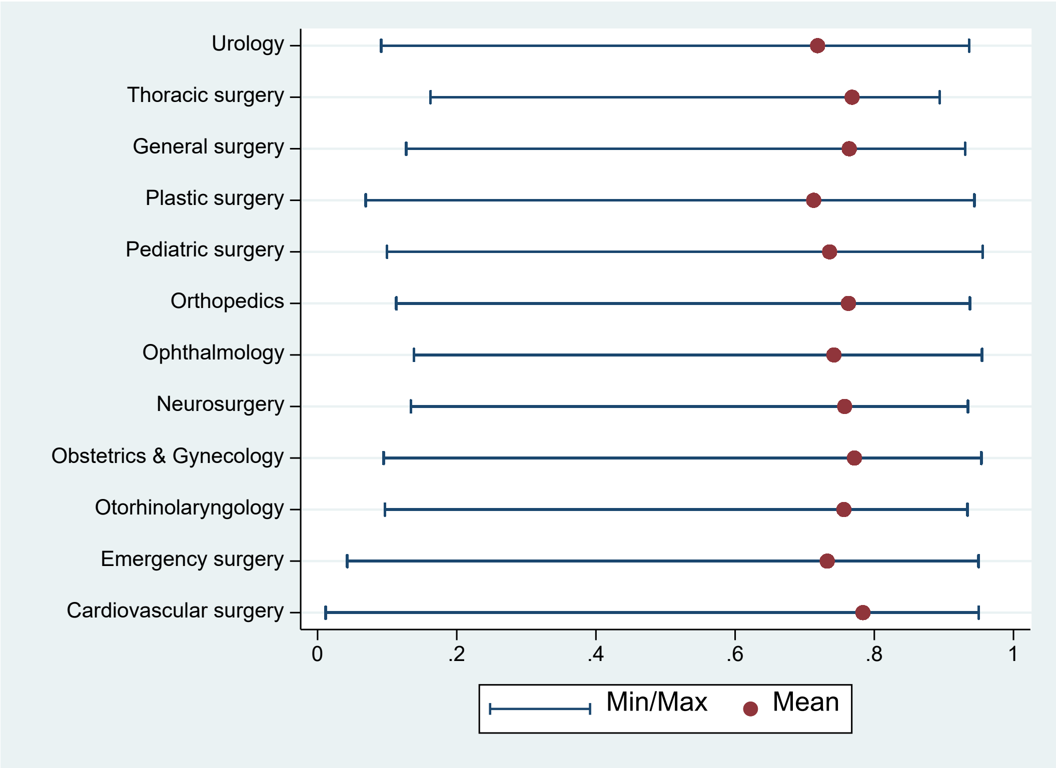


Figure 1.2 Technical efficiency by surgical specialties from main estimation

(Panel: Translog)

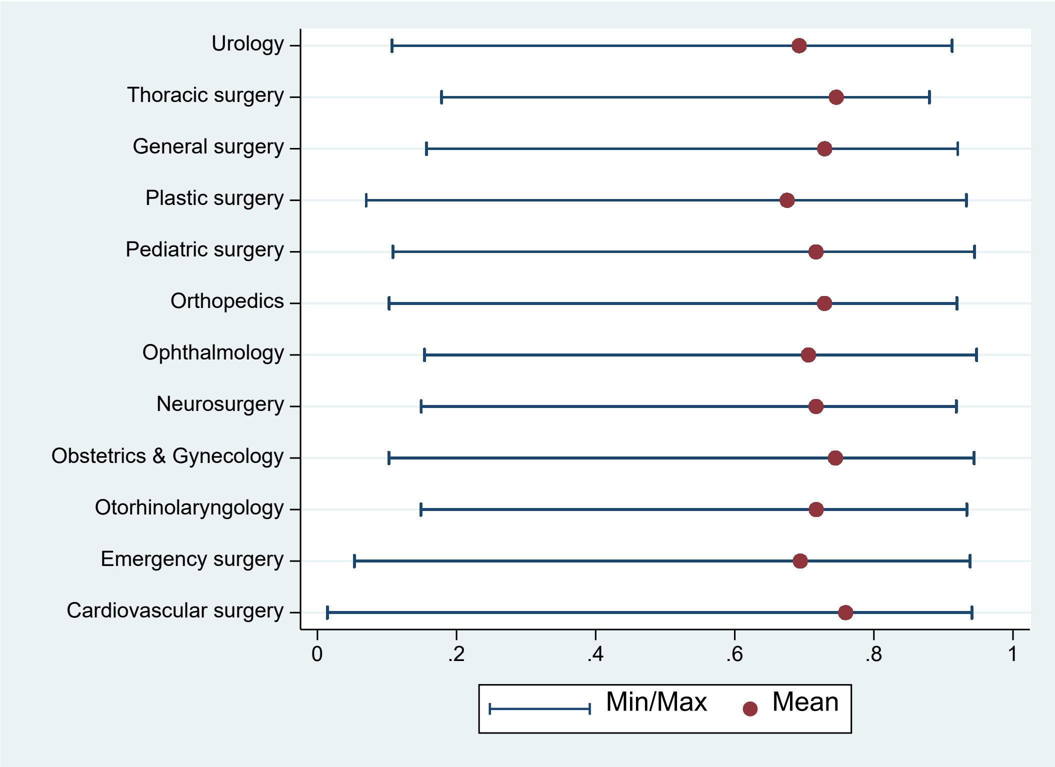
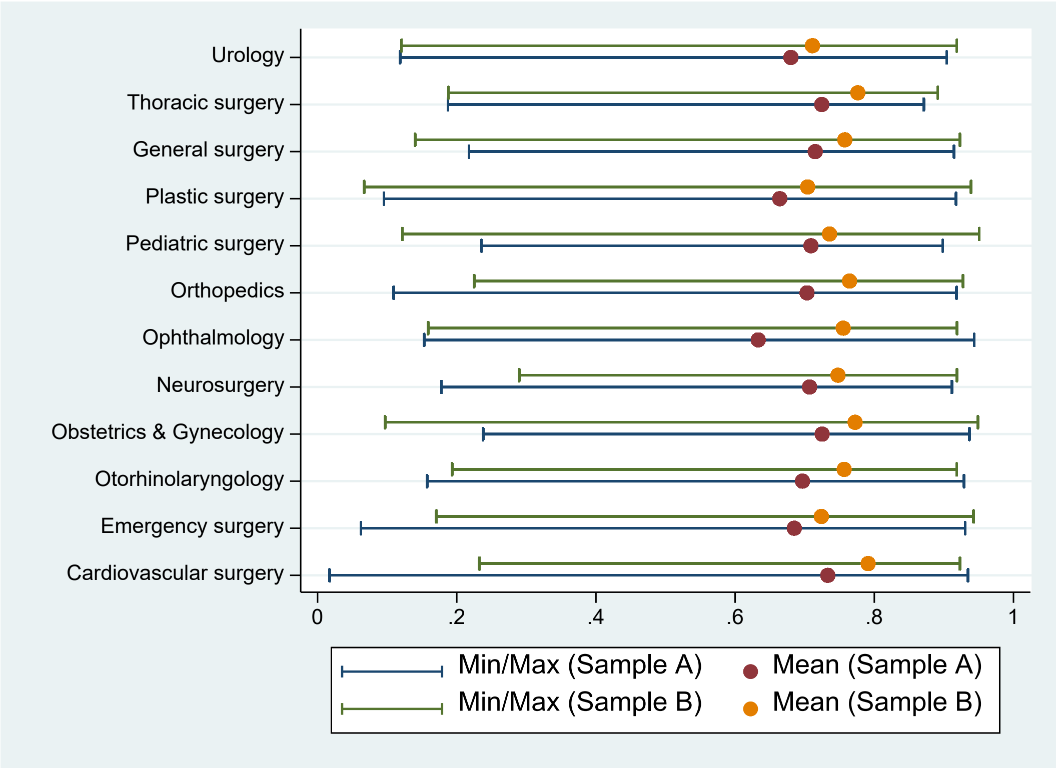


Figure 1.3 Technical efficiency by surgical specialties from robustness checks (Sample A: Translog, Sample B: Cobb-Douglas)



Chapter 2

Long-run measurement of income-related inequalities in health care under universal coverage: Evidence from longitudinal analysis in Korea[*]

2.1 Introduction

Many countries seek to promote well-being for their entire populations by achieving universal health coverage (UHC), which is one of the health-related targets proposed among the Sustainable Development Goals. According to the World Health Organization (WHO), UHC has the goal of ensuring that every individual, regardless of their circumstances, including standard of living, should be able to receive safe, effective, and high-quality essential health care services as needed at an affordable cost without the need for financial hardship (WHO and World Bank, 2017). Strengthening the health care systems plays an important role in making progress toward UHC: health financing that influences the level of people's direct payments for the use of health services may be a key policy instrument for providing a population with equal access to needed services, along with other components of health systems, such as the health care workforce and organizations, service delivery, and health information (WHO, 2010).[1] To measure the extent to which UHC is attained, it is necessary to evaluate equity of access to use of needed care and the cost burden of health services for a country's entire population, including the most vulnerable and disadvantaged in that society (WHO and World Bank, 2017).

This chapter investigates the extent of income-related inequality in health care utilization and spending in the case of the Republic of Korea (Korea). Korea first introduced mandatory health insurance based on a social insurance system in 1977, and this has been a major financing scheme

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[*] This chapter is the outgrowth of the preprint article listed as follows: Watanabe, Y., "Longitudinal analysis of income-related inequalities in health care under universal coverage in Korea", IDE Discussion Paper No.909, Institute of Developing Economies (IDE-JETRO), December 2023 (https://www.ide.go.jp/English/Publish/Reports/Dp/909.html). The paper was submitted to *Health Economics Review* and is currently under review. Ethical approval from an institutional review board was not required. The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this study. The author also declares that he has no relevant or material financial interests that relate to the research described in this chapter.

[1] Although health financing does not necessarily refer to financial mechanisms involving an insurance scheme more than through tax-based systems, the percentage of the population covered by health insurance can be a crucial determinant of progress on UHC in some countries (Kutzin, 2013).

for health care nationwide since then. Gradually expanding health insurance coverage,[2] Korea ultimately achieved UHC in 1989, with more than 90% of the population covered by national health insurance and the remaining falling under the tax-financed Medical Aid Program.

Within the bounds of this universal health insurance scheme, managed by a single insurer (National Health Insurance Service), however, the government has taken a laissez-faire position in providing health services for citizens; health care delivery relies heavily on the private sector to directly respond to the increased demand for health care (Kwon et al., 2015). Health care providers are generally reimbursed on a fee-for-service basis, where the fee schedule set by the insurer is enforced only for insured services, with higher prices allowable for uninsured services at their discretion to increase their profit margins. In the absence of a gatekeeping system, patients have a high degree of freedom to choose health care providers at any facility level they wish so long as they can afford to pay for the services they need (Kwon et al., 2015).

Despite the rapid achievement of universal health insurance coverage within a period of only 12 years, health financing in Korea has been characterized by the shrinking role of government and a limited range of covered services,[3] as well as a greater dependence on private spending,[4] which could result in weak financial protections from the benefits package. According to OECD health statistics for Korea, health care spending from public sources accounted for 57% of total health expenditures (OECD average of 71%), and the proportion of out-of-pocket payments and voluntary health insurance were 34% and 7%, respectively, of total spending (OECD averages of

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[2] Korea's national health insurance was first implemented among formal sector employees of large corporations (with more than 500 workers), and was incrementally extended to civil servants and private school teachers/employees, workers in smaller-sized firms, and finally to the self-employed (Chun et al., 2009; Kwon et al., 2015).

[3] Nevertheless, the benefits package has been expanded gradually over the past 30 years. Benefits covered by national health insurance encompass curative health care services (e.g., diagnosis, treatment, traditional medical care, emergency care, dental care, etc.), prescription pharmaceuticals, disease prevention (e.g., health check-ups and cancer screening), health promotion and rehabilitation (Chun et al., 2009; Kwon et al., 2015). The criteria for the inclusion of the benefits package are based on safety, clinical effectiveness, cost-effectiveness, financial burden on patients and fiscal impacts on national health insurance, which are examined and evaluated predominantly by the Health Insurance Review and Assessment Service (Mathauer et al., 2009; Kwon et al., 2015).

[4] In recent years, the largest share of health insurance revenues are covered by social insurance contributions. Health insurance premiums are levied on the basis of wage income for employees and are shared equally between the employee and employer where the uniform contribution rate is applied to them. Health insurance premiums for the self-employed are assessed on the basis of income and the value of household assets, such as houses and vehicles (Chun et al., 2009; Kwon et al., 2015).

21% and 4%) in 2017 (OECD, 2019). The large share of out-of-pocket spending on health care is partly attributable to relatively high cost-sharing for insured services,[5] and it is also driven by additional payments for increased uninsured services, most of which involve the adoption of new technology and medicines with uncertain levels of cost effectiveness (Kwon et al., 2015). To cover copayments for insured services and full payments for services not included in the benefits package, many Koreans purchase complementary private health insurance in recent years (Shin, 2012).[6] The wide coverage provided by voluntary private health insurance, however, is likely to encourage beneficiaries to overuse health services. On the other hand, high out-of-pocket payments may lead to limited access to needed care for low-income groups due to the financial burden,[7] which has caused inequity in health care utilization by different income groups.

Across a long period of time, many studies have been conducted to examine socioeconomic inequalities in the use of health care services in European countries. However, there has been little empirical study of inequity in health care utilization in Asian regions.[8] Lu et al. (2007), in a pioneering work on this issue in Asian economies, compared the equity performance of health systems with the egalitarian goals of Hong Kong, South Korea, and Taiwan around 2000. They showed that Korea appeared to feature almost equal distribution in outpatient visits overall but a strong pro-poor bias for outpatient care in health centers and inpatient admissions, accounted for

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[5] Patients' cost-sharing for inpatient care services is generally set at 20% of the total amount of medical treatment. On the other hand, the copayment rate for insured outpatient care varies from 30% to 60%, according to the level and location of healthcare facilities. A reduced rate of copayment is specially applied to vulnerable groups (e.g., the elderly, children under six, pregnant women at high risk, patients with chronic illnesses, etc.). Low-income people enrolled in the Medical Aid Program are also exempt from cost-sharing at the time of health care use (Kwon et al., 2015).

[6] Private health insurance in Korea either pays a lump-sum disbursement upon diagnosis of critical illness, or provides compensation for itemized medical expenses upon service use (Shin, 2012).

[7] To alleviate the financial burden on households against catastrophic health spending and to prevent them from falling into bankruptcy, the government sets the cumulative cost-sharing ceiling (out-of-pocket maximum) at the thresholds of 2 to 4 million Korean won per person depending on income level within a period of six consecutive months, beyond which the patients are exempt from further copayments. However, it is applicable only to out-of-pocket payments for insured care services without the stop-loss mechanism in practice (Chun et al., 2009; Mathauer et al., 2009; Kwon et al., 2015).

[8] There has also been a few empirical studies on socioeconomic inequalities in health care access in Japan, which has a the similar healthcare system to Korea: universal health insurance coverage, price regulation by the government, fee-for-service reimbursement in general, high dependence on the private sector in health care delivery, and free access by the patient to healthcare facilities. Major relevant works include those of Ohkusa and Honda (2003), Toyokawa et al. (2012), and Watanabe and Hashimoto (2012).

by non-need factors, such as lower levels of education and unemployment, combined with significant pro-rich inequality in outpatient use of tertiary medical institutions. Kim et al. (2012) demonstrated horizontal inequity favoring the better-off in both outpatient and inpatient care for the elderly in the late 1990s and early 2000s, and they also revealed that the prevalence of chronic disease, educational attainment and income level may have significantly contributed to that disproportionate distribution. Kim et al. (2013) found that pro-poor patterns appeared in terms of the probability of using secondary care and inpatient care relative to a pro-rich tendency that emerged in the number of visits and inpatient stays in the late 2000s. They also showed a modest pro-rich inequity in the amount of medical expenditures due to the substantial contributions of income, education, and private insurance. Furthermore, Kim et al. (2014b) separately estimated two age groups, below and above 60 years old, in 2010 and 2011, finding that health care utilization was concentrated on the worse-off in general and equally distributed, especially in emergency care and inpatient care, for the non-elderly.[9] On the other hand, larger amounts of medical expenses were seen for outpatient and inpatient care services among high-income groups, and pro-rich inequalities appeared to be greater among the elderly, who showed a higher need of health care utilization.

Exploiting longitudinal data from a nationally representative health survey from 2008 to 2018, this chapter investigates how income-related inequalities in health care utilization and spending in Korea have varied over time and examines the extent to which different factors have contributed to them by using an in-depth decomposition analysis, allowing for heterogeneity. This clearly differs from the previous studies mentioned above that capture a sequence of independent snapshots of inequalities for each year in several ways: I use short-run and long-run concentration indices as measures of the degree of inequality, with an index of health-related income mobility defined as the difference between two concentration indices. Moreover, I employ an extended decomposition method that allows for variation in individual responses to need and non-need determinants across income groups. In short, this study adds to the literature by expanding the standard methods of the concentration index and decomposition analysis with the use of the panel data to take into account medium- to long-term inequalities and heterogeneous responses to factor

[9] Kim et al. (2014a) showed the similar empirical results for pro-rich inequity in outpatient care payments by pooling the entire population over the age of 20 during the same study period.

contributions. Longitudinal analysis also enables me to derive policy implications for the long-run mechanism behind the equity performance of the Korean health care system under the universal coverage, which would otherwise be missing from a series of short-term cross-sectional analysis.

The remainder of this chapter is structured as follows: Section 2.2 presents the empirical methods I use to quantify the degree of income-related inequalities and factor decomposition. Section 2.3 describes the data used in this study and presents the summary statistics. Section 2.4 outlines the results for the concentration indices and mobility indices and reports the results of estimation in the regression and decomposition analysis. Section 2.5 discusses the implications and limitations of this study.

2.2 Methodology

2.2.1 Concentration indices in the short and long run

The concentration index method developed by Wagstaff et al. (1991) and Kakwani et al. (1997) is a standard tool used in health economics to quantify the extent of socioeconomic inequalities in a health-related variable. The concentration index (CI) can be simply calculated as follows:

$$CI = \frac{2}{\bar{y}} cov(y_i, r_i), \tag{1}$$

where y_i is the health-related measure for individual i $(i = 1, \dots, N)$,[10] $\bar{y}$ is the mean of y_i for all individuals $(= \sum_i y_i / N)$, and r_i is the individual's fractional rank in the distribution of their socioeconomic status, that is, household income per equivalent household member;[11] this

[10] Health-related outcomes are assumed to be unbounded variables for the concentration index, which measures relative inequality. For bounded outcomes (e.g., binary variables that represent the mirror condition), however, it is more appropriate to use the Erreygers index (Erreygers, 2009; Erreygers and Van Ourti, 2011), the Wagstaff index (Wagstaff, 2011), or the generalized concentration index as an absolute inequality measure.

[11] Kakwani et al. (1997) suggested that the concentration index can also be computed from a simple linear regression model, such that $2\sigma_r^2 \left(\frac{y_i}{\bar{y}}\right) = \alpha + \beta r_i + \varepsilon_i$, where σ_r^2 is the variance of the fractional rank r_i. The OLS estimator of β is equivalent to the concentration index obtained from equation (1).

value ranges from −1 to 1 and becomes zero when the health outcome is equally distributed among individuals irrespective of their standard of living (the values of −1 and 1 represent perfect inequality). When the concentration index takes a negative value ($CI < 0$), the outcome measure (e.g., the use of health services) is concentrated on the poor, while a positive value ($CI > 0$) indicates that it is biased toward the rich.

Because the concentration index above depicts the degree of inequality at a point in time, it corresponds to the short-run concentration index (CI^t) as presented in Jones and López Nicolás (2004) and Allanson et al. (2010). Alternatively, following those works, equation (1) can be rewritten as

$$CI^t = \frac{2}{\bar{y}^t} cov(y_{it}, r_i^t) = \frac{2}{N\bar{y}^t} \sum_i (y_{it} - \bar{y}^t)\left(r_i^t - \frac{1}{2}\right), \quad (2)$$

where y_{it}, $\bar{y}^t$, and r_i^t are defined in the same way as above for time period t ($t = 1, \dots, T$). Similarly, they proposed that when longitudinal data are available, the long-run concentration index (CI^T) over T periods can be derived as

$$CI^T = \frac{2}{\bar{\bar{y}}^T} cov(y_i^T, r_i^T) = \frac{2}{N\bar{\bar{y}}^T} \sum_i (y_i^T - \bar{\bar{y}}^T)\left(r_i^T - \frac{1}{2}\right), \quad (3)$$

where y_i^T is the average health measure of individual i after T periods ($= \sum_t y_{it}/T$), $\bar{\bar{y}}^T$ is the mean of y_i^T for all individuals in T periods ($= \sum_t \bar{y}^t/T$), and r_i^T is the individual's fractional rank in the distribution of their average equivalized incomes over all T periods. Note that both concentration indices over the short and long run have the same properties as the standard concentration index, in terms of an interpretation of the inequity.

2.2.2 Index of health-related income mobility

Next, to measure how much the long-run concentration index differs from the concentration index over the short run, based on cross-sectional data at a single point in time, I use an index of health-related income mobility (M^T), defined by Jones and López Nicolás (2004) as

$$M^T = \frac{\sum_t w_t CI^t - CI^T}{\sum_t w_t CI^t} = 1 - \frac{CI^T}{\sum_t w_t CI^t}, \tag{4}$$

where weights are calculated as $w_t = \bar{y}^t / T\bar{\bar{y}}^T$. This expression captures the difference between the concentration index for longitudinal averages and the weighted average of the cross-sectional concentration index. It takes either positive or negative values, depending on a systematic association between changes in individual income ranking and differences in measures of his/her health over the given time period (Jones and López Nicolás, 2004; Allanson et al., 2010). A larger absolute value of M^T shows a larger difference between two inequality measures, and it is equal to zero when there is no difference between them. Mathematically, a negative (positive) sign for M^T can be obtained when the absolute value of the long-run concentration index is greater (smaller) than that of the weighted average short-run concentration index.

Allanson et al. (2010) found that the index of health-related income mobility could be further decomposed into the (short-term) within- and (long-term) between-individuals components, as $M^T = M^W + M^B$, the values of which stem from the variation in individual health over time and in average health between individuals. The within-individuals index (M^W) is defined as

$$M^W = \sum_i v_i \left(\frac{2\sum_t (y_{it} - y_i^T)(r_i^t - \bar{r}_i)/T}{y_i^T \sum_t w_t CI^t} \right), \tag{5}$$

where $\bar{r}_i$ is the mean of r_i^t over T periods ($= \sum_t r_i^t / T$), and the individual weights are calculated as $v_i = y_i^T / N\bar{\bar{y}}^T$. The sign for M^W is generally dependent on the direction of the association between short-run movements in income rank and health measure, as presented in the numerator in (5), given the sign of the weighted average short-run concentration index. On the other hand, the between-individuals index (M^B) is defined as

$$M^B = \frac{2\sum_i (y_i^T - \bar{\bar{y}}^T)(\bar{r}_i - r_i^T)/N}{\bar{\bar{y}}^T \sum_t w_t CI^t}. \tag{6}$$

M^B could be positive or negative according to the direction of the correlation between average health and changes in income rank over time, as indicated in the numerator in (6), conditional on the sign of the weighted average short-run concentration index. Thus, the values for health-related income mobility measure M^T can also be explained by the signs and magnitudes of both M^W and M^B.[12]

2.2.3 Decomposition method with heterogeneity

Inequalities in health-related variables across the income distribution can be decomposed into the contributions of their potential determinants (Wagstaff et al., 2003). First, the individual's health measure y_i is assumed to be explained by a linear combination of J need variables x_{ji} that are likely to directly influence the health outcome (e.g., age, sex, health status, physical condition, etc.) and K non-need variables z_{ki}, which are generally defined as socioeconomic characteristics, including income level, such that

$$y_i = \alpha + \sum_{j=1}^{J} \beta_j x_{ji} + \sum_{k=1}^{K} \gamma_k z_{ki} + \varepsilon_i, \tag{7}$$

where β_j and γ_k are their corresponding coefficients, α is the intercept, and ε_i is the error term. Wagstaff et al. (2003) demonstrated that, based on the linear regression model in (7), the concentration index (CI) can be rewritten as follows:

$$CI = \sum_j \left(\beta_j \frac{\bar{x}_j}{\bar{y}}\right) CI_{x_j} + \sum_k \left(\gamma_k \frac{\bar{z}_k}{\bar{y}}\right) CI_{z_k} + \frac{2}{\bar{y}} cov(\varepsilon_i, r_i), \tag{8}$$

where $\bar{x}_j$ and $\bar{z}_k$ are the means of the covariates x_{ji} and z_{ki}, CI_{x_j} and CI_{z_k} are their concentration indices with respect to the fractional rank in the income distribution,[13] and the final term is the generalized concentration index for the error term reflecting income-related inequality in health that is not explained by any systematic variation in the regressors. In other words, the

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[12] Allanson et al. (2010) argue that M^T will often be negative due to the stronger positive association between income and health over the long run than the short run (i.e., $M^W > 0$ and $|M^W| < |M^B|$) and due to the negative correlation between average health status and changes in income rank over time, based on the typically unimodal shape of the income distribution (i.e., $M^B < 0$), given that the weighted average short-run concentration index is positive.

[13] CI_{x_j} and CI_{z_k} are defined analogously to the equation (1) by replacing y with x_j and z_k respectively, namely $CI_{x_j} = 2cov(x_{ji}, r_i)/\bar{x}_j$ and $CI_{z_k} = 2cov(z_{ki}, r_i)/\bar{z}_k$.

concentration index in the decomposition method can be defined as the weighted sum of the concentration indices of the explanatory variables x_j and z_k, where the weights provide the elasticity of the health measure with respect to each factor, evaluated at the sample mean (i.e., $\beta_j \bar{x}_j / \bar{y}$ and $\gamma_k \bar{z}_k / \bar{y}$), plus the residual component (O'Donnell et al., 2008). Therefore, each term in (8) comprises factor contributions to the overall concentration index.

However, the standard decomposition method often involves the drawback that it only captures homogeneous responses to need and non-need determinants over the entire sample, due to the fixed parameters that are on average adjusted by the sample means. In addition, the contribution of the residuals is likely to be sufficiently large unless the regression model is well specified. Following Jones and López Nicolás (2006) and Van de Poel et al. (2012), I thus employ an extended decomposition method that allows for heterogeneity across certain socioeconomic groups. I hypothesize a heterogeneous responsiveness of health care to need and non-need factors according to individual income levels. Suppose that each individual belongs to one of G groups differentiated by the level of equivalized income. Then, equation (7) can be transformed into the similar linear function of a set of the same need and non-need variables, excluding the indicators of the income group g $(g = 1, \dots, G)$, such that

$$y_i = \alpha_g + \sum_{j=1}^{J} \beta_{jg} x_{ji} + \sum_{k=1}^{K} \gamma_{kg} z_{ki} + u_i, \quad \forall i \in g \tag{9}$$

where β_{jg} and γ_{kg} are the differential parameters by income groups, α_g is the group-specific intercepts, and u_i is the error term. Based on the estimation of separate regressions for each group in (9), the concentration index in (8) can also be further decomposed into detailed factor contributions as follows:

$$\begin{aligned} CI = {} & \sum_j \left(\beta_j \frac{\bar{x}_j}{\bar{y}}\right) CI_{x_j} + \frac{2}{\bar{y}N} \sum_j \sum_i x_{ji} \left(\beta_{jg} - \beta_j\right) \left(r_i - \frac{1}{2}\right) \\ & + \sum_k \left(\gamma_k \frac{\bar{z}_k}{\bar{y}}\right) CI_{z_k} + \frac{2}{\bar{y}N} \sum_k \sum_i z_{ki} \left(\gamma_{kg} - \gamma_k\right) \left(r_i - \frac{1}{2}\right) \\ & + \frac{2}{\bar{y}} cov\left(\alpha_g, r_i\right) + \frac{2}{\bar{y}} cov\left(u_i, r_i\right). \end{aligned} \tag{10}$$

The first and third terms in (10) are the same as the first two terms in (8), obtained from the pooled regression, which indicates the homogeneous contributions of need and non-need factors, respectively, as their effects are constant over the entire sample. The second and fourth terms represent the heterogeneous contributions of the need and non-need determinants, respectively, defined as covariance between the differential parameters across income groups and fractional rank in income distribution, weighted by the values of the corresponding covariates. The fifth term refers to the direct contribution of income-group differences to income-related inequalities in the health outcome. We understand that it is transformed from the contribution of income level in the second term of equation (8), which is no longer captured in (10). The sixth term is the unexplained residual component of the concentration index, which is expected to be smaller than the last term in (8) due to the better specification, allowing for heterogeneity (Van de Poel et al., 2012).

2.3 Data

2.3.1 Korea Health Panel Survey

This study uses individual-level longitudinal data from the Korea Health Panel Survey (KHPS) for 2008 to 2018 (Version 1.7.2).[14] The KHPS is a nationwide comprehensive survey carried out by the Korea Institute for Health and Social Affairs and the National Health Insurance Service on a household or individual basis, using a dually stratified cluster sampling frame of the National Population and Housing Census. It provides a variety of information on individuals' health status and behaviors, health care utilization, and expenditure by type of care service (e.g., emergency care, inpatient and outpatient care, childbirth, long-term care, and medication utilization), covering the demographic and socioeconomic characteristics of individuals as well. The survey data also include sampling weights to enable adjustment for unequal selection probabilities and non-responses based on the distribution of population totals, which enable nationally representative estimates to be obtained.

Participants in the KHPS are required to collect receipts for each instance of health care expenses to alleviate the problems of recall bias and increase the credibility of the survey data. The complete dataset contains a full sample of 195,032 person-years in 68,347 household-years

[14] The Korea Health Panel Survey data are provided upon request to the Korea Institute for Health and Social Affairs. Additional information is available at https://www.khp.re.kr:444/eng/main.do.

across the entire survey that are all available in this study as a 11-year unbalanced panel data set.[15] New samples were selected and added to the panel in 2012 to ensure the reliability of the survey in response to the decreasing number of households and household members originally included in the sample who persisted in supplying data. These new participants' data became available from the 2014 survey data as an aggregated panel with the original sample.

2.3.2 Outcome variables and need/non-need determinants

The health-related outcome measures of primary interest in this study are health care utilization and spending in a year. I use six types of outcome variable: (1) length of hospital stay, (2) number of outpatient visits, (3) number of instances of emergency care use for health care utilization, (4) amount of inpatient care expenses, (5) amount of outpatient care expenses, and (6) total amount of medical expenses for health care spending. All of these outcomes are assumed to be continuous non-negative variables starting from 0.[16]

The need determinants of health care utilization and spending are proxied by individual's age, sex,[17] number of chronic diseases, and whether he/she is physically handicapped. The needs for health care services could also include variables such as self-reported health status, mental health problems, or various risk factors (e.g., smoking, drinking, eating habits, exercise, etc.), which are partly available in the KHPS. However, it would be better not to use these variables to prevent selection bias due to attrition. On the other hand, following previous studies on socioeconomic inequalities in health care, non-need determinants are defined as follows: individual's income

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[15] Some individual observations are dropped from the following analysis due to missing values.
[16] Length of hospital stay is in practical terms assumed to range from 0 to 366 days in a leap year. However, because it is calculated as a summation of days of stay in each episode of inpatient care utilization within a survey year, some samples exceed the supposed upper bound. I use the outcome variable as it is given in the analysis without manipulating the original data.
[17] Individual's sex is defined as a binary variable, taking a value of 1 if the sex is female, and a value of 0 if it is male.

level,[18] educational attainment,[19] labor force participation,[20] marital status,[21] number of household members, residential area,[22] whether he/she receives public assistance, number of private health insurance policies purchased, and total amount of monthly premium for private health insurance. To reflect the growing popularity of the purchase of voluntary private health insurance in Korea, even under the UHC, I use two variables that capture variation in capacity to pay for insurance rather than simply defining a binary variable that indicates whether he/she has it.

In addition to need and non-need determinants, survey year fixed-effects are also taken into account in the regression and decomposition analysis. Note that monetary variables, expressed in ten thousand Korean won (i.e., equivalized income, medical expenses, and monthly premium for private health insurance) are transformed into real values adjusted by the consumer price index for each year to compare them across survey years.

2.3.3 Descriptive statistics

Table 2.1 reports the descriptive statistics, including concentration indices for outcome and need/non-need variables across the entire sample. The concentration indices for health care utilization show negative values, indicating that it is disproportionately concentrated on poorer people as a whole. Nevertheless, the utilization for inpatient care (about 2 days on average per year) is more biased toward the poor than outpatient and emergency care use (on average, 15.4 and merely 0.1 times per year, respectively). However, the concentration indices for health care

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[18] When I calculate the concentration indices, individual's income levels (i.e., household income divided by the square root of household size) is used as a continuous variable to rank the samples. On the other hand, these are categorized as quintiles of equivalized income for each survey year in the regression analysis, and then these income groups are transformed into dummy variables. The reference group is determined as the poorest quintile.

[19] Educational attainment is represented by three categories by highest level of educational achievement: junior high school graduate or lower education, high school graduate, and university graduate or higher education. Dummies for the first and third categories are used in the analysis, and the second category is set as a benchmark.

[20] Labor force participation refers to whether the respondent worked in a survey year. Note that those under the age of 15 are systematically identified as not working.

[21] Marital status is defined as a binary variable taking the value of 1 if the respondent is married and 0 otherwise.

[22] Residential area refers to whether he/she lives in the capital regions (i.e., Seoul, Incheon, and Gyeonggi Province). Residential information on whether urban or rural areas is not available in the KHPS.

spending demonstrate a different tendency: inpatient care expenses show a pro-poor concentration, while the inequality favors the better-off in outpatient care spending, which is higher than the former on average. Total medical expenses are almost equally distributed among all of the samples available, even if the concentration index has a small positive value with no statistical significance. The concentration indices for outcome variables in descriptive statistics are slightly different from those calculated in the regression and decomposition analysis, where some of the observations are dropped due to missing values of other covariates than equivalized income.

A graphical representation of the concentration indices for outcome variables is shown in the form of the concentration curves in Appendix Figures A.2.1 and A.2.2. The concentration curve plots the cumulative percentage of a health-related variable against that of the population according to socioeconomic status, from poorest to richest. The concentration index is equal to twice the area between the concentration curve and the 45-degree line of perfect equality (Kakwani et al., 1997). If the health variable is concentrated among the poor (rich), the concentration curve lies above (below) the line of equality (O'Donnell et al., 2008). The concentration curves for health care utilization and inpatient care spending are plotted above the 45-degree line, due to the negative values of the concentration indices, while the opposite is true for the case of outpatient care spending. However, it is worth noting that the concentration curve for the total amount of medical spending apparently crosses the line of equality.

Table 2.1 also indicates that older people and females are more likely to belong to the poorer population, and having more chronic diseases and disabilities is more common prevalent among the poor. Individuals who have completed education beyond high school are concentrated in the richer groups, and those with lower education are biased toward the poorer groups. Approximately half of those sampled are married and have worked during the survey year, and these respondents are more prevalent among the wealthier people. Those who live in the capital regions were more than 40% of the samples and also showed a pro-rich prevalence, while public assistance recipients accounted for only 4% and were strongly concentrated in the poor group. Moreover, the richer population is likely to pay for more private health insurance that has higher monthly premiums.

2.4 Results

2.4.1 Short-run/long-run concentration indices and mobility indices

Figures 2.1–2.6 show changes in concentration indices for six outcome measures over the short and long run [equations (2) and (3)], using a weighted average for the short-run concentration indices [given as the denominator in equation (4)] that are used to calculate the health-related income mobility indices. The confidence intervals for concentration indices are also obtained from the linear regression. As with the descriptive statistics across the entire sample, both the concentration of the indices of health care utilization (inpatient, outpatient, and emergency care) show negative values with sufficient statistical significance, implying a disproportionate concentration of overall health care utilization among the poor over the short and long run. The concentration indices for inpatient care spending also demonstrate a pro-poor concentration, while outpatient care spending is consistently biased toward the rich over the long run (although this relationship shows no statistical significance over the short run in some later years). The total amount of medical expenses, however, is more or less equally distributed across the population, as the concentration indices are not statistically different from zero in most survey years.

Figures 2.7–2.12 show changes in the indices of health-related income mobility for six outcomes [equation (4)], composed of the within- and between-individuals indices, respectively [equations (5) and (6)]. The mobility indices for inpatient care utilization and spending indicate downwardly negative trends over the long run, although we find a distinct jump to the positive values between 2013 and 2014.[23] The negativity of these indices is led by the dominance of the negative between-individuals effects due to the positive correlation between average inpatient care services and changes in income rank over time, as well as by the negative within-individuals effects for some years, due to a positive association between short-run movements in income rank and inpatient care, given the negative weighted average of the short-run concentration indices. The short-run concentration indices for inpatient care use and spending are likely to be underestimations of the long-run inequalities by 8% and 4%, respectively, for the 11 years. The mobility index of outpatient care utilization shows an upwardly positive movement over the long run, mostly attributable to the positive within- and between-individuals effects, due to a negative

[23] This might be caused by additional sampling for the KHPS in 2014, where a negative association between income rank and inpatient care services is likely to be found in the short term.

association between outpatient care use and income rank, suggesting that the short-run concentration index overestimates the long-run inequality by more than 20%. We find a downwardly negative trend over the long run for the mobility index of outpatient care spending, as a result of the dominance of the negative between-individuals effects, conditional on the positive weighted average short-run concentration index, giving rise to an increase in long-run inequality by approximately 60%. The mobility index of emergency care utilization also incorporates negative values over the long run that are generally explained by the stronger negative within-individuals effects, whereas that for total amount of medical expenses unstably fluctuates across entire survey years because the weighted average short-run and long-run concentration indices are near to each other around zero.

2.4.2 Regression analysis

The estimation results of the pooled regressions over the entire sample [equation (7)] and separate regressions across income groups [equation (9)] for six outcome measures are fully reported in Tables 2.2 and 2.3. They indicate a linear association between health care outcomes and need/non-need determinants while allowing for heterogeneous responses according to income group. Among the need factors, age is positively associated with inpatient care utilization/spending and total medical expenses, but it is negatively correlated with outpatient and emergency care use ($p < 0.01$). Females are less likely to use inpatient and emergency care than males, and they tend to use outpatient care more and to spend more on it, with higher spending on total medical care ($p < 0.01$), and this effect tends to grow as income level grows. The number of chronic diseases shows a positive relationship with health care utilization and spending, as expected ($p < 0.01$), and their impacts become smaller for health care use but greater for expenditures as income level goes up. Being physically handicapped is also significantly associated with increasing frequency of overall health care utilization and higher amount of medical spending, with the exception of spending for outpatient care ($p < 0.01$).

Among the non-need factors, lower educational attainment than graduation from high school is significantly correlated with greater use of health care as a whole and greater expenses for outpatient and total medical care, while those who have achieved higher education than high school graduates are less likely to utilize and spend on outpatient care ($p < 0.01$). The working population reveals a negative association with health care utilization and spending, as expected, likely due to the healthy worker effect ($p < 0.01$). People who are married tend to use more outpatient and emergency care and spend more on outpatient and total medical care, but they also show shorter hospital stays for inpatient care ($p < 0.01$). The number of household members is negatively associated with health care utilization (except for inpatient care) and spending ($p < 0.01$). Living in the capital regions is significantly associated with higher spending on outpatient and total medical care, although it is reverse-correlated with a decreasing frequency of overall health care use and lower expenses for inpatient care ($p < 0.05$). We also find a clear contrast such that public assistance recipients are likely to utilize more health care services but spend less on them, owing to the tax-funded Medical Aid Program ($p < 0.01$). Finally, purchasing more private health insurance raises the probability of using more outpatient care and spending more on health care in general, and those who pay higher monthly premiums tend to increase their utilization for inpatient and emergency care ($p < 0.01$). However, positive gradients were not found across income levels in the effects of private health insurances on health care utilization and spending, as had been expected.

2.4.3 Decomposition analysis

The decomposition results of the concentration indices allowing for heterogeneity for six outcomes [equation (10)] are graphically displayed in Figures 2.13–2.18. The corresponding results, expressed in numerical values and percentage shares, are also presented in Appendix Tables A.2.1 and A.2.2. It can be recalled that the homogeneous contributions of need and non-need determinants are evaluated as the product of the elasticity of health care measures with respect to each explanatory variable and the concentration index for each variable, whereas the heterogeneous contributions depend on the covariance of the differential parameters across income groups, with a fractional rank in the income distribution weighted by the values of the corresponding covariates. Note likewise that the direct contribution of income-group differences can be obtained from the covariance between the group-specific intercepts and the fractional income rank.

Within the result for inpatient care utilization, age makes the largest positive contribution in total to the income-related inequality (-0.254), where the positive heterogeneous contribution (i.e., the effect on length of hospital stay is stronger for high-income groups) overwhelms the negative homogeneous contribution, which is derived from its positive association with inpatient care use and pro-poor inequality in its distribution. Another large positive contribution for gender is also shown in the positive heterogeneous effect such that females for whom the (negative) association with inpatient care utilization is greater tend to enjoy a lower than average income level, while the number of chronic diseases forms a negative contribution to income-related inequality, mainly due to the negative heterogeneous contribution, in which the positive correlation is stronger for low-income groups. The total contribution of need factors takes a positive value (0.072) due to the greater positive effect of the heterogeneous contribution. Among the non-need determinants, marital status makes a larger negative (heterogeneous) contribution, where married people, who have their strong association with shorter days of hospital stay, belong to higher income groups. The total contribution of non-need factors (−0.053) accounts for 21% of the income-related inequality, and the largest contributor is the direct impact of income-group differences (−0.271), which accounts for 107%. The result for inpatient care spending is similar to that for inpatient care use with respect to the direction of each need factor, but the homogeneous and heterogeneous contributions of need determinants compensate for each other (−0.003). The number of household members and marital status produce the largest negative (heterogeneous) contributions among the non-need factors, while the number of private health insurance policies and receiving public assistance is larger for positive (homogeneous) contributors. The total contribution of non-need determinants (−0.037) accounts for 41% of income-related inequality in inpatient care expenses (−0.091). It is also noteworthy that the direct effect of income-group differences (−0.05), which accounts for 55% of inequality, is one of the most important contributors, implying that individuals who belong to lower income groups are likely to spend more on inpatient care, despite the greater financial burden on them.

The decomposition result for outpatient care utilization shows a different picture, although outpatient care is also disproportionately concentrated on the poor. Income-related inequality in outpatient care use (−0.129) is mostly attributable to the contribution of need factors (−0.122), which accounts for 95%, among which the prevalence of chronic disease makes the largest negative (homogeneous) contribution, due to its positive association with utilization for outpatient care and pro-poor inequality in its distribution. Among the non-need determinants, educational attainment is the largest negative (homogeneous) contributor, in terms of the combination of the effects and pro-poor/rich inequalities in the education dummies, whereas marital status and residential area contribute positively (and heterogeneously) on a larger scale to income-related inequality. Thus, the total contribution of non-need factors (−0.015) results in a smaller share of 11%, and the direct impact of income-group differences also makes less of a contribution in the opposite direction (0.008). The result for outpatient care spending reveals an insightful pattern of homogeneous and heterogeneous contributions. We find that the status of public assistance is the greatest positive (homogeneous) contributor, deriving from its negative correlation to outpatient care expenses and strong pro-poor concentration, while number of family members and working status[24] make larger negative contributions among the non-need determinants. Consequently, the homogeneous and heterogeneous contributions of non-need and need factors turn out to nearly cancel out (0.003 and 0.001 in total, respectively). Therefore, a large share, 75%, of income-related inequality in outpatient care spending (0.036) can be accounted for by the direct contribution of income-group differences (0.027), suggesting that the better-off tend to have expenses from costlier outpatient care, probably including uninsured services.

Finally, the result for emergency care utilization shows that income-related inequality (−0.072) is mostly explained by the contribution of non-need factors (−0.05), which accounts for 69%, among which the number of household members and public assistance status make relatively larger negative contributions. It also shows a negative contribution according to need determinants (−0.037), accounting for 51%, where the number of chronic diseases plays the most important role. However, the direct contribution of income-group differences involves a smaller share in the opposite direction (0.013). The result for overall medical care spending is found to be similar to that for outpatient care expenses, in terms of the contribution of each component. However, the offsetting effect of the contributions of need/non-need factors and income-group differences leads to small income-related inequality (0.003), which is close to perfect equality, indicating that total amount of medical expenses is almost uniformly spent across the population, irrespective of their income level.

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[24] The negative heterogeneous contribution of labor force participation is largely found because working individuals for whom its negative association with outpatient care spending is stronger are likely to have a higher than average level of income.

2.5 Discussion

This chapter investigates long-term, income-related inequalities in health care utilization and spending in Korea, and it examines the extent to which need and non-need factors contribute in a longitudinal setting using an extended decomposition analysis, allowing for heterogenous responses across income groups. The empirical findings are summarized and discussed as follows: First, we find a disproportionate concentration of overall health care utilization among the poor over the short and long run. Income-group differences and household characteristics, such as marital status, make larger pro-poor contributions to inequality in inpatient care use, while the prevalence of chronic diseases greatly pushes outpatient care utilization in a pro-poor direction. Income-related inequality in emergency care use is largely explained with the contribution of non-need determinants, such as the number of household members, as well as health status as a need factor, proxied by the distribution of chronic diseases. The pro-poor concentration of health care utilization and its decomposition results suggest that poor people consume more health care services because they are likely to be in physically worse condition. This finding is consistent with some of the previous studies such as Lee and Shaw (2014) and Kim et al. (2014a). It is important for health care policy in Korea to focus more on improvement in the health status and well-being of low-income groups.

By contrast, income-related inequalities in health care spending unveil insightfully different patterns, depending on types of care services, although total amount of medical care expenses is almost equal across the population, regardless of income level. Inpatient care expenses are biased toward the poor, and the decomposition result shows that the direct effect of income-group differences and non-need determinants contribute to most of the income-related inequality. This implies that higher spending especially on inpatient care may be a heavy financial burden to low-income people. Although the cost-sharing for insured inpatient care is set at the relatively lower rate of 20% and the cost-sharing ceiling scheme also works for insured care services, extra payments for uninsured services such as special treatments and room charges account for a large amount of high out-of-pocket expenditure on hospitalization (Mathauer et al., 2009).[25] Lee and Shaw (2014) and Kim et al. (2014a) point out that poor people are likely to be provided with less sufficient or advanced care services, as the quality and intensity of care increase in direct proportion to income level, which could bring about longer periods of hospital stays with higher spending for them. Furthermore, an increase in the out-of-pocket payment for inpatient care is highly correlated with the probability of facing catastrophic health expenditure that could occur more often among vulnerable low-income groups (Mathauer et al., 2009; Lee and Shaw, 2014). Thus, additional financially supportive measures should be provided for low-income people to mitigate their heavy burden of inpatient care spending and prevent them from suffering economic hardship. This may also lead to institutional issues in terms of the charging of inpatient care services. On the other hand, we find that long-run inequality favors the better-off in outpatient care expenses, while the direct contribution of income-group differences accounts for the largest share of overall pro-rich inequality. This finding implies that people in high-income groups are more likely to spend costly services for outpatient care, including uninsured services with the help of voluntary private health insurance, which currently brings about a policy debate on how to regulate uninsured health care services and the growing market for private health insurance.

This study has some limitations. First, the need and non-need determinants of health care utilization and spending, as defined above, might omit other potentially influential variables. For example, as noted, potential needs for health care services could include such variables as subjective health status, mental health condition, and lifestyle-related risk factors, which are not fully available for analysis. Other possible non-need factors could include such socioeconomic variables as individual expected rate of copayment or out-of-pocket payment, health insurance premium rate, and distance to nearest health care facilities, which are all difficult to calculate from the available dataset. Nevertheless, the residual components in decomposition analysis that are explained by a set of omitted or unobservable factors show small enough contributions, owing to the detailed specification allowing for heterogeneity. Secondly, individual heterogeneity is

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[25] Many Korean citizens try to lessen their financial burden of inpatient care utilization due to additional uninsured services by purchasing private health insurance. However, the elderly and low-income individuals who need more health care services are less likely to be enrolled in private health insurance (i.e., more likely to be driven out of the market) because of price discrimination and redlining (Ko, 2020).

adjusted for only by sampling weights, although one of the benefits of using panel data is being able to control for individual fixed-effects as time-invariant unobserved heterogeneity. However, employing the fixed-effects model usually has the side effect of cancelling out other time-invariant variables, such as gender and educational attainment which contributions are preferred to be estimated in decomposition analysis. Again, relatively small contributions of residual components may imply that individual fixed-effects are also sufficiently small. Finally, as outcome measures in this study are defined by general types of health care (i.e., inpatient, outpatient, and emergency care), they do not take into account differences in quality of care. Decomposition results suggest that people in low-income groups are likely to utilize insured basic care services that are necessary for them, while the better-off tend to use and spend more on premium services, especially in outpatient care, that are not usually covered by national health insurance. Room remains for future research on examining socioeconomic inequalities in the use of quality-adjusted care services in the context of universal coverage.

Table 2.1 Summary statistics for outcome and need/non-need variables

	N	Mean	SD	Min	Max	CI	N for CI
Length of stay (inpatient)	195,032	1.96	15.20	0	2,920	-0.254	194,607
Num. of visits (outpatient)	195,032	15.40	22.93	0	455	-0.129	194,607
Num. of emergency	195,032	0.11	0.49	0	60	-0.072	194,607
Exp. for inpatient care	194,513	15.21	93.35	0	16,264	-0.091	194,088
Exp. for outpatient care	194,689	38.21	76.63	0	4,048	0.036	194,268
Total medical exp.	194,936	53.99	131.20	0	16,264	0.003	194,513
Eq. income (10K KRW)	194,607	2,509	1,904	0	149,921	N/A	N/A
1st quintile	39,088	823	279	0	1,470	N/A	N/A
2nd quintile	38,825	1,565	244	1,046	2,221	N/A	N/A
3rd quintile	38,911	2,204	295	1,606	3,004	N/A	N/A
4th quintile	38,963	2,971	389	2,184	4,050	N/A	N/A
5th quintile	38,820	4,992	2,753	3,024	149,921	N/A	N/A
Age	195,031	41.92	22.59	0	105	-0.053	194,606
Female	195,032	0.52	0.50	0	1	-0.026	194,607
Chronic diseases	195,032	1.41	2.03	0	18	-0.181	194,607
Disabled	195,032	0.06	0.23	0	1	-0.388	194,607
Education							
Jr. high sch. grad. or lower	195,032	0.46	0.50	0	1	-0.194	194,607
High sch. graduate	195,032	0.31	0.46	0	1	0.008	194,607
Univ. grad. or higher	195,032	0.23	0.42	0	1	0.251	194,607
Labor participation	195,023	0.46	0.50	0	1	0.092	194,598
Married	194,993	0.53	0.50	0	1	0.019	194,569
Num. of family members	195,032	3.48	1.29	1	11	0.036	194,607
Capital area	195,032	0.41	0.49	0	1	0.080	194,607
Public assistance	195,032	0.04	0.20	0	1	-0.762	194,607
Num. of priv. health ins.	195,032	1.38	1.33	0	17	0.154	194,607
Monthly premium	194,630	8.20	11.50	0	765	0.198	194,213

Note: Underscored variables are used as reference categories in the regression analysis.

Table 2.2 Estimation results for health care utilization

	Inpatient care						Outpatient care						Emergency care					
	Pooled	Q1	Q2	Q3	Q4	Q5	Pooled	Q1	Q2	Q3	Q4	Q5	Pooled	Q1	Q2	Q3	Q4	Q5
Age	0.050	0.025	0.054	0.070	0.039	0.086	-0.044	0.008	-0.063	-0.073	-0.052	-0.049	-0.001	-0.001	-0.001	-0.002	-0.002	-0.001
	(0.004)	(0.008)	(0.008)	(0.010)	(0.009)	(0.016)	(0.004)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.0001)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Female	-0.422	-1.877	-0.484	-0.111	-0.229	0.290	2.025	1.314	1.765	1.762	2.012	2.672	-0.019	-0.050	-0.026	-0.018	-0.006	-0.001
	(0.063)	(0.276)	(0.130)	(0.097)	(0.103)	(0.100)	(0.081)	(0.275)	(0.184)	(0.167)	(0.149)	(0.154)	(0.002)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
Chronic diseases	0.502	0.763	0.600	0.365	0.342	0.277	5.197	5.901	5.281	4.934	4.549	4.488	0.026	0.031	0.027	0.026	0.020	0.020
	(0.036)	(0.084)	(0.065)	(0.057)	(0.060)	(0.098)	(0.046)	(0.096)	(0.103)	(0.101)	(0.105)	(0.105)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Disabled	3.844	4.273	3.514	2.363	3.934	3.524	3.090	2.376	4.014	1.429	4.556	3.685	0.045	0.024	0.052	0.086	0.044	0.021
	(0.470)	(0.894)	(0.647)	(0.638)	(1.115)	(1.761)	(0.334)	(0.582)	(0.685)	(0.733)	(0.837)	(0.961)	(0.007)	(0.013)	(0.015)	(0.018)	(0.016)	(0.017)
Lower education	0.415	0.175	0.286	0.717	0.426	0.877	6.156	5.318	6.268	6.523	5.783	5.396	0.041	0.027	0.034	0.041	0.053	0.055
	(0.096)	(0.349)	(0.169)	(0.142)	(0.147)	(0.261)	(0.105)	(0.288)	(0.215)	(0.212)	(0.213)	(0.252)	(0.003)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Higher education	0.113	-0.679	0.099	0.246	0.071	0.178	-0.432	-0.701	-0.350	-0.387	-0.443	-1.210	-0.003	-0.018	-0.001	-0.002	-0.009	0.0001
	(0.059)	(0.292)	(0.130)	(0.104)	(0.117)	(0.123)	(0.085)	(0.326)	(0.194)	(0.168)	(0.154)	(0.180)	(0.002)	(0.008)	(0.007)	(0.005)	(0.005)	(0.005)
Labor	-1.156	-1.741	-1.422	-0.960	-0.853	-0.892	-1.617	-0.598	-1.750	-1.922	-1.874	-1.516	-0.018	-0.032	-0.018	-0.017	-0.009	-0.007
	(0.077)	(0.239)	(0.166)	(0.145)	(0.178)	(0.162)	(0.100)	(0.278)	(0.219)	(0.203)	(0.196)	(0.220)	(0.003)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)
Married	-0.597	0.518	-0.918	-1.215	-0.389	-1.510	2.993	2.434	2.424	3.266	3.659	4.262	0.026	0.032	0.001	0.041	0.026	0.020
	(0.131)	(0.339)	(0.238)	(0.274)	(0.235)	(0.385)	(0.121)	(0.348)	(0.274)	(0.261)	(0.235)	(0.231)	(0.003)	(0.008)	(0.008)	(0.006)	(0.007)	(0.006)
Family members	0.022	-0.025	0.043	0.032	-0.038	-0.008	-0.944	-0.608	-1.056	-1.007	-0.718	-0.753	-0.008	0.003	-0.009	-0.012	-0.009	-0.010
	(0.037)	(0.122)	(0.063)	(0.058)	(0.059)	(0.077)	(0.039)	(0.117)	(0.089)	(0.079)	(0.078)	(0.080)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Capital area	-0.412	-0.808	-0.562	-0.321	-0.275	-0.215	-0.518	-2.353	-0.549	-0.348	0.004	0.217	-0.012	-0.024	-0.010	-0.016	-0.003	-0.013
	(0.060)	(0.259)	(0.120)	(0.098)	(0.092)	(0.107)	(0.078)	(0.274)	(0.178)	(0.159)	(0.142)	(0.148)	(0.002)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Public assistance	2.453	2.128	2.082	1.621	0.341	24.84	3.125	3.527	3.138	3.453	-4.514	-1.889	0.068	0.083	0.017	0.036	-0.001	0.204
	(0.400)	(0.456)	(0.912)	(1.183)	(1.984)	(11.73)	(0.376)	(0.457)	(0.843)	(1.661)	(1.750)	(3.210)	(0.011)	(0.013)	(0.020)	(0.048)	(0.041)	(0.235)
Num. of private	0.038	0.034	-0.094	0.065	0.098	0.029	0.131	0.670	0.138	0.139	0.077	0.094	0.001	-0.004	0.003	0.001	0.001	0.001
health insurance	(0.027)	(0.122)	(0.059)	(0.064)	(0.066)	(0.048)	(0.037)	(0.166)	(0.095)	(0.082)	(0.072)	(0.063)	(0.001)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Monthly premium	0.008	0.031	0.032	0.010	0.007	0.004	0.003	-0.053	0.011	0.007	-0.003	0.006	0.0004	0.001	0.001	0.0005	0.001	0.0002
	(0.002)	(0.020)	(0.008)	(0.005)	(0.006)	(0.003)	(0.004)	(0.023)	(0.012)	(0.010)	(0.007)	(0.006)	(0.0001)	(0.001)	(0.0003)	(0.0003)	(0.0003)	(0.0001)
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income quintiles	Yes	No	No	No	No	No	Yes	No	No	No	No	No	Yes	No	No	No	No	No
Constant	-0.112	2.132	-0.016	-0.863	-0.119	-0.905	7.155	3.930	7.837	8.146	6.274	6.045	0.137	0.097	0.150	0.166	0.132	0.125
	(0.351)	(1.091)	(0.456)	(0.406)	(0.388)	(0.504)	(0.274)	(0.719)	(0.565)	(0.509)	(0.490)	(0.486)	(0.007)	(0.021)	(0.017)	(0.014)	(0.013)	(0.014)
Observations	194,172	39,007	38,720	38,830	38,888	38,727	194,172	39,007	38,720	38,830	38,888	38,727	194,172	39,007	38,720	38,830	38,888	38,727

Note: Robust standard errors adjusted by sampling weights are reported in parentheses.

Table 2.3 Estimation results for health care spending

	Inpatient care						Outpatient care						Total medical care					
	Pooled	Q1	Q2	Q3	Q4	Q5	Pooled	Q1	Q2	Q3	Q4	Q5	Pooled	Q1	Q2	Q3	Q4	Q5
Age	0.199	0.118	0.275	0.200	0.218	0.255	0.008	-0.045	0.042	0.016	0.134	-0.010	0.198	0.066	0.308	0.207	0.334	0.248
	(0.022)	(0.033)	(0.067)	(0.036)	(0.059)	(0.069)	(0.014)	(0.024)	(0.029)	(0.031)	(0.038)	(0.044)	(0.027)	(0.043)	(0.073)	(0.050)	(0.072)	(0.085)
Female	-0.677	-3.122	-2.895	-0.694	0.333	2.394	6.615	1.855	5.569	6.770	6.267	11.16	5.944	-1.439	2.637	6.005	6.547	13.79
	(0.400)	(1.026)	(1.123)	(0.711)	(0.851)	(0.791)	(0.376)	(0.753)	(0.738)	(0.741)	(0.853)	(0.975)	(0.584)	(1.355)	(1.394)	(1.091)	(1.265)	(1.364)
Chronic diseases	4.669	4.382	4.869	4.661	4.823	5.106	11.94	9.149	12.22	13.15	13.13	15.47	16.71	13.70	17.22	17.96	18.09	20.44
	(0.230)	(0.319)	(0.446)	(0.470)	(0.739)	(0.787)	(0.169)	(0.219)	(0.362)	(0.398)	(0.452)	(0.587)	(0.305)	(0.413)	(0.603)	(0.650)	(0.922)	(1.058)
Disabled	12.19	4.412	17.80	11.21	22.76	19.13	-0.452	-2.142	3.629	-1.992	2.886	-1.799	11.67	2.246	21.32	9.461	26.07	16.04
	(2.205)	(1.881)	(7.804)	(3.248)	(5.762)	(7.332)	(0.898)	(1.126)	(2.179)	(2.341)	(2.977)	(3.140)	(2.417)	(2.304)	(8.099)	(4.225)	(6.701)	(7.940)
Lower education	0.481	-0.484	1.716	1.829	-0.816	0.828	2.228	3.788	2.483	2.941	2.435	2.072	2.663	3.297	4.295	4.763	1.800	2.407
	(0.534)	(1.211)	(1.137)	(0.964)	(1.318)	(1.565)	(0.477)	(0.889)	(1.014)	(0.973)	(1.204)	(1.353)	(0.765)	(1.601)	(1.591)	(1.455)	(1.874)	(2.215)
Higher education	0.689	-4.647	3.949	1.351	1.242	-0.376	-1.862	-1.513	-1.422	-1.222	-1.873	-0.401	-1.330	-6.428	2.580	-0.025	-0.537	-1.230
	(0.635)	(1.419)	(2.587)	(1.019)	(1.139)	(0.997)	(0.502)	(1.450)	(1.005)	(0.956)	(1.057)	(1.188)	(0.858)	(2.153)	(2.813)	(1.490)	(1.633)	(1.714)
Labor	-6.111	-5.941	-9.278	-5.702	-5.983	-4.362	-3.392	-0.267	-3.262	-3.721	-3.479	-6.596	-9.743	-6.371	-12.38	-9.506	-9.564	-11.90
	(0.598)	(1.107)	(1.791)	(1.053)	(1.454)	(1.214)	(0.481)	(0.884)	(1.018)	(0.999)	(1.118)	(1.373)	(0.828)	(1.504)	(2.113)	(1.540)	(1.937)	(2.145)
Married	1.220	5.665	-0.784	1.122	-0.762	-1.379	10.37	10.89	6.210	8.781	7.142	12.62	12.00	16.88	5.398	10.12	6.804	12.17
	(0.731)	(1.237)	(2.350)	(1.175)	(1.630)	(1.833)	(0.526)	(0.885)	(1.136)	(1.099)	(1.370)	(1.378)	(0.946)	(1.605)	(2.650)	(1.720)	(2.179)	(2.432)
Family members	-0.725	-0.624	-0.568	-1.144	-0.979	-1.228	-2.905	-2.711	-3.538	-3.497	-3.219	-3.464	-3.767	-3.328	-4.152	-4.678	-4.326	-5.141
	(0.212)	(0.457)	(0.539)	(0.343)	(0.444)	(0.547)	(0.180)	(0.310)	(0.329)	(0.322)	(0.437)	(0.543)	(0.300)	(0.581)	(0.644)	(0.501)	(0.656)	(0.894)
Capital area	-1.608	-2.950	-1.656	-1.415	-0.161	-2.133	3.037	2.320	1.362	3.061	2.942	4.721	1.410	-0.605	-0.089	1.766	2.933	2.044
	(0.399)	(0.995)	(1.134)	(0.718)	(0.850)	(0.810)	(0.359)	(0.796)	(0.726)	(0.708)	(0.813)	(0.905)	(0.576)	(1.347)	(1.393)	(1.074)	(1.239)	(1.381)
Public assistance	-9.509	-7.873	-10.39	-11.57	-16.66	10.21	-28.57	-28.82	-20.52	-17.52	-31.18	-47.69	-38.49	-37.25	-31.28	-28.44	-48.88	-37.67
	(1.027)	(1.095)	(2.500)	(3.395)	(4.705)	(23.41)	(0.880)	(1.026)	(2.288)	(6.536)	(6.095)	(5.962)	(1.420)	(1.575)	(3.619)	(7.774)	(8.570)	(21.57)
Num. of private	0.899	1.829	-0.299	0.712	1.811	0.603	2.024	3.426	1.581	1.602	1.983	1.426	2.900	5.333	1.335	2.328	3.780	1.861
health insurance	(0.210)	(0.740)	(0.474)	(0.444)	(0.470)	(0.404)	(0.198)	(0.561)	(0.418)	(0.424)	(0.450)	(0.407)	(0.307)	(1.006)	(0.667)	(0.650)	(0.683)	(0.636)
Monthly premium	0.047	-0.023	0.154	0.087	-0.008	0.060	-0.018	-0.078	0.067	0.050	-0.065	0.007	0.026	-0.112	0.216	0.136	-0.071	0.064
	(0.026)	(0.110)	(0.070)	(0.054)	(0.049)	(0.041)	(0.023)	(0.092)	(0.063)	(0.066)	(0.052)	(0.032)	(0.035)	(0.155)	(0.097)	(0.089)	(0.075)	(0.053)
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income quintiles	Yes	No	No	No	No	No	Yes	No	No	No	No	No	Yes	No	No	No	No	No
Constant	3.818	9.232	6.494	5.464	2.308	6.443	11.89	20.24	20.48	19.44	20.02	26.04	16.73	30.02	27.54	25.38	23.32	35.29
	(1.374)	(2.864)	(3.447)	(2.072)	(2.893)	(2.986)	(1.163)	(2.358)	(2.178)	(2.114)	(2.632)	(3.164)	(1.908)	(3.915)	(4.180)	(3.140)	(4.067)	(4.993)
Observations	193,654	38,876	38,624	38,735	38,790	38,629	193,833	38,954	38,664	38,711	38,867	38,637	194,083	38,975	38,703	38,824	38,869	38,712

Note: Robust standard errors adjusted by sampling weights are reported in parentheses.

Figure 2.1

Concentration indices for inpatient care utilization

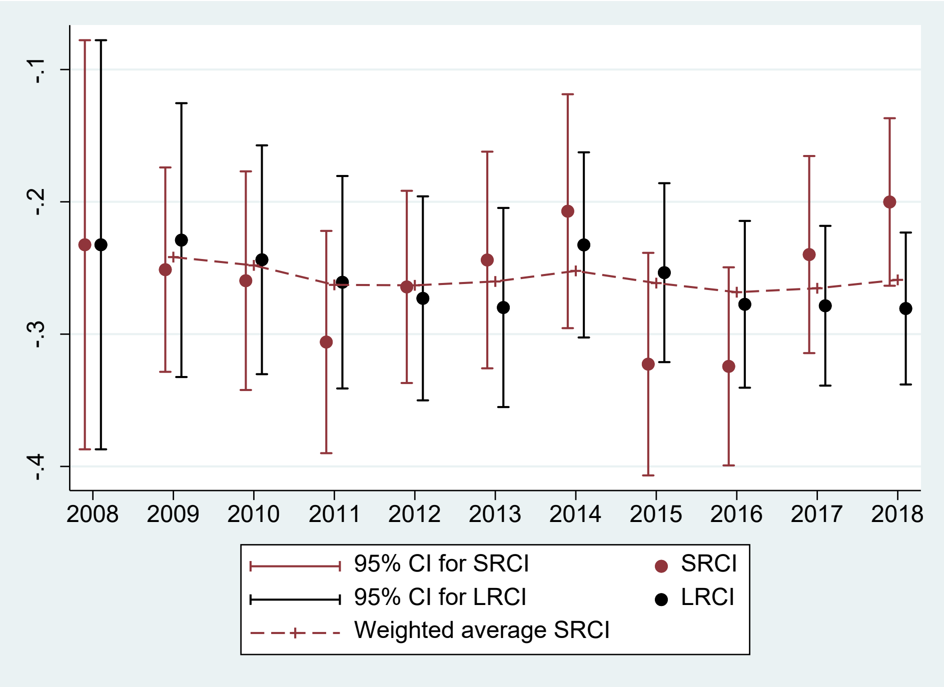


Figure 2.7

Mobility indices for inpatient care utilization

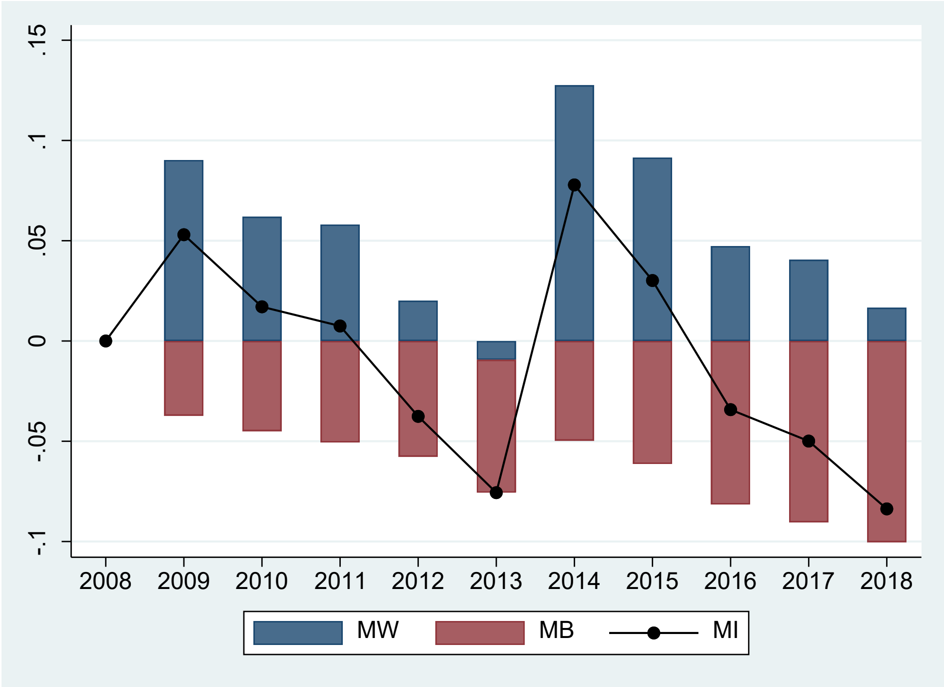


Figure 2.2

Concentration indices for inpatient care spending

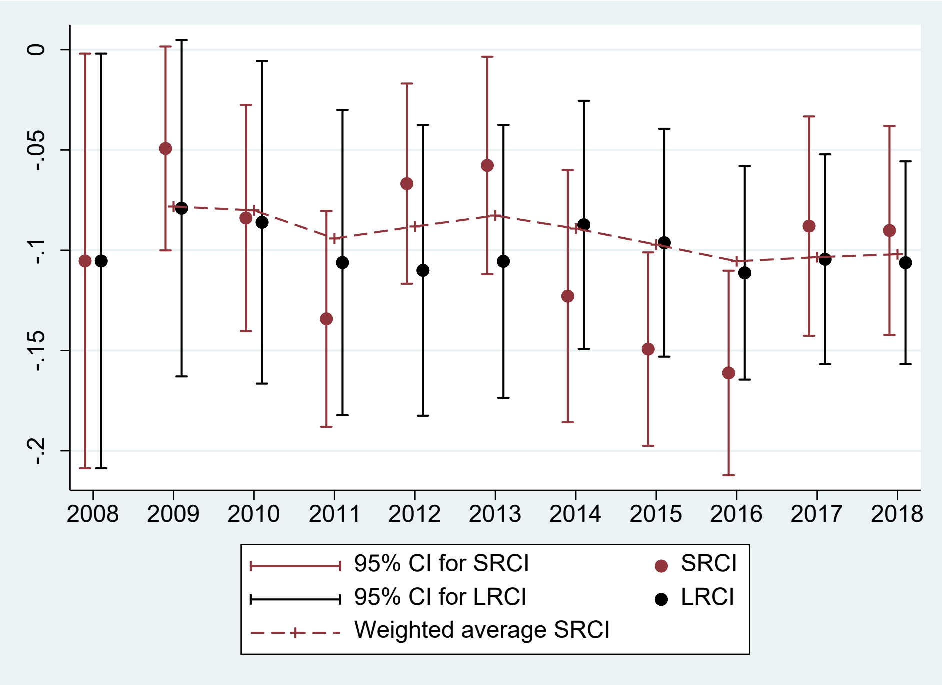


Figure 2.8

Mobility indices for inpatient care spending

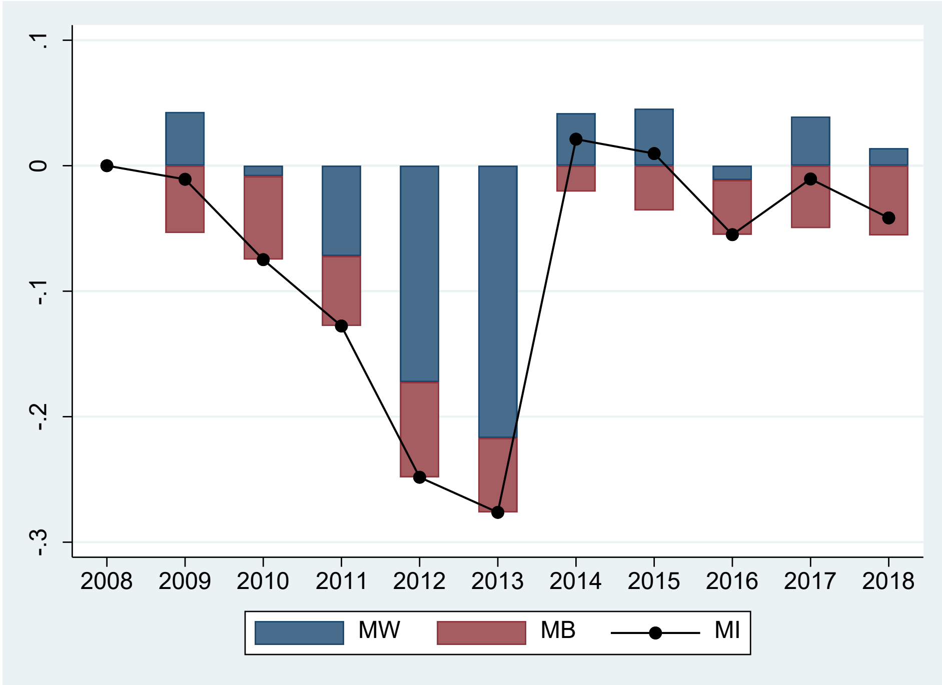


Figure 2.3

Concentration indices for outpatient care utilization

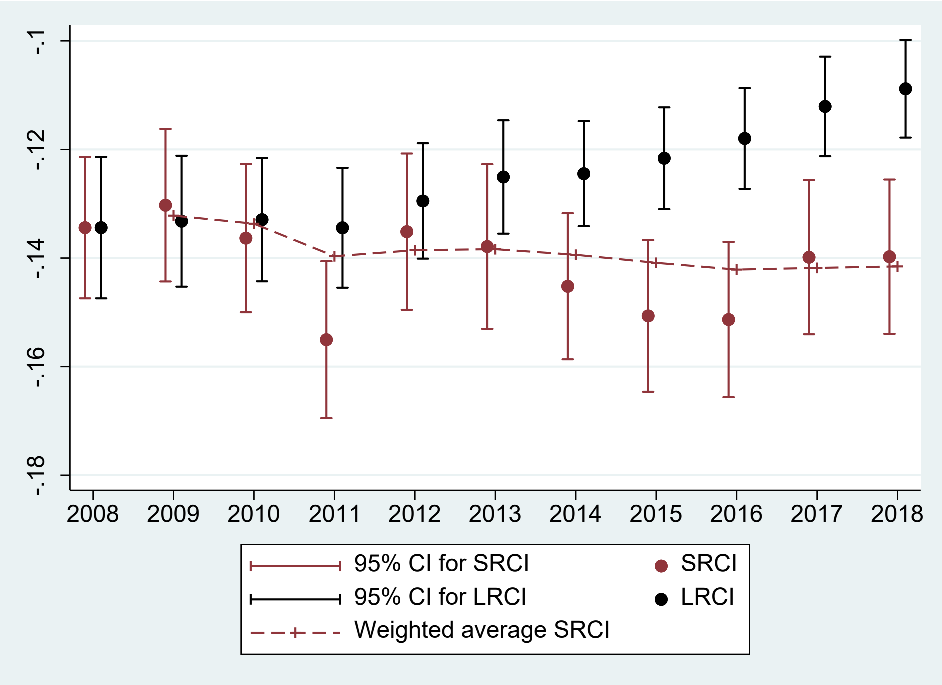


Figure 2.9

Mobility indices for outpatient care utilization

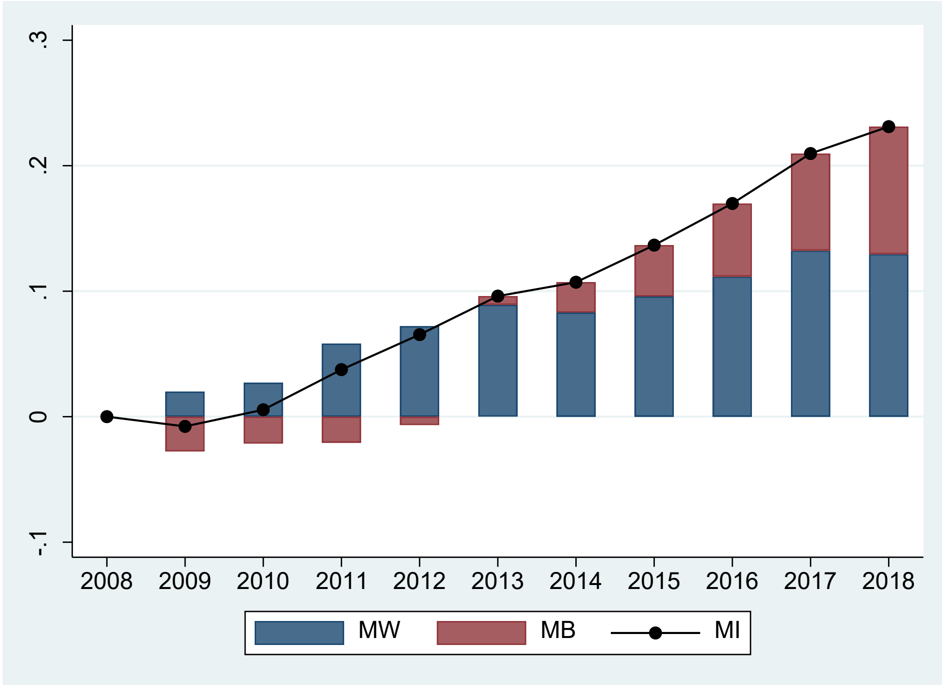


Figure 2.4

Concentration indices for outpatient care spending

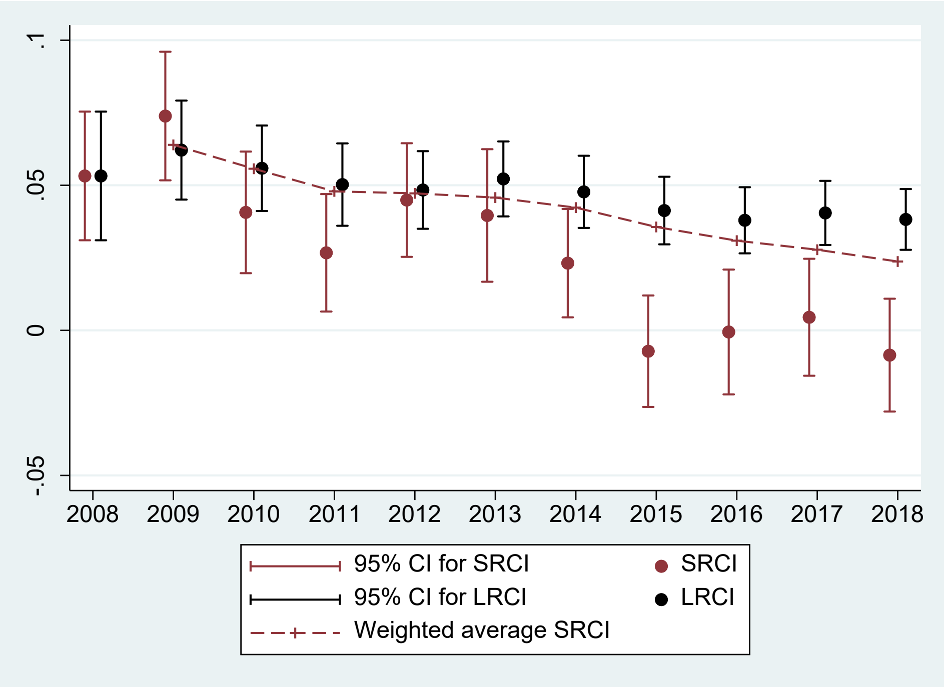


Figure 2.10

Mobility indices for outpatient care spending

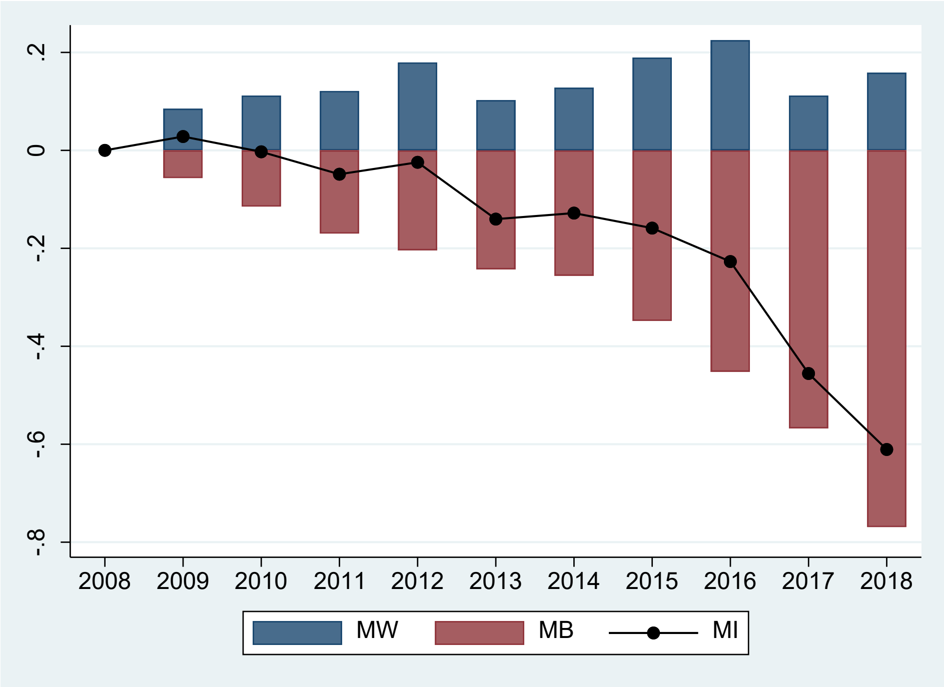


Figure 2.5

Concentration indices for emergency care utilization

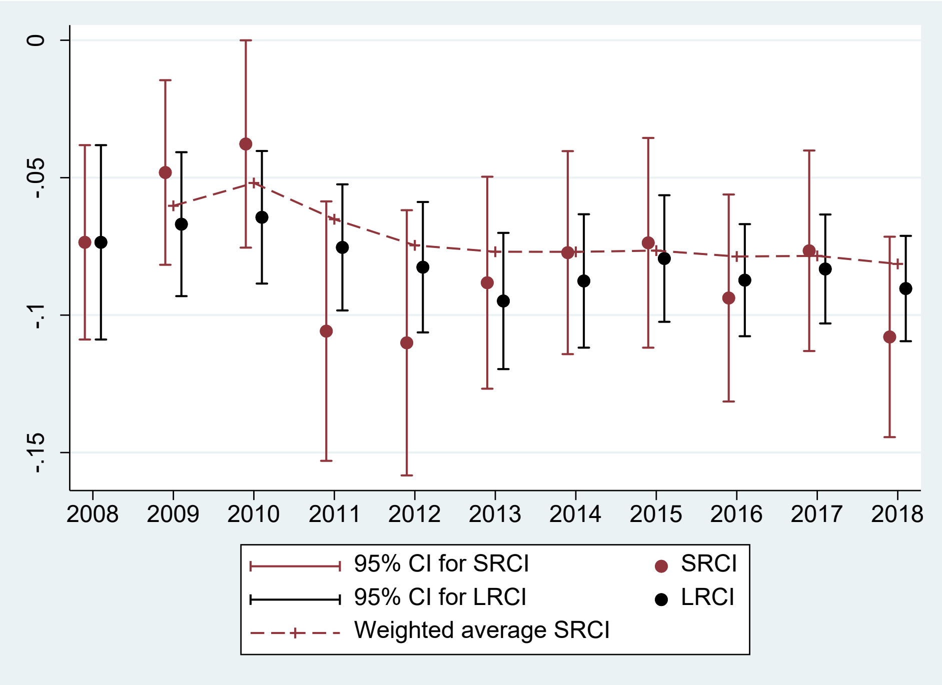


Figure 2.11

Mobility indices for emergency care utilization

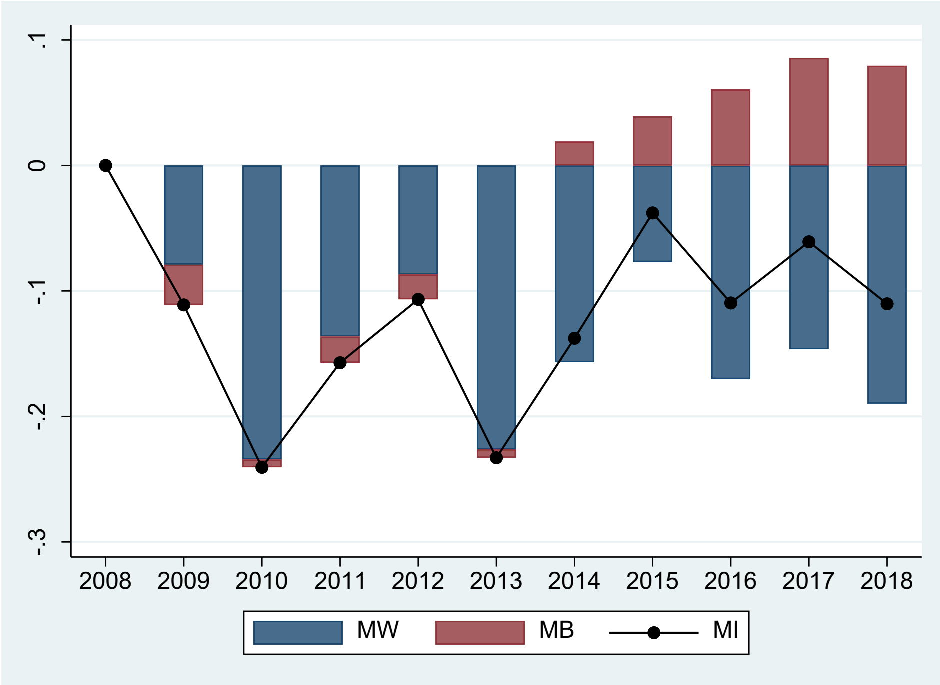


Figure 2.6

Concentration indices for total amount of medical spending

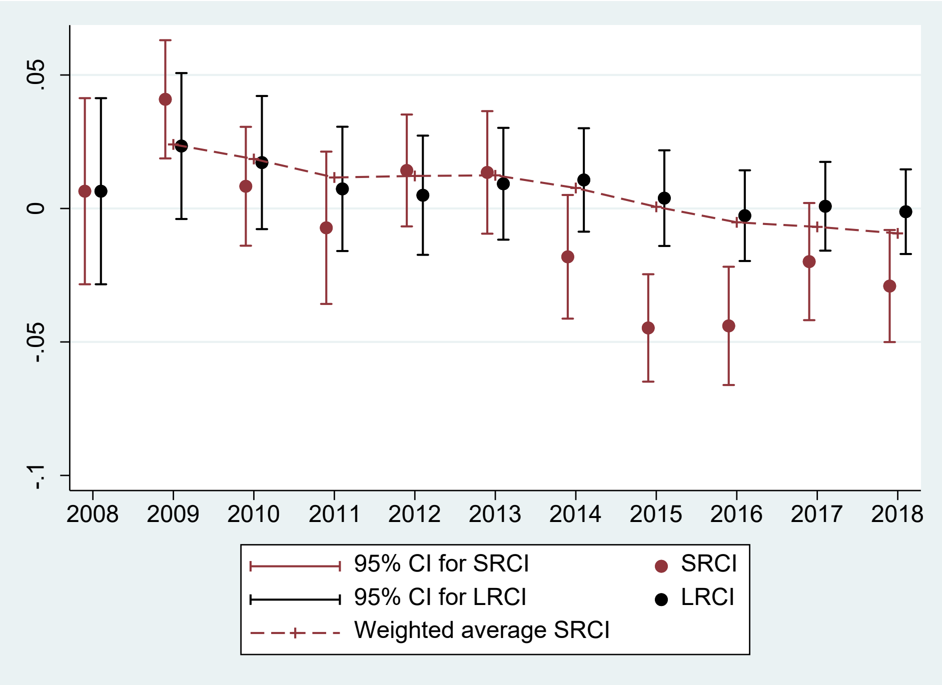


Figure 2.12

Mobility indices for total amount of medical spending

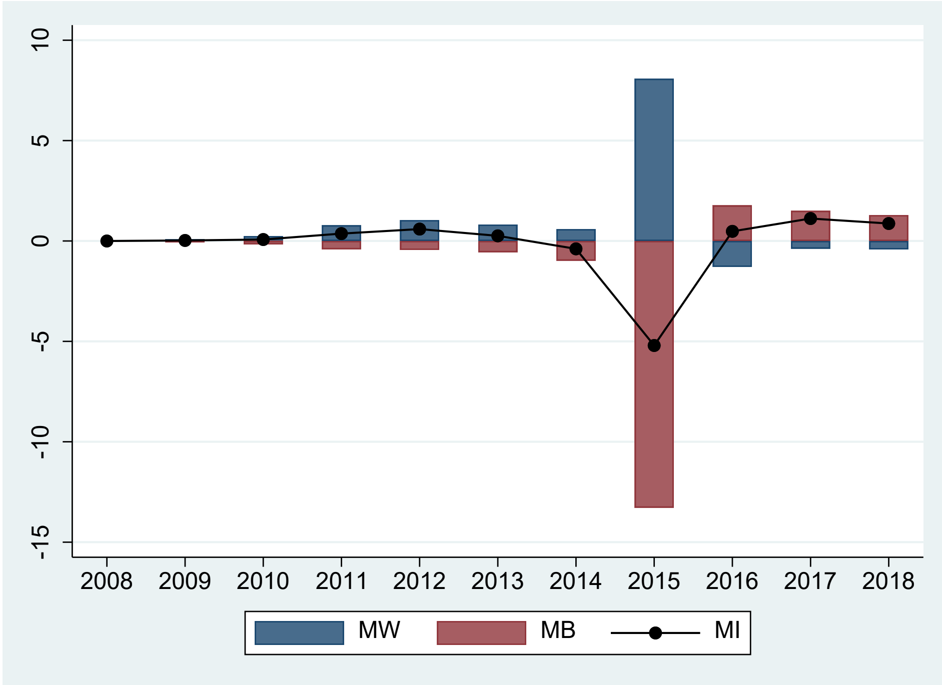


Figure 2.13

Decomposition results for inpatient care utilization

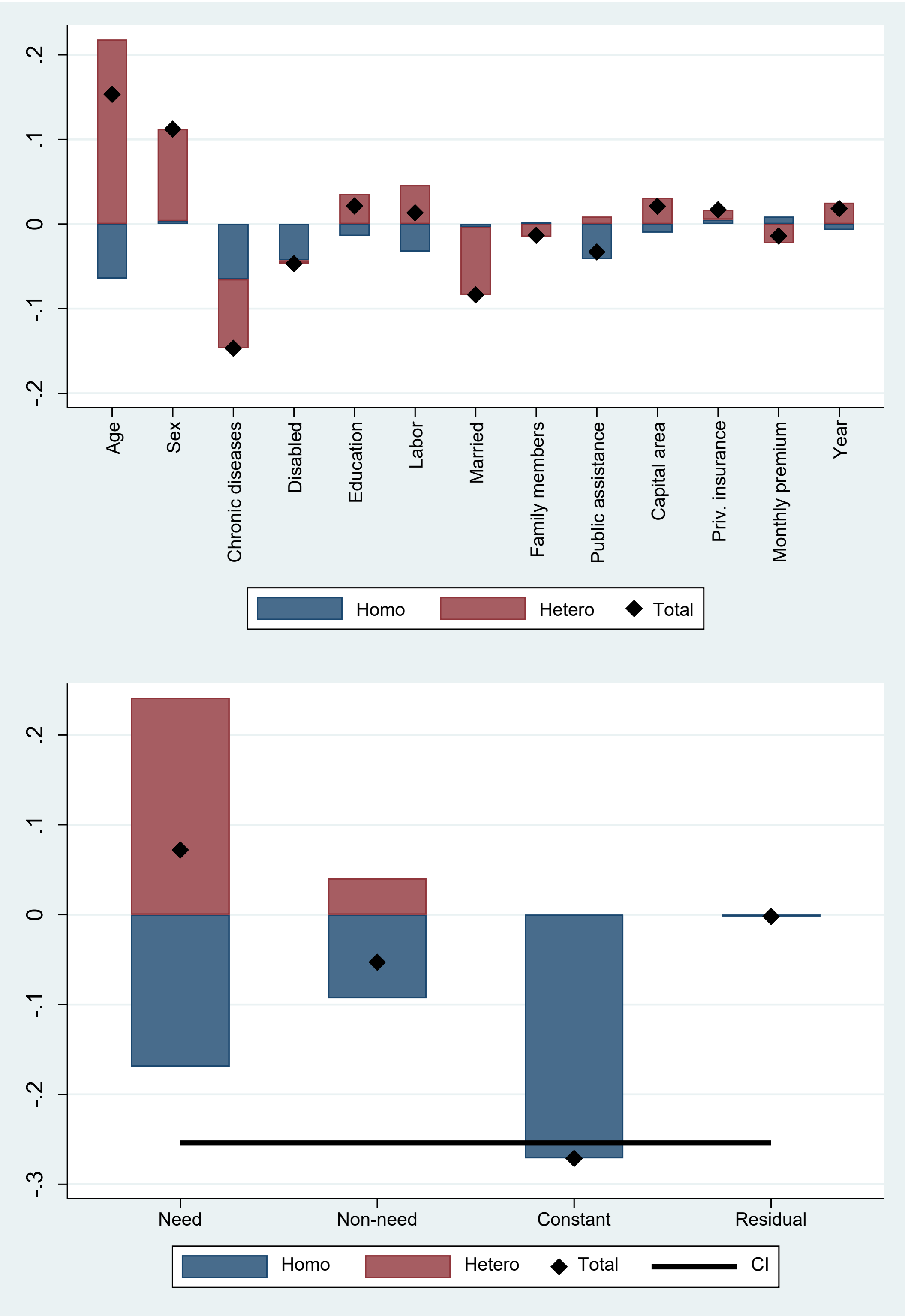


Figure 2.14

Decomposition results for inpatient care spending

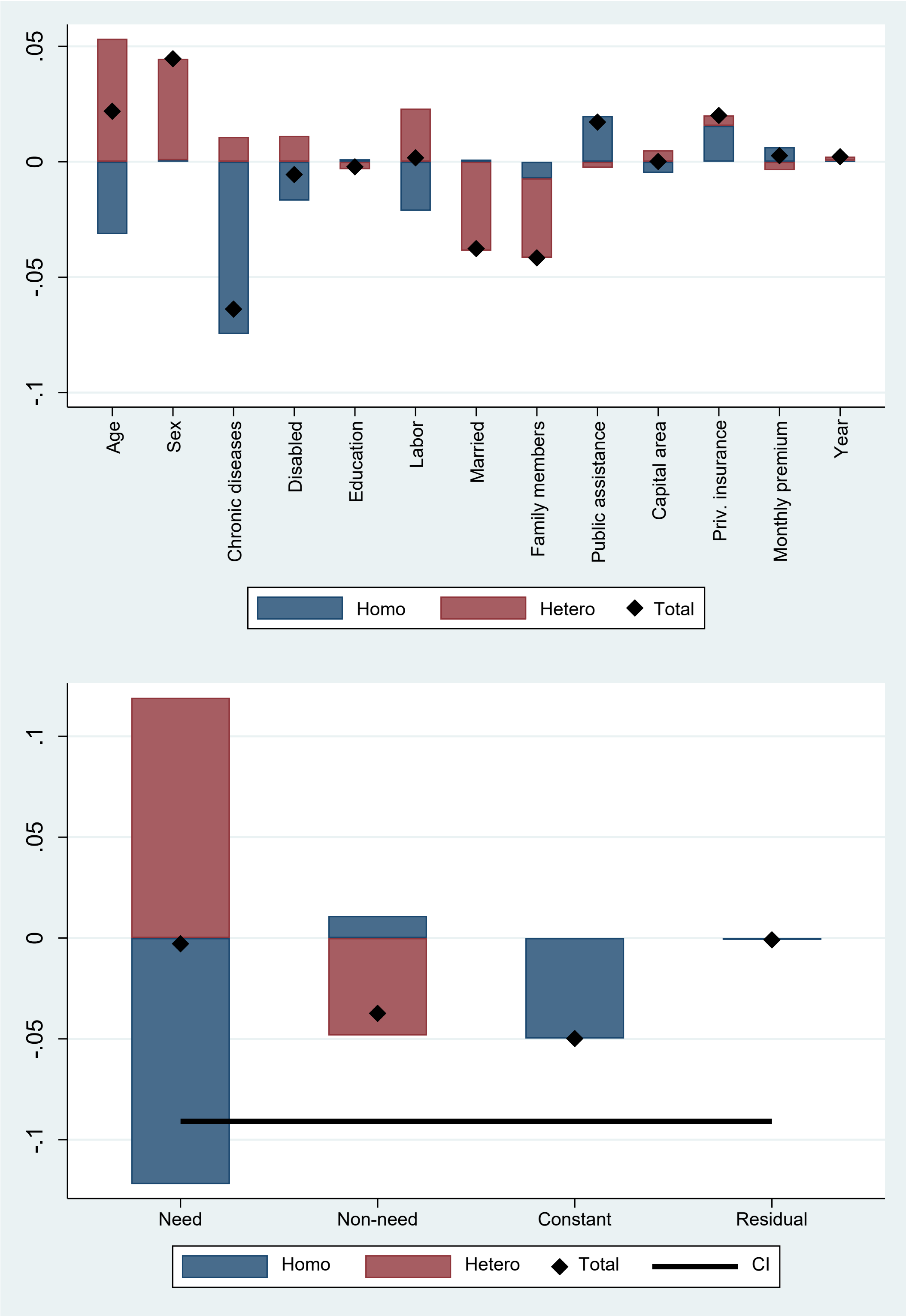


Figure 2.15

Decomposition results for outpatient care utilization

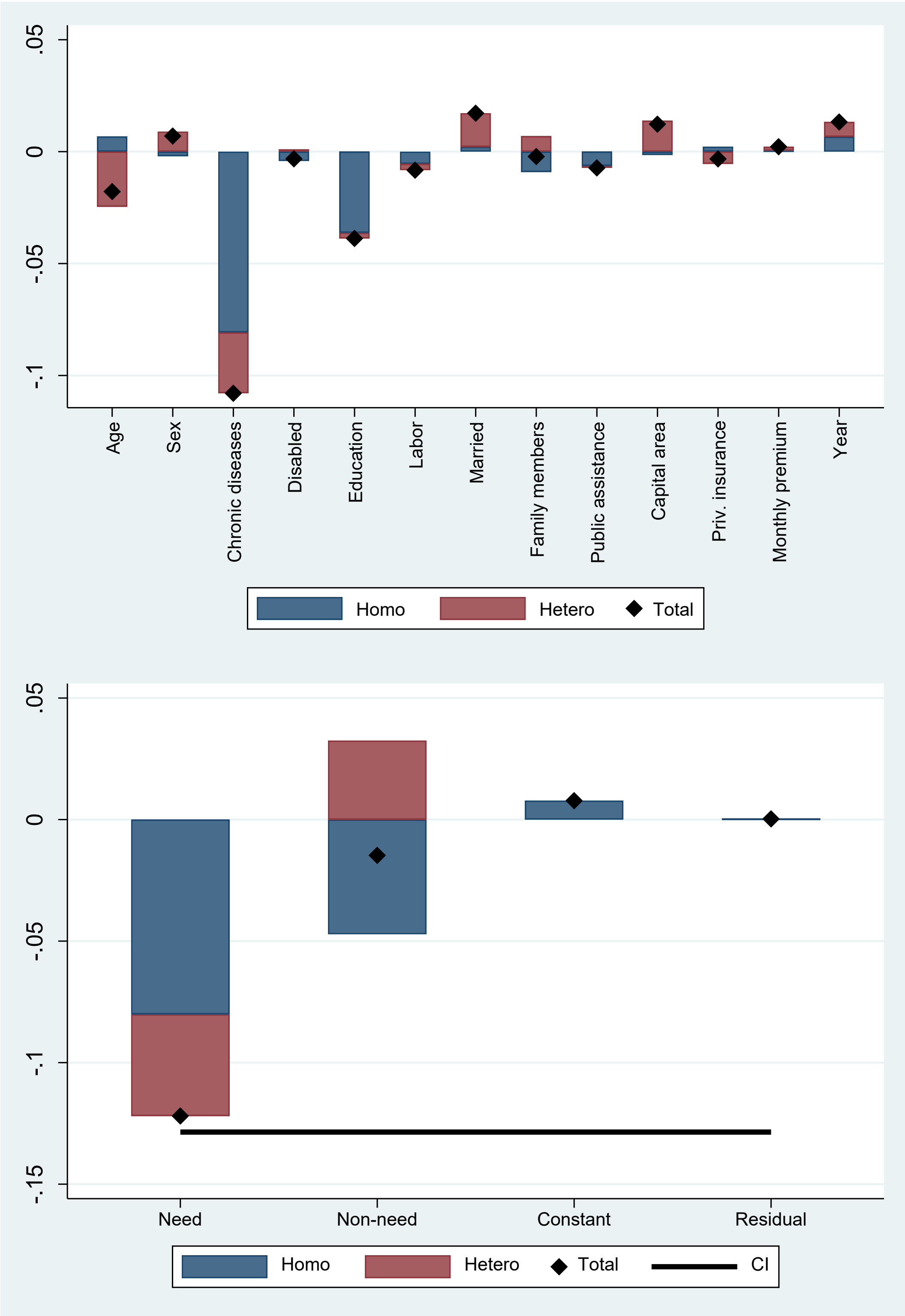


Figure 2.16

Decomposition results for outpatient care spending

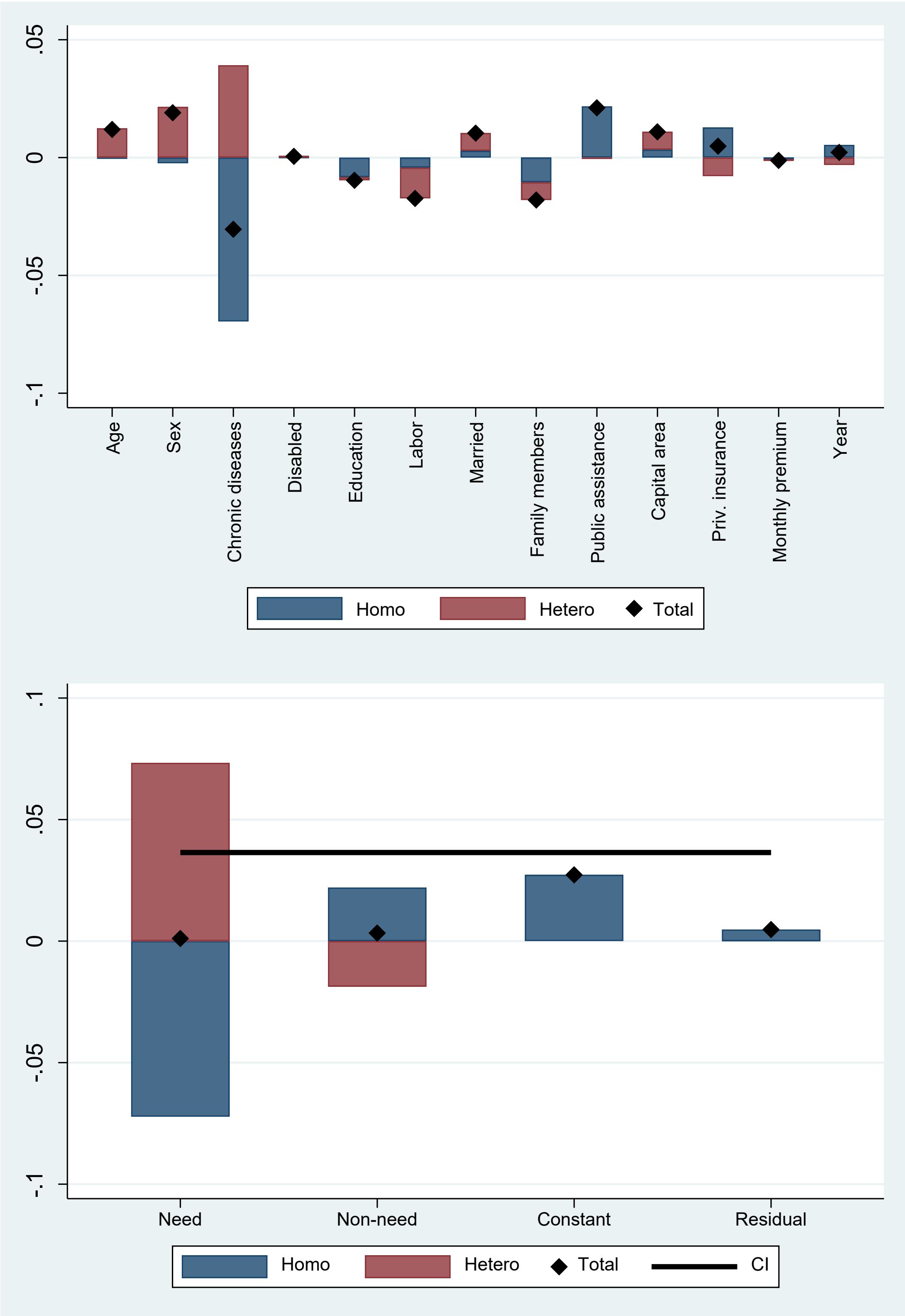


Figure 2.17

Decomposition results for emergency care utilization

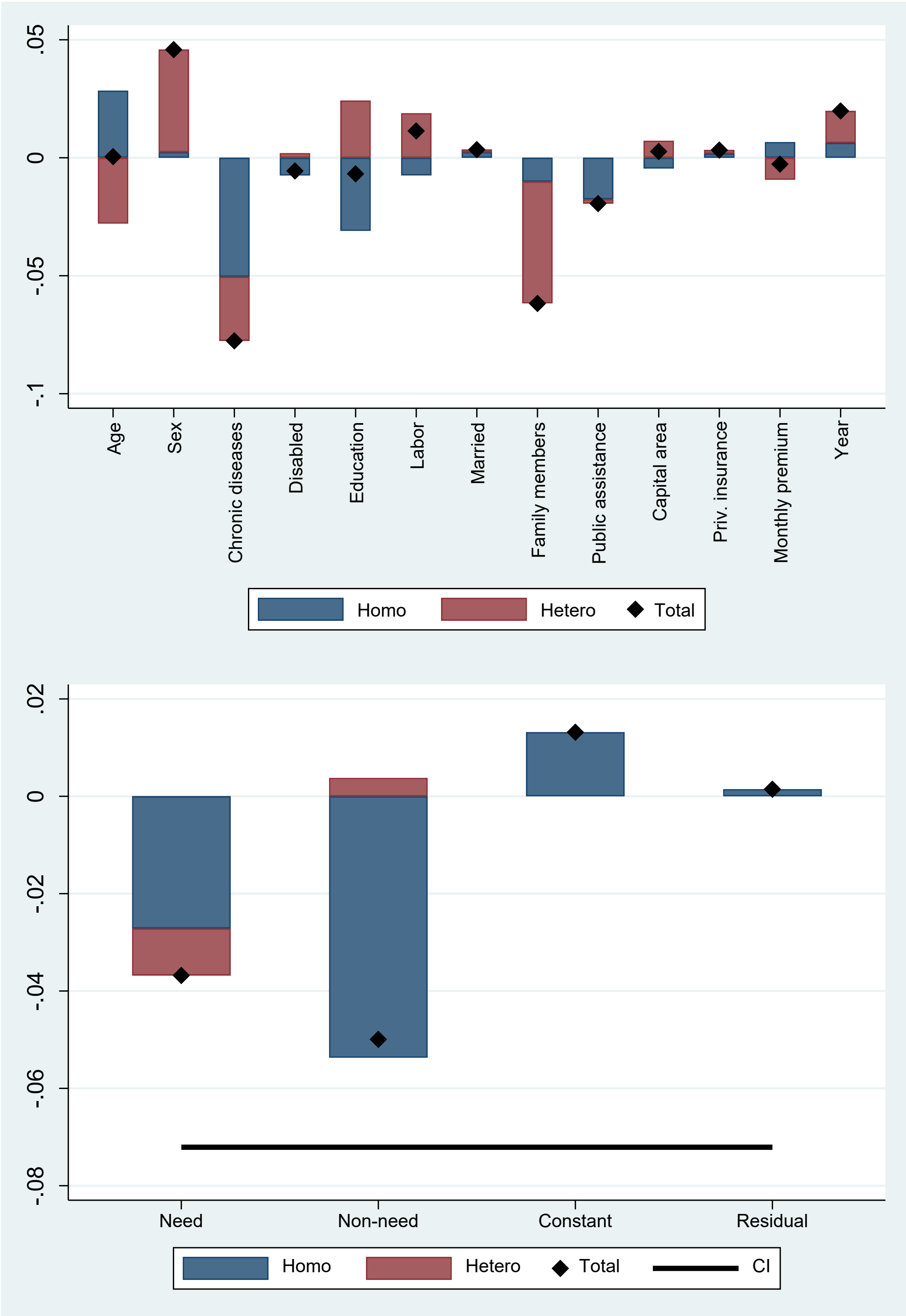
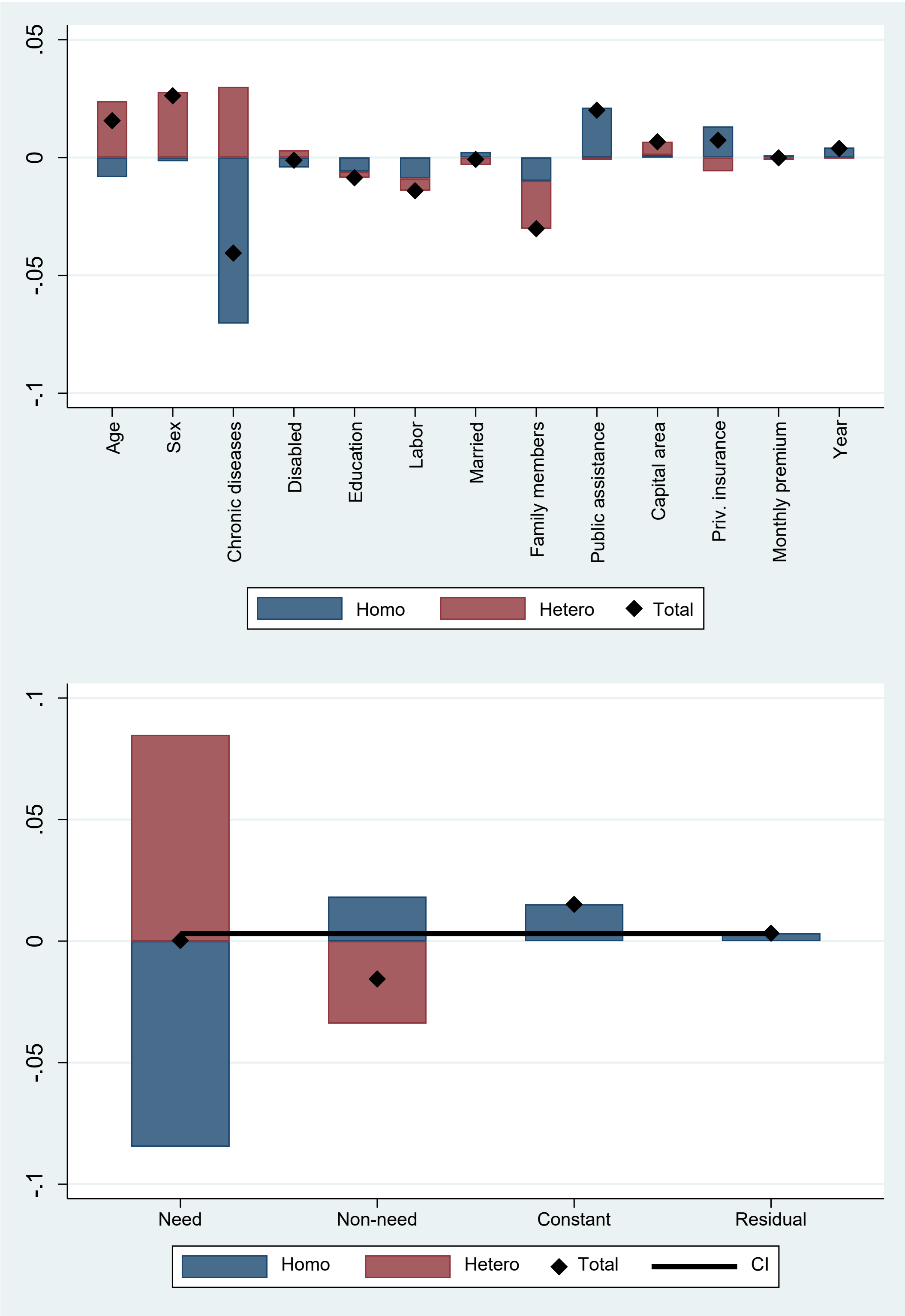


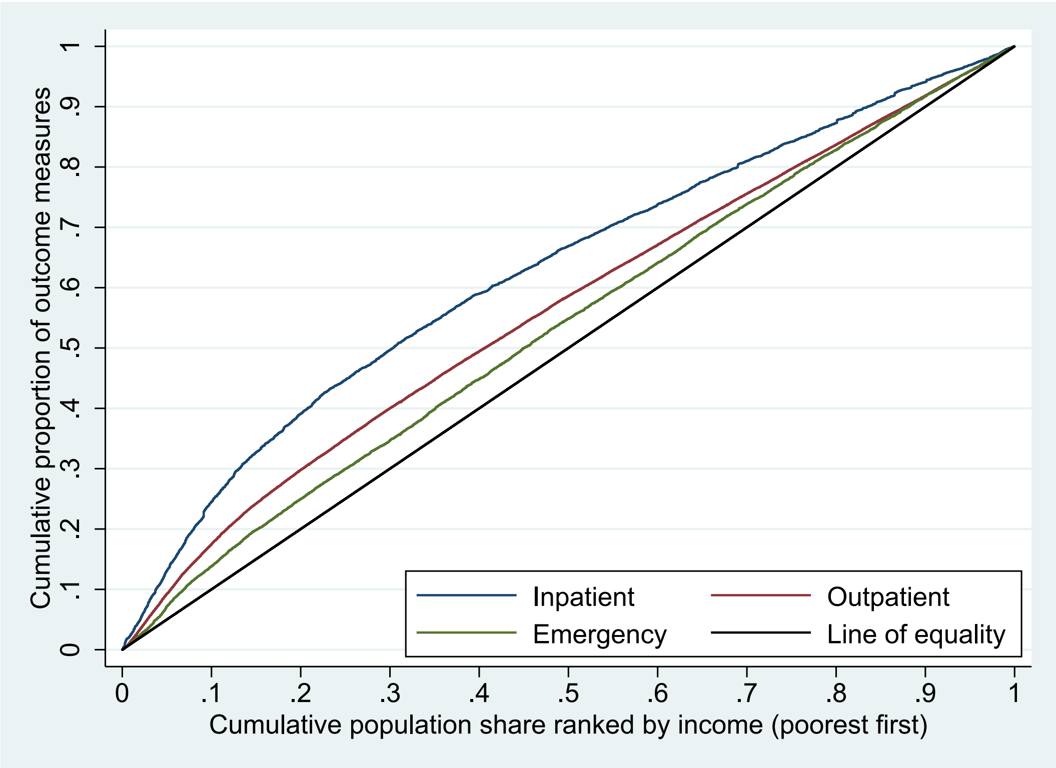
Figure 2.18

Decomposition results for total amount of medical spending



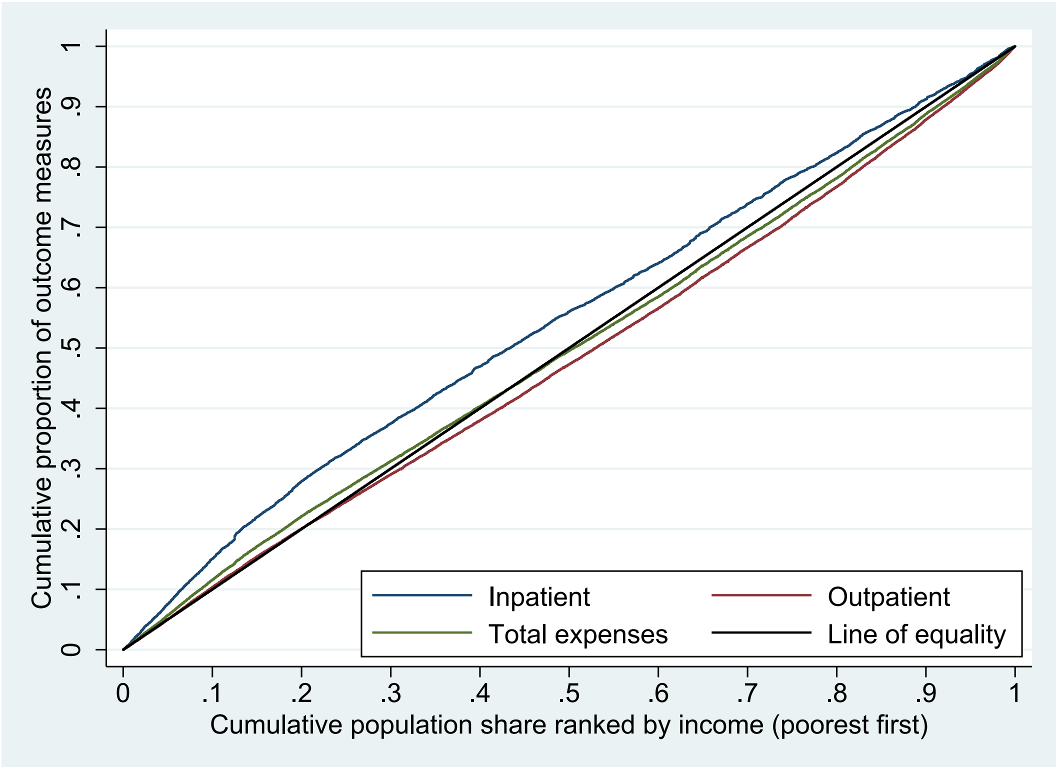
Appendix Figure A.2.1

Concentration curves for health care utilization



Appendix Figure A.2.2

Concentration curves for health care spending



Appendix Table A.2.1 Decomposition results for health care utilization

	Inpatient care						Outpatient care						Emergency care					
	Homo	(%)	Hetero	(%)	Total	(%)	Homo	(%)	Hetero	(%)	Total	(%)	Homo	(%)	Hetero	(%)	Total	(%)
Need																		
Age	-0.064	25.38	0.218	-85.74	0.153	-60.36	0.007	-5.27	-0.025	19.13	-0.018	13.86	0.028	-39.46	-0.028	38.77	0.001	-0.69
Female	0.003	-1.37	0.109	-42.82	0.112	-44.19	-0.002	1.55	0.009	-6.99	0.007	-5.43	0.002	-3.27	0.043	-60.32	0.046	-63.59
Chronic diseases	-0.065	25.62	-0.082	32.16	-0.147	57.78	-0.081	62.82	-0.027	21.13	-0.108	83.94	-0.050	69.93	-0.027	37.69	-0.078	107.61
Disabled	-0.043	16.94	-0.004	1.47	-0.047	18.41	-0.004	3.22	0.001	-0.75	-0.003	2.47	-0.008	10.48	0.002	-2.76	-0.006	7.72
Total need	-0.169	66.57	0.241	-94.93	0.072	-28.36	-0.080	62.33	-0.042	32.52	-0.122	94.85	-0.027	37.67	-0.010	13.37	-0.037	51.04
Non-need																		
Lower education	-0.019	7.16	0.026	-9.74	0.007	-2.58	-0.034	28.23	0.002	-1.63	-0.032	26.59	-0.029	34.61	0.021	-25.74	-0.007	8.87
Higher education	0.005	-1.88	0.009	-3.55	0.015	-5.43	-0.002	1.91	-0.004	3.72	-0.007	5.63	-0.002	2.55	0.003	-3.27	0.001	-0.73
Labor participation	-0.033	12.83	0.046	-18.07	0.013	-5.24	-0.005	4.25	-0.003	2.19	-0.008	6.44	-0.008	10.43	0.019	-26.23	0.011	-15.80
Married	-0.004	1.42	-0.080	31.49	-0.084	32.91	0.002	-1.68	0.015	-11.69	0.017	-13.37	0.002	-3.27	0.001	-1.54	0.003	-4.81
Family members	0.002	-0.69	-0.015	5.94	-0.013	5.25	-0.009	7.06	0.007	-5.38	-0.002	1.68	-0.010	14.06	-0.052	71.56	-0.062	85.62
Capital area	-0.010	3.96	0.031	-12.27	0.021	-8.30	-0.002	1.18	0.014	-10.74	0.012	-9.56	-0.005	6.33	0.007	-10.04	0.003	-3.71
Public assistance	-0.042	16.36	0.009	-3.40	-0.033	12.96	-0.006	4.93	-0.001	0.70	-0.007	5.64	-0.018	24.37	-0.002	2.54	-0.019	26.90
Num. of priv. health ins.	0.005	-2.08	0.012	-4.59	0.017	-6.68	0.002	-1.72	-0.005	4.22	-0.003	2.51	0.002	-2.44	0.002	-2.12	0.003	-4.56
Monthly premium	0.009	-3.39	-0.023	8.94	-0.014	5.55	0.0004	-0.32	0.002	-1.40	0.002	-1.72	0.007	-9.26	-0.009	12.98	-0.003	3.72
Years	-0.007	2.75	0.025	-9.95	0.018	-7.20	0.007	-5.17	0.007	-5.15	0.013	-10.32	0.006	-8.74	0.014	-18.82	0.020	-27.56
Total non-need	-0.093	36.72	0.040	-15.89	-0.053	20.82	-0.047	36.72	0.032	-25.28	-0.015	11.45	-0.054	74.51	0.004	-5.26	-0.050	69.26
Constant	-0.271	106.76			-0.271	106.76	0.008	-6.06			0.008	-6.06	0.013	-18.27			0.013	-18.27
Residual	-0.002	0.78			-0.002	0.78	0.0003	-0.23			0.0003	-0.23	0.001	-2.03			0.001	-2.03
Total CI					-0.254	100.00					-0.129	100.00					-0.072	100.00

Note: Percentages (%) refer to each factor's share of total CI.

Appendix Table A.2.2 Decomposition results for health care spending

	Inpatient care						Outpatient care						Total medical care					
	Homo	(%)	Hetero	(%)	Total	(%)	Homo	(%)	Hetero	(%)	Total	(%)	Homo	(%)	Hetero	(%)	Total	(%)
Need																		
Age	-0.031	34.50	0.053	-58.59	0.022	-24.09	-0.0005	-1.26	0.012	34.06	0.012	32.80	-0.008	-268.08	0.024	776.95	0.016	508.86
Female	0.001	-0.76	0.044	-48.38	0.045	-49.14	-0.002	-6.72	0.021	58.94	0.019	52.22	-0.002	-51.79	0.028	904.79	0.026	853.01
Chronic diseases	-0.075	82.12	0.011	-11.87	-0.064	70.24	-0.070	-190.94	0.039	107.46	-0.030	-83.47	-0.071	-2290.95	0.030	974.15	-0.041	-1316.81
Disabled	-0.017	18.43	0.011	-12.34	-0.006	6.09	0.0002	0.62	0.0003	0.81	0.001	1.43	-0.004	-137.96	0.003	100.91	-0.001	-37.05
Total need	-0.122	134.28	0.119	-131.18	-0.003	3.10	-0.072	-198.30	0.073	201.27	0.001	2.98	-0.085	-2748.78	0.085	2756.80	0.0002	8.02
Non-need																		
Lower education	-0.003	2.95	0.001	-0.67	-0.002	2.28	-0.005	-8.57	-0.004	-7.78	-0.009	-16.35	-0.004	-23.26	-0.003	-19.34	-0.007	-42.60
Higher education	0.004	-4.08	-0.004	4.15	-0.0001	0.07	-0.004	-6.91	0.003	5.32	-0.001	-1.59	-0.002	-11.21	0.001	3.93	-0.001	-7.28
Labor participation	-0.021	23.36	0.023	-25.27	0.002	-1.91	-0.004	-11.78	-0.013	-35.79	-0.017	-47.57	-0.009	-290.58	-0.005	-166.86	-0.014	-457.44
Married	0.001	-1.00	-0.039	42.40	-0.038	41.40	0.003	7.77	0.008	20.71	0.010	28.48	0.002	76.74	-0.003	-101.80	-0.001	-25.06
Family members	-0.007	7.89	-0.034	37.90	-0.042	45.79	-0.010	-28.77	-0.008	-20.61	-0.018	-49.37	-0.010	-320.03	-0.020	-660.80	-0.030	-980.83
Capital area	-0.005	5.32	0.005	-5.47	0.0001	-0.15	0.003	9.14	0.008	20.87	0.011	30.00	0.001	36.41	0.006	182.31	0.007	218.72
Public assistance	0.020	-21.82	-0.003	2.88	0.017	-18.94	0.022	59.69	-0.001	-1.72	0.021	57.97	0.021	688.47	-0.001	-34.99	0.020	653.48
Num. of priv. health ins.	0.016	-17.11	0.005	-5.00	0.020	-22.12	0.013	35.00	-0.008	-21.69	0.005	13.31	0.013	430.36	-0.006	-190.51	0.007	239.84
Monthly premium	0.006	-6.97	-0.004	4.05	0.003	-2.92	-0.001	-2.50	-0.0003	-0.80	-0.001	-3.30	0.001	29.95	-0.001	-33.54	-0.0001	-3.59
Years	0.0005	-0.54	0.002	-1.91	0.002	-2.45	0.005	14.76	-0.003	-8.70	0.002	6.05	0.004	136.19	-0.0003	-9.16	0.004	127.03
Total non-need	0.011	-12.02	-0.048	53.11	-0.037	41.09	0.022	60.46	-0.019	-51.35	0.003	9.11	0.018	595.37	-0.034	-1101.29	-0.016	-505.92
Constant	-0.050	54.85			-0.050	54.85	0.027	74.83			0.027	74.83	0.015	492.01			0.015	492.01
Residual	-0.001	0.96			-0.001	0.96	0.005	13.09			0.005	13.09	0.003	105.89			0.003	105.89
Total CI					-0.091	100.00					0.036	100.00					0.003	100.00

Note: Percentages (%) refer to each factor's share of total CI.

Chapter 3

How heterogeneous are the effects of health checkups on health care?*

3.1 Introduction

There exists a growing concern on a global scale, spanning both developed and developing countries, regarding the prevention and control of non-communicable diseases (NCDs), such as cardiovascular diseases, cancers, chronic respiratory diseases and diabetes. This mounting apprehension stems from the escalating incidence of individuals afflicted with NCDs across the world in the recent decades. According to the World Health Organization (WHO), a substantial majority, exceeding 60%, of global mortality was attributed to NCDs by the mid-2000s. Projections indicated a persistent rise in the prevalence and mortality rates of NCDs throughout the 2010s due to population aging and modifiable behavioral risk factors, including tobacco consumption, unhealthy diet, physical inactivity and excessive alcohol intake (WHO, 2005).[1] Premature deaths arising from NCDs before reaching the age of 70 years have become pervasive, encompassing over 80% of such occurrences prevalent in low- and middle-income countries (WHO, 2022). The overarching economic burden of NCDs on a global scale has been estimated at around USD 30 trillion in cumulative foregone output over the period of 2011-2030, with nearly USD 47 trillion including mental illness. The annual average of such an output loss corresponds to approximately 5% of global gross domestic product (GDP) in the year 2010 (Bloom et al., 2011).

Japan, a high-income nation experiencing rapid population aging, is no exception wherein lifestyle-related NCDs have a significant impact on public health. According to the Vital Statistics and Estimates of National Medical Care Expenditure for the fiscal year (FY)[2] 2019, complied by the Ministry of Health, Labour and Welfare (MHLW), lifestyle-related diseases were responsible

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* This chapter is based on the unpublished manuscript coauthored by Yuichi Watanabe and Haruko Noguchi. Ethical approval from an institutional review board was not required. The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this study. The authors also declare that they have no relevant or material financial interests that relate to the research described in this chapter.

[1] By the early 2020s, NCDs accounted for 74% of all deaths worldwide (WHO, 2022).

[2] Japan's fiscal year runs from April 1 to March 31 of the following year.

for 53% of deaths in Japan. Furthermore, these ailments accounted for about 37% and 32% of national medical expenditures for inpatient and outpatient care, respectively. Japan has notably upheld a better health profile within its population under universal health insurance coverage. This has been achieved through regular health checkups provided by schools, workplaces and local governments, as well as people's attention to hygiene in their daily lives and well-balanced dietary intake (Ikeda et al., 2011). However, to prevent the prevalence of metabolic syndrome, a precursor to NCDs, and to control the rising healthcare costs, the Japanese government initiated a novel annual health checkup initiative targeting individuals aged 40-74 years in April 2008. This program, known as the Specific Health Checkups (SHC) and Specific Health Guidance (SHG), represented standardized protocols across local health providers functioning as public health insurers. This chapter investigates the causal relationship between participation in these health checkups and health care, delving into specifics of this Japanese healthcare system.

Preventive measures such as health checkups and screening tests are expected to motivate individuals to modify their health consciousness or behaviors and enhance their overall health by imparting knowledge about their health status and potential health risks to them. In the context of the health production function, prevention is generally considered as an investment decision aimed at augmenting or preserving the stock of individual health capital. This, in turn, serves to promote their well-being or utility (Kenkel, 2000; Hall, 2011). Kenkel (2000) underscored the importance of policy interventions from a social perspective to rectify market failures that could result in inadequate prevention due to insufficient consumer awareness, alongside the presence of externalities and moral hazards of health insurance. Nevertheless, an individual's response to health care varies depending on the information acquired through health checkups or screening programs. Favorable outcomes, accompanied by the absence of health warnings, may instill into people self-confidence regarding their health, potentially leading to reduced utilization of health care services. Conversely, adverse findings and the detection of health risks may provoke anxiety, resulting in an increase in their use of health care services (Hall, 2011).

While a multitude of previous studies have delved into the effectiveness of preventive interventions on health care and health outcomes, it is noteworthy that the empirical results have yet to yield a consensus. For example, Hackl et al. (2015) found that engaging in screening program in Austria led to an immediate increase in both inpatient and outpatient care costs.

However, they observed no long-run effects on health care costs or discernible effects on overall health status. Jones et al. (2019) provided no causal effects of workplace wellness programs in the U.S. on medical expenditures, health behaviors, or self-reported health status, despite higher lifetime health screening rates. In the context of direct exposure to risk information or signals from the national health screening and checkups, limited causal impacts were noted on increased outpatient care utilization and marginal improvement in health outcomes for higher-risk individuals in Korea (Kim et al., 2019) and Japan (Iizuka et al., 2021). Several studies have focused on the effects of the SHC policy reform in Japan. Inui et al. (2017) found that it had negligible impacts on individual health status, behavior, and medical expenses. Conversely, Kang et al. (2021) demonstrated that participation in the SHC was associated with healthier lifestyle choices and longer working hours among people with lifestyle-related diseases. Likewise, Oikawa (2023) highlighted a significant improvement in health behaviors and outcomes among university graduates at higher risk of metabolic syndrome, following the policy reform. Moreover, the expansion of the administrative per capita expense regarding the SHC program leads to decrease in outpatient visits, hospital admissions, and medical expenditures at the municipality level (Oikawa et al., 2023). On the other hand, Suzuki et al. (2015) studied the specific impact of the SHG intervention for individuals who had undergone the SHC, finding modest effects on the subsequent checkup results, specifically in abdominal circumference and body mass index (BMI) measurements. Fukuma et al. (2020) also showed a decrease in obesity status only in the short run, with no discernible change in cardiovascular risk factors attributed to the causal effects of the SHG intervention for Japanese men.

By utilizing distinctive longitudinal administrative data at the individual enrollee level for the periods between FY 2011 and FY 2016, graciously provided by a local municipality identified as 'city X' in Japan,[3] this chapter aims to examine the causal impacts of taking the SHC on their health care expenditures and utilization for inpatient and outpatient care services. Our approach significantly deviates from prior studies in several aspects. Firstly, we encompass the entire population of the insured under the national health insurance program in the municipality, including those who did not participate or never participated in the SHC. This contrasts with the

[3] Anonymity of the provided data has been strictly maintained by de-identification. Thus, we did not need to obtain ethical approval from an institutional review board in this study.

literatures (Suzuki et al., 2015; Kim et al., 2019; Fukuma et al., 2020; Iizuka et al., 2021), as they typically confined their analysis to individuals who had participated in health checkups or screening programs. Secondly, we employ an instrumental variable (IV) estimation as an identification strategy, which distinguishes our study from others that used various methodologies such as regression discontinuity design (Inui et al., 2017), randomized controlled trial (Jones et al., 2019), propensity score matching (Kang et al., 2021) and difference-in-differences analysis (Oikawa, 2023; Oikawa et al., 2023). Our IV estimation mitigates concerns related to sample selection bias and attrition problems stemming from characteristics of the dataset. Our study aligns most closely with Hackl et al. (2015), who also adopted an IV estimation. They utilized exogenous variation in screening participation due to supplier-determined demand, assuming that an individual's decision to partake in the screening program is primarily influenced by his/her general practitioner's recommendation, thus identifying the causal impact of screening participation. However, our Japanese sample, characterized by a high degree of freedom in the SHC participation, necessitates a distinct approach. We rely on regional variation in peer effects as a determinant in the individual's decision to account for the issue of self-selection into treatment.

The remainder of the chapter is structured as follows: Section 3.2 provides an overview of the historical context of health checkup programs in Japan as an institutional background. Section 3.3 describes the dataset used in this study and presents summary statistics. Section 3.4 outlines our empirical strategies to address the endogeneity concerns about the SHC participation. Section 3.5 presents the estimation results for the main analysis using the entire sample and also reports the results of the subsample stratification analysis. Finally, Section 3.6 discusses the implications and limitations of this study.

3.2 Institutional background

In 1972, Japan launched the routine health checkup programs primarily for individuals in middle-age and older as a part of the health management and promotion policy.[4] The inception

[4] The Japanese health checkup system prior to the policy reform in 2008 is thoroughly elaborated upon in Oikawa et al. (2023) which are based on the following web site:

of these programs initially focused on salaried workers in companies with a workforce exceeding 50 employees. Subsequently, the coverage extended to incorporate employees in smaller-sized firms and organizations. By law, all employers are mandated to conduct annual health checkups for their employees. In contrast, health checkups for other types of workers, such as the self-employed, part-time workers, the unemployed and retirees, have been facilitated by local governments through national health insurance system since the 1980s. Insured residents in municipalities have the option to undergo health checkups on a voluntary basis, given that local governments are legally obliged to exert their best efforts to implement these programs. Consequently, a noticeable disparity in participation rates of health checkups emerged between salaried workers provided by their employers and the self-employed who were covered by local governments: the former consistently exhibited substantially higher participation rates than the latter (Oikawa, 2023).

Despite the extensive history of the regular health checkups in Japan, there has been a notable increase in the number of individuals diagnosed with metabolic syndrome, such as visceral fat obesity and diabetes, often categorized as lifestyle-related diseases. This surge has been accompanied by a corresponding rise in medical expenditures related to these conditions. In an effort to counteract the prevalence of metabolic syndrome and mitigate the relevant healthcare costs, the Japanese government newly initiated an annual health checkup system in 2008 for all beneficiaries aged 40-74 years. This program, known as the SHC and SHG, was introduced as a uniform nationwide initiative, irrespective of the type of public health insurance an individual holds. The SHC and SHG were designed to screen for individuals who had exhibited a high risk of developing lifestyle-related diseases, as opposed to the prior health checkups that predominantly focused on those already in the early stages of these diseases (Oikawa et al., 2023). The SHC consists of a comprehensive examination, including measurements of parameters such as BMI, abdominal circumference, blood pressure and more. Additionally, it integrates blood and urine tests to analyze various markers such as blood lipids, blood sugar, liver function, urinal constituents like sugar and proteins. Furthermore, lifestyle habits and medication histories are recorded through questionnaires. Based on the results of the SHC, the participants are determined

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https://www.mhlw.go.jp/shingi/2005/07/s0725-7b01.html.

whether they have metabolic syndrome or are at the high risk for developing it.[5]

Following the SHC, the SHG is extended to the participants who demonstrate multiple risk factors associated with metabolic syndrome (i.e., surpassing the established thresholds of blood sugar, blood lipids and blood pressure). These risk factors are accompanied by abdominal obesity or overweight as determined by BMI.[6] The SHG is composed of two distinct types of health guidance tailored to the individual's risk profile; one-off motivative support and continuous active support provided over a duration of six months. Both types of health guidance involve the engagement of health care professionals, including doctors and public health nurses. Their role is to motivate those at the high risk to instigate lifestyle modifications and improve their health status. This support commences immediately following the SHC and ends up to the final evaluation after the six-months support period.[7] It is essential to note that most of the administrative and operational costs associated with the SHC and SHG are borne by local governments or employers providing these programs. Consequently, participants generally incur minimal to no out-of-pocket expenses for their involvement.[8]

3.3 Data

3.3.1 Description of data

This study uses compiled administrative data from the national health insurance in city X, which has a population of approximately 35 thousand people during the study period. Our dataset initially contains medical care claims records for each enrollee, documented on a monthly basis. These records represent all expenditures related to medical treatment, examination, medication

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[5] A summary of the SHC program is available at https://www.mhlw.go.jp/english/wp/wp-hw3/dl/2-007.pdf.
[6] Individuals currently undergoing treatments for diabetes, hypertension or dyslipidemia are exempt from participating in the SHG.
[7] A summary of the SHG program is also available at https://www.mhlw.go.jp/english/wp/wp-hw3/dl/2-007.pdf.
[8] The central government has provided monetary support to public health insurers since 2013 to incentivize better health outcomes among their enrollees. This financial support is tied to the implementation results of the SHC and SHG. The amount of financial aid allocated for the medical care system for the elderly, which public health insurers are obliged to pay in a lump sum, varies according to the results achieved through the SHC and SHG. These results encompass the participation rates, the percentage of the participants identified with metabolic syndrome, and the rates of improvement observed through the SHG (Oikawa et al., 2023).

and other relevant health care expenses,[9] including out-of-pocket expenses incurred by the insured.[10] For the purpose of our analysis, we aggregate the monthly data over a span of 12 months for each individual, thereby creating a yearly medical claims dataset. Then, we integrate this dataset using a unique individual identifier with the master data for each year. The master data includes fundamental information on citizens' demographics, such as date of birth, gender and the periods of enrollment and withdrawal from the national health insurance. This integration enables us to distinguish between enrollees who are eligible to undergo the SHC and non-enrollees in each FY, allowing us to construct yearly longitudinal data at the individual enrollee level.

The panel dataset is further linked using the same unique individual identifier to the annual SHC data, individual income records from the preceding calendar year, and the roster of citizens' addresses. The SHC data pertain solely to individuals who undergo the health checkups in each FY and include various information, including results from physical examination and blood/urine tests, lifestyle habits, and medication histories.[11] The income data originate from income tax records and are collected separately from those of national health insurance such as medical claims bill and SHC records. These income records contain annually aggregated pre-tax income, inclusive of salary, pension and business revenue for each individual. Additionally, they include a unique household identifier for each year, facilitating the calculation of total household income by summing the income and pension of each member within the household. Moreover, we obtain information on residential addresses of the insured in FY 2015.[12] This data allows for the construction of a regional indicator that proves instrumental in addressing the endogeneity issue

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[9] The fee schedule codes in medical claims bill are classified into various categories such as medical care (e.g., treatment and examination), dentistry, medication, bone-setting, and home care. However, it is important to note that long-term care expenses are not covered within these codes. This study takes up the expenses for medical care and medication regarding metabolic syndrome.

[10] In Japan, patients' cost-sharing for health care services varies based on their age. For instance, the copayment rate for children before the commencement of compulsory education (around 6-year-old) is set at 20% of the total medical care expenses. For individuals up to the age of 69 years, the copayment rate is 30%. Those in the age bracket of 70-74 years have a copayment rate of 20% (10% before April 2014), and the elderly aged 75 years or older have a copayment rate of 10%. However, those over 70-year-old with income comparable to current workforce have a copayment rate of 30% (https://www.mhlw.go.jp/bunya/iryouhoken/iryouhoken01/dl/01_eng.pdf).

[11] It is worth noting that this study relies on information regarding participation histories among the insured and does not utilize the results of the SHC.

[12] Given that residential information from the address book is available for only a single year, for the purpose of this study, we assume that citizens do not change their residence within the municipality during the entire study period.

related to the participation in the SHC, a concern elaborated upon in detail in Section 3.4.

The compiled dataset covers six FYs from 2011 to 2016 and contains a comprehensive sample of 42,310 person-years who are enrolled in the national health insurance throughout each FY. However, some individual observations are excluded from our analysis based on the predefined criteria. Firstly, individuals lacking income and pension records, as well as household identifiers, are excluded due to the inability to calculate their household income. Secondly, individuals who are not listed in the address book or reside outside of city X are also excluded. Thirdly, singleton individuals with only one observation during the study period are dropped out due to the empirical strategies described in Section 3.4. Following these exclusion criteria, a final sample of 37,984 person-years is obtained, representing 8,387 unique individuals for the entire study period, forming an unbalanced panel.

Although our data set shares similarities with those utilized by Ibuka et al. (2016) and Imahori et al. (2019), it incorporates additional crucial information such as the annual SHC data and the address book specific to city X. It is important to note that even the entire sample of the insured individuals under the national health insurance within a single municipality does not fully represent the entire Japanese population. As highlighted by Ibuka et al. (2016), city X exhibits an overrepresentation of the elderly, and the insured population predominantly consists of individuals aged over 40, a trend explored further in this chapter. Furthermore, national health insurance generally covers the self-employed, part-time workers, the unemployed, retirees, and their dependents, as opposed to salaried workers and employees in corporations. However, our dataset remains free from sample selection bias and attrition issues, capturing the entire sample who are eligible for the national health insurance.

3.3.2 Outcome measures and covariates

In this study, the health-related outcome measures of primary interest are health care expenditures and utilization for both inpatient and outpatient care services within a FY. Health care expenses consist of annual medical care fees and drug dispensation fees, expressed in one thousand units, convertible to monetary values through the ratio of 1,000 units equating to 10,000 Japanese yen (i.e., approximately USD 100 during our study period). Health care use represents the duration of hospitalization for inpatient care and frequency of consultations with physicians for outpatient care. These metrics are computed as an aggregate of medical service utilization in each claims bill episode within a FY. Specifically, we restrict the scope of these outcomes to those attributable to lifestyle-related diseases and metabolic syndrome, notably diabetes, hypertension, dyslipidemia, ischemic heart disease (e.g., angina pectoris and myocardial infarction), cerebrovascular accident (stroke) and hyperuricemia.

Covariates, in this context, encompass demographic and socio-economic characteristics, comprising individual's age, gender, household size, whether he/she is a household head, cumulative number of the SHC participation since FY 2008, and the level of annual household income per equivalent member from the preceding calendar year. The cumulative number of the previous SHC participation represents the difference in individual health consciousness and risk detections. The equivalent household income is calculated as total household income, inclusive of public pension and business revenue, divided by the square root of household size. The resulting equivalized income is then categorized into quartile groups for positive income and organized into two distinct groups for zero and negative income, respectively,[13] for each year. Subsequently, these income groups are transformed into binary variables, with a zero-income group serving as the reference category.

3.3.3 Summary statistics

Figure 3.1 shows the age distribution of the insured in city X, discerning the male and female cohorts during the study period. Notably, we find a conspicuous demographic pattern skewed toward an aging population within the ambit of the national health insurance system. A significant majority, surpassing 50% of the male cohort and 60% of the female cohort, exceeds the age threshold of 60 years. Furthermore, a predominant segment of enrollees, constituting approximately 80% of the insured, falls within the age bracket of 40 to 74 years, representing the targeted demographic for the SHC and SHG initiatives. Figure 3.2 shows the progression of participation rates of the SHC within city X from FY 2008 to FY 2019, stratified by distinct age

[13] Annual pre-tax income is calculated by subtracting gross expenses/costs or various tax deduction from gross earnings including pension income and business revenue for each year in a final income tax return. Negative or zero income occurs when gross expenses/costs, inclusive of tax deduction, are greater than or equal to gross earnings. Therefore, zero-income and negative-income groups do not necessarily represent the poor people.

groups. The engagement rate among the age cohort under 65 has exhibited a consistent upward trajectory since 2011, owing to a sharp decline in the population targeted by these programs. Consequently, this participation rate has surpassed the national average in recent years. Nevertheless, the involvement rate within the age cohort over 65 also has shown an increasing trend but has consistently lagged behind the national average. It is noteworthy to emphasize that overall participation rate within city X has remained below the national average, albeit exceeding the average within its respective prefecture.

Table 3.1 provides an overview of summary statistics pertaining to outcome measures and covariates throughout the entire study period. The mean annual health care expenditures for inpatient and outpatient care services stand at 116.8 and 85.8 thousand Japanese yen, respectively. The average duration of hospitalization for inpatient care is 4.4 days, while the frequency of physician visits for outpatient care amounts to 8.6 times annually on average. In terms of demographics, the mean age hovers 64 years for individuals eligible for the SHC, and the average household size is 2 individuals. Approximately 45% and 60% of the sample comprise males and household heads, respectively. The equivalized annual income averages about 2.36 million Japanese yen, including households with zero and negative income. Notably, 30% of the individual sample received the SHC during the study period, and the number of the previous SHC participation since FY 2008 is merely 0.85 times on average.

Next, Tables 3.2 and 3.3 present the mean values alongside their respective standard deviations for outcome measures and covariates categorized by participation in the SHC. Individuals engaging in the SHC manifest notably lower health care expenditures for both inpatient and outpatient care services, as well as shorter length of hospital stay, with statistically significant differences. Conversely, the statistically significant disparity is not observed in terms of the frequency of physician visits among the entire sample as well as within the age cohort over 65. Additionally, participants in the SHC tend to be older and earn higher annual income, along with larger family sizes. However, they are comparatively less likely to hold the position of household heads, on average.

3.4 Empirical strategies

With the aim of estimating the impacts of participating in the SHC on health care expenses and utilization, we employ the subsequent linear probability model with fixed-effects:

$$Y_{it} = \boldsymbol{X}'_{it}\boldsymbol{\beta} + H_{it}\delta + \alpha_i + \pi_b + \tau_p + \gamma_t + u_{it}, \tag{1}$$

where Y_{it} represents health care outcomes for both inpatient and outpatient care services for individual i in FY t. $\boldsymbol{X}_{it}$ signifies the vector of time-varying covariates encompassing demographic and socio-economic characteristics, inclusive of a dummy variable distinguishing copayment rates by age.[14] H_{it} denotes a binary variable capturing whether individual i participated in the SHC during period t. We also incorporate several fixed-effects; individual fixed-effects (α_i), fixed-effects at the block number level for local communities (π_b),[15] fixed-effects corresponding to residential postal code area (τ_p),[16] and FY fixed-effects (γ_t). Finally, u_{it} stands for the random error term. δ is the parameter of primary interest, indicating the impacts of the SHC participation on the health care outcomes while controlling for enrollees' observable characteristics and unobserved time-invariant heterogeneity.

Indeed, as previously discussed, the straightforward estimation outlined earlier faces the endogeneity issue with regards to participation in the SHC. In this scenario, it is presumed that the individual decision-making process concerning the SHC participation, denoted as H_{it}, is correlated with time-varying unobservable factors that are absorbed in the error term u_{it}. Particularly, if individuals with higher health consciousness (higher health risks and less preventive behavior) are more inclined to participate in the health checkups, ordinary least squares (OLS) estimates would lead to a selection bias, potentially overestimation (underestimation) regarding the effects of the SHC participation (Hackl et al., 2015). To address this endogeneity concern, we propose an IV estimation defined as the following first-stage equation:

$$H_{it} = \boldsymbol{X}'_{it}\boldsymbol{\varphi} + Z_{jt}\theta + \alpha_i + \pi_b + \tau_p + \gamma_t + \varepsilon_{it}, \tag{2}$$

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[14] We delineate a binary variable for the copayment rate, assuming a value of 1 for individuals aged 70-74 years, and a value of 0 for all others, effectively distinguishing between the copayment rates of 20% (or 10% before FY 2014) and 30%.

[15] We undertake the creation of 924 discrete local communities, delineated at the granularity of block numbers, aligning with the residential address information of each citizen within city X.

[16] City X is demarcated by 51 distinct postal code areas.

where Z_{jt} is the instrumental variable indicating local participation rates in the SHC within block number j ($j = 1, \dots, 924$) at time t. The computation of these region-specific participation rates involves summing the total SHC participants in block number j during period t, subtracting one (representing individual i) only if he/she received it, divided by the total number of the insured individuals in block number j during period t minus one (excluding individual i). Notably, approximately half (90%) of the sample live in blocks where the annual population size is less than or equal to 10 (less than 50),[17] with the maximum population size within a single block during a FY being 109. The fundamental premise underpinning this IV approach is the notion that individual's local surroundings, specifically the participation rates within a small community, could influence his/her decision-making and behavior due to the close-knit social relationships or peer effects. For example, if a higher number of nearby friends or acquaintances participate in the SHC, the individual is more likely to participate as well, and vice versa. Consequently, we assume that regional variation in the SHC participation is strongly and positively correlated with an individual's decision to participate: the parameter θ is expected to be positive and statistically significant. Moreover, we reasonably assume that local participation rates are exogenous and affect the individual's health care outcomes solely through the channel of his/her participation behavior.

In extending our analysis beyond the current period t, we consider the outcome measures in the subsequent FY ($t + 1$) to estimate the effects of the SHC participation on health care expenses and utilization in the next time period. Furthermore, considering the zero-inflated distributional characteristics of our health care outcomes, we augment our analysis by conducting separate regressions for the sample with positive outcomes. This facilitates a more nuanced analysis, distinguishing between individuals with zero and non-zero outcomes. To ensure the robustness of our primary analysis using the entire sample, we also conduct the age cohort, gender and income group stratification analysis, allowing for a deeper investigation into the heterogenous impacts of

[17] In instances where a block has an annual population size of only one individual, we implement a strategy of merging these blocks with neighboring ones. By consolidating these sparsely populated blocks with adjacent ones, we create larger local communities comprising more than 2 people. This consolidation enables the computation of local participation rates in the SHC for these merged communities, ensuring a meaningful assessment of the SHC participation even in cases of quite small initial populations.

the SHC participation with specific age cohorts or gender and income categories.

3.5 Estimation results

In our initial analysis including the entire sample, as presented in Tables 3.4 and 3.5, the OLS estimates show a statistically significant association between participating in the SFC and reduced health care expenses and utilization, primarily within the same FY. However, this association is not statistically significant for outpatient care use.

Contrastingly, the IV estimation demonstrates the results where the SHC participation does not necessarily exhibit significant effects on health care expenditures and utilization in either the same or the subsequent FY, except for inpatient care use in the following FY at the 10% level of statistical significance (i.e., reduced hospital stay by approximately 9 days per year). This suggests that the SHC might play a partial role in preventing participants from suffering from the severe conditions due to metabolic syndrome that would bring about hospital admission. Our selected IV, local participation rates in the SHC, is positively and significantly correlated with the endogenous SHC participation in the first-stage estimation. The coefficients of the instrument are estimated to be approximately 0.13, implying that one unit increase in the local participation rate increases the individual's probability of receiving the SHC by 13% on average. Furthermore, it proves to be a sufficiently strong instrument, as evaluated by the Cragg-Donald Wald F statistic that rejects the null hypothesis of weak instruments (except for the subsample regressions related to positive outcomes for inpatient care services). Given the validity of our IV estimation, it is important to emphasize that the observed negative correlation between the SHC participation and health care expenses or inpatient care use does not necessarily imply a causal relationship. Further investigation and careful interpretation are essential to draw conclusive causal inferences.

Tables 3.6–3.9 report the estimation results for the age cohort stratification analysis. For individuals aged between 40 and 64, the observed positive correlation between receiving the SHC and outpatient care services in the same FY, based on the OLS estimates, does not establish a causal relationship, regardless of employing the valid IV estimation. Nevertheless, we find a reduction in inpatient care utilization even at the 10% level of statistical significance by approximately 16 days of hospital stay in the subsequent FY without a change in the associated spending. A distinct pattern emerges for individuals aged between 65 and 74, while the OLS estimates align with the pattern observed in the analysis of the entire sample. The IV estimation demonstrates at the 10% level of statistical significance that the SHC participation is associated with increased annual expenses for physician visits in the subsequent FY (equivalent to 184 thousand Japanese yen or around 1,840 USD) without a change in the frequency. These findings suggest that participation in the SHC appears to mitigate the severity of lifestyle-related diseases among younger enrollees under the age of 65 years, reducing their need for hospitalization in the year following the SHC. On the other hand, it might lead to higher spending on outpatient care services due to risk detections related to these conditions among the elderly over 65 years of age.

Tables 3.10–3.13 present the estimation results for the gender stratification analysis. For males, the initially observed negative correlation between the SHC participation and inpatient care services in the same FY, based on the OLS estimation, manifests as a positive causal relationship for inpatient care expenses at the 10% level of significance when estimated through the IV approach. This suggests that participating in the SHC is likely to lead to an increase in annual hospital admission costs by 315 thousand Japanese yen (equivalent to 3,150 USD) in the same year. This finding implies that males with detected lifestyle-related diseases through the SHC may be provided with intensive inpatient care services soon after without prior outpatient care consultation. On the other hand, our IV estimates for females show the significantly reduced inpatient care use following the SHC, both in the same and the subsequent FYs, without a change in the associated spending. This reduction translates to shorter length of hospital stay by approximately 17 days per year. This finding suggests that the SHC participation plays a vital role in preventing females from experiencing severe impacts of metabolic syndrome that might necessitate hospital admission. However, it does not appear to have any causal impacts on inpatient care expenditures and overall outpatient care services.

Finally, Tables 3.14–3.17 report the estimation results for the income group stratification analysis. We consider two distinct income groups: populations below and over 50% of the median income (poverty threshold) in the income distribution for each year that excludes individuals with negative income.[18] Our IV estimation for both income groups demonstrates no significant effects

[18] The poverty line ranges from 1,069,105 Japanese yen to 1,151,318 Japanese yen for each year during our study period.

of the SHC participation on health care expenditures and utilization in either the same or the subsequent FY, given the sufficiently strong instruments. This implies that there exist no heterogeneous effects on health care regardless of income level under the national health insurance.

3.6. Discussion

This chapter unravels the causal impacts of participating in the SHC on health care expenses and use, both in inpatient and outpatient care services. We employ an IV strategy that utilizes regional variation in peer effects, leveraging unique Japanese administrative data from the national health insurance at the individual enrollee level. We summarize and discuss our empirical findings as follows:

(1) Little impacts on health care for the entire sample:

Firstly, our IV estimation for the entire sample demonstrates little significant effects of the SHC participation on health care expenses and utilization in both the same and the subsequent FYs at the intensive margin. We only find that it may have a small possibility of reducing inpatient care use in the following FY. This suggests that implementing the SHC in city X may not be cost-effective, as it does not lead to an overall reduction in health care expenditures and use. It prompts a reevaluation of the intervention or promotion approach from a public health policy perspective, especially considering the relatively lower participation rate in city X.

Our findings regarding the impacts of the SHC participation are partly consistent with the evidence of little effects on medical expenses obtained in Inui et al. (2017). However, they are inconsistent with the findings observed in Oikawa et al. (2023) who demonstrate the cost-effectiveness of the expansion of the per capita expense for the SHC program due to the reduced medical spending on lifestyle-related diseases accompanied by the improvement in health outcomes at the municipality level. This may be attributed to the difference in the subject of study and identification strategies. Nevertheless, the strengthen of our study exists in compiled data characteristics in the individual longitudinal setting with taking advantage of regional variation in the SHC participation as an instrument.

(2) Heterogeneous effects on health care across demographic groups:

Secondly, the subsample stratification analysis uncovers distinct patterns. Individuals under the age of 65 years may decrease their inpatient care use in in the subsequent FY, while the elderly over 65 years of age are inclined to raise their annual expenses for physician visits in the year following the SHC participation. Additionally, males tend to increase their annual expenses for hospital admission after participating in the SHC. In contrast, females are more likely to reduce their use of hospitalization through the SHC participation. These findings emphasize the necessity of providing the SHC participants with tailor-made follow-up care, beyond the SHG, considering the heterogenous causal effects within different demographic groups. Moreover, differential intervention approaches to the targeted population according to their frequency and pattern of the SHC participation may also be worth considering, as different patterns of the SHC participation are usually observed across demographic groups.[19]

This study acknowledges certain limitations. Firstly, it focuses on a specific municipality in Japan, implying that the results may not be universally applicable to the entire Japanese population due to variation in demographic characteristics. Secondly, it primarily covers the self-employed, part-time workers, the unemployed, retirees and their dependents, potentially yielding different results for those under the employer-based health insurance. Lastly, the analysis is confined to the short-term effects due to the constraints on our data availability. Future research will extend the study period to explore medium- to long-term effects on medical and long-term care.

[19] For example, our sample shows higher cumulative number of the previous SHC participation for females than males on average with a statistically significant difference.

Figure 3.1 Age distribution of the insured in city X by gender

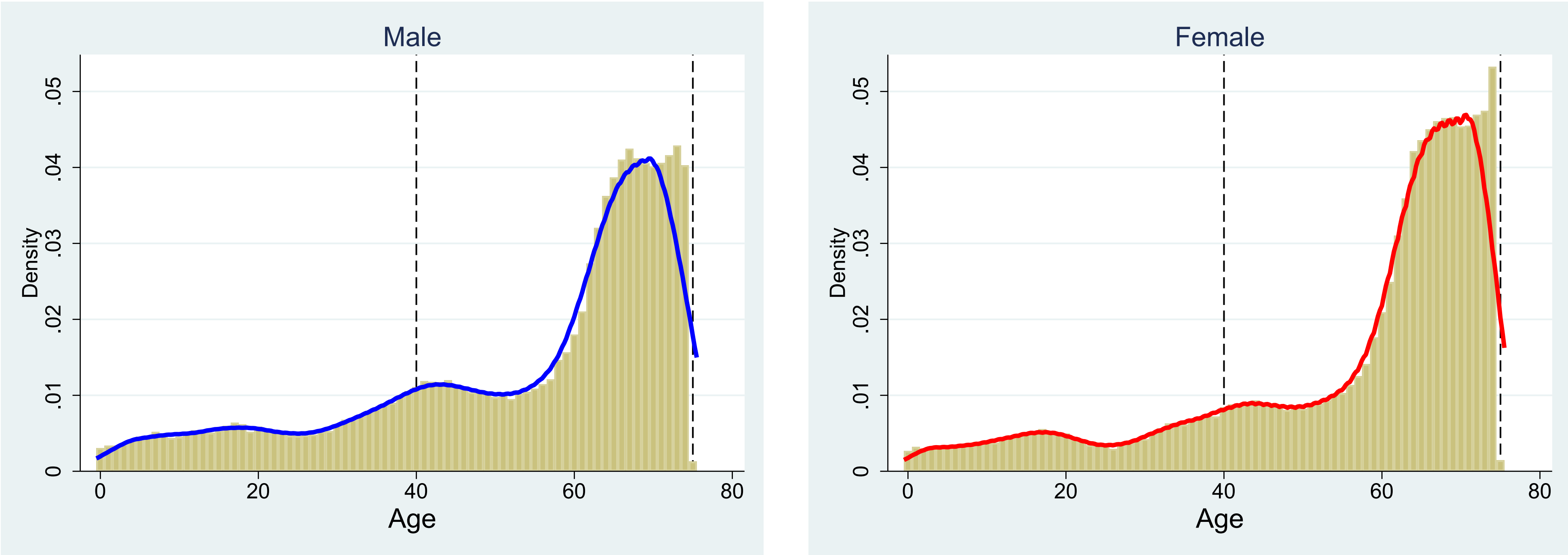

Figure 3.2 Participation rates in the SHC in city X by age cohort

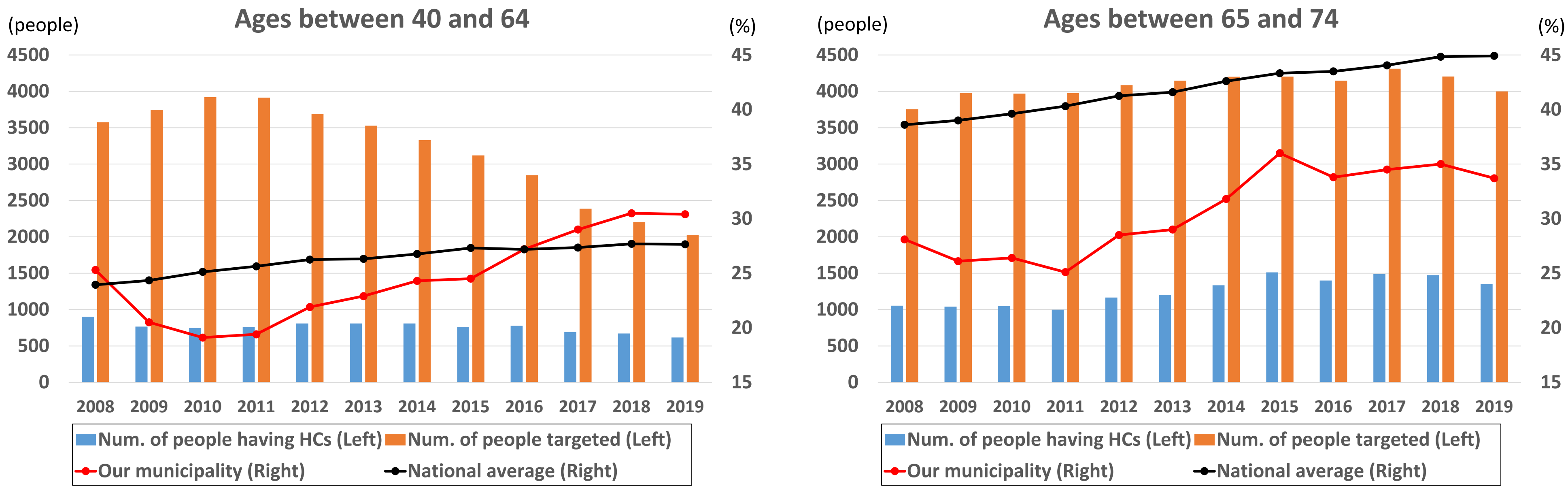

Table 3.1 Summary statistics for outcome measures and covariates

	N	Mean	Std. Dev.	Min	Max
Exp. for inpatient care	37,984	11.68	63.97	0	2,075.8
Exp. for outpatient care	37,984	8.58	29.81	0	884.44
Length of stay (inpatient)	37,984	4.36	31.91	0	369
Num. of visits (outpatient)	37,984	8.59	14.51	0	242
Age	37,984	64.00	8.65	40	75
Gender (male=1)	37,984	0.45	0.50	0	1
Household head	37,984	0.61	0.49	0	1
Household members	37,984	2.02	0.88	0	8
Eq. income (1K JPY)	37,984	2,363.4	2,231.2	-12,832.8	69,571.5
Negative income	370	-1,025.1	1,944.9	-12,832.8	-0.21
Zero income	3,204	0	0	0	0
1st quartile	8,472	666.9	337.9	0.003	1,292.3
2nd quartile	8,617	1,871.4	353.5	1,168.7	2,506.6
3rd quartile	8,680	2,923.5	288.5	2,389.6	3,509.1
4th quartile	8,641	4,976.0	2,938.4	3,391.4	69,571.5
Num. of HC participation	37,984	0.85	1.78	0	8
Health checkups	37,984	0.30	0.46	0	1

Table 3.2 Summary statistics for outcome measures by the SHC participation and age cohort

Ages 40-74	Taking health checkups		Not taking health checkups		t-test
	N	Mean (Std. Dev.)	N	Mean (Std. Dev.)	
Fees (inpatient)	11,429	5.24 (31.72)	26,555	14.45 (73.44)	***
Fees (outpatient)	11,429	6.77 (10.39)	26,555	9.36 (34.97)	***
LOS (inpatient)	11,429	1.03 (7.47)	26,555	5.79 (37.76)	***
NOV (outpatient)	11,429	8.67 (13.37)	26,555	8.56 (14.97)	

Ages 40-64	Taking health checkups		Not taking health checkups		t-test
	N	Mean (Std. Dev.)	N	Mean (Std. Dev.)	
Fees (inpatient)	3,878	3.78 (26.22)	11,336	14.21 (75.71)	***
Fees (outpatient)	3,878	5.06 (11.63)	11,336	8.28 (39.34)	***
LOS (inpatient)	3,878	1.08 (9.30)	11,336	7.32 (45.10)	***
NOV (outpatient)	3,878	6.70 (16.04)	11,336	7.20 (17.21)	*

Ages 65-74	Taking health checkups		Not taking health checkups		t-test
	N	Mean (Std. Dev.)	N	Mean (Std. Dev.)	
Fees (inpatient)	7,551	5.99 (34.18)	15,219	14.63 (71.72)	***
Fees (outpatient)	7,551	7.64 (9.58)	15,219	10.16 (31.29)	***
LOS (inpatient)	7,551	1.00 (6.33)	15,219	4.65 (31.15)	***
NOV (outpatient)	7,551	9.68 (11.64)	15,219	9.57 (12.97)	

Note: ***p<0.01, **p<0.05, *p<0.1.

Table 3.3 Summary statistics for covariates by the SHC participation and age cohort

Ages 40-74	Taking health checkups		Not taking health checkups		t-test
	N	Mean (Std. Dev.)	N	Mean (Std. Dev.)	
Age	11,429	65.36 (7.78)	26,555	63.41 (8.93)	***
Gender (male=1)	11,429	0.45 (0.50)	26,555	0.45 (0.50)	
Household head	11,429	0.59 (0.49)	26,555	0.62 (0.49)	***
Household members	11,429	2.10 (0.87)	26,555	1.99 (0.88)	***
Eq. income (1K JPY)	11,429	2,837 (2,360)	26,555	2,160 (2,141)	***

Ages 40-64	Taking health checkups		Not taking health checkups		t-test
	N	Mean (Std. Dev.)	N	Mean (Std. Dev.)	
Age	3,878	56.68 (6.92)	11,336	55.20 (7.68)	***
Gender (male=1)	3,878	0.46 (0.50)	11,336	0.49 (0.50)	***
Household head	3,878	0.57 (0.49)	11,336	0.65 (0.48)	***
Household members	3,878	2.30 (1.14)	11,336	2.00 (1.04)	***
Eq. income (1K JPY)	3,878	2,431 (2,905)	11,336	1,603 (2,267)	***

Ages 65-74	Taking health checkups		Not taking health checkups		t-test
	N	Mean (Std. Dev.)	N	Mean (Std. Dev.)	
Age	7,551	69.81 (2.91)	15,219	69.52 (2.79)	***
Gender (male=1)	7,551	0.45 (0.50)	15,219	0.42 (0.49)	***
Household head	7,551	0.59 (0.49)	15,219	0.60 (0.49)	
Household members	7,551	2.00 (0.67)	15,219	1.98 (0.74)	***
Eq. income (1K JPY)	7,551	3,045 (1,993)	15,219	2,574 (1,941)	***

Note: ***p<0.01, **p<0.05, *p<0.1.

Table 3.4 Estimation results for health care expenditures (entire sample)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-2.994***		2.501		-0.598**		2.102	
	(0.829)		(13.758)		(0.254)		(4.715)	
Health checkup (-1)		2.158*		-20.515		-0.242		4.143
		(1.124)		(17.274)		(0.369)		(6.095)
Local participation rate			0.131***	0.129***			0.131***	0.129***
(First-stage)			(0.018)	(0.018)			(0.018)	(0.018)
N of obs.	37,984	36,821	37,984	36,821	37,984	36,821	37,984	36,821
Adj. / Centered R2	0.489	0.443	0.614	0.576	0.668	0.634	0.749	0.724
Cragg-Donald Wald F stat.	—	—	189.61	180.92	—	—	189.61	180.92

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-15.443		-96.553		-0.882**		1.397	
	(13.006)		(389.133)		(0.356)		(6.121)	
Health checkup (-1)		11.196		-250.500		-0.278		2.806
		(17.003)		(167.459)		(0.479)		(7.770)
Local participation rate			0.055	0.167***			0.142***	0.144***
(First-stage)			(0.043)	(0.048)			(0.020)	(0.021)
N of obs.	1,695	1,915	1,695	1,915	26,570	26,442	26,570	26,442
Adj. / Centered R2	0.241	0.059	0.732	0.608	0.673	0.652	0.765	0.749
Cragg-Donald Wald F stat.	—	—	2.58	25.81	—	—	149.80	154.55

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.5 Estimation results for health care utilization (entire sample)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-0.902***		-4.351		0.074		-0.547	
	(0.298)		(4.521)		(0.151)		(1.991)	
Health checkup (-1)		0.031		-9.024*		0.066		2.108
		(0.381)		(5.125)		(0.165)		(2.623)
Local participation rate			0.131***	0.129***			0.131***	0.129***
(First-stage)			(0.018)	(0.018)			(0.018)	(0.018)
N of obs.	37,984	36,821	37,984	36,821	37,984	36,821	37,984	36,821
Adj. / Centered R2	0.762	0.735	0.820	0.797	0.744	0.713	0.807	0.784
Cragg-Donald Wald F stat.	—	—	189.61	180.92	—	—	189.61	180.92

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-8.016		43.342		-0.136		-0.716	
	(5.201)		(141.407)		(0.204)		(2.547)	
Health checkup (-1)		-4.249		-99.653		-0.074		2.300
		(5.455)		(61.926)		(0.216)		(3.324)
Local participation rate			0.055	0.167***			0.142***	0.144***
(First-stage)			(0.043)	(0.048)			(0.020)	(0.021)
N of obs.	1,695	1,915	1,695	1,915	26,566	26,438	26,566	26,438
Adj. / Centered R2	0.719	0.615	0.898	0.840	0.721	0.695	0.800	0.779
Cragg-Donald Wald F stat.	—	—	2.58	25.81	—	—	149.83	154.39

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.6 Estimation results for health care expenditures (age cohort between 40 and 64)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-2.296		-19.481		0.610***		-2.632	
	(1.394)		(18.249)		(0.189)		(6.488)	
Health checkup (-1)		-1.518		-18.867		0.499*		-5.749
		(1.736)		(19.512)		(0.263)		(7.339)
Local participation rate			0.138***	0.136***			0.138***	0.136***
(First-stage)			(0.031)	(0.032)			(0.031)	(0.032)
N of obs.	14,673	14,323	14,673	14,323	14,673	14,323	14,673	14,323
Adj. / Centered R2	0.624	0.616	0.738	0.733	0.788	0.760	0.854	0.834
Cragg-Donald Wald F stat.	–	–	89.19	86.01	–	–	89.19	86.01

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-22.700		102.452		0.808**		-2.969	
	(17.468)		(350.292)		(0.363)		(9.634)	
Health checkup (-1)		29.388		-266.697		1.052**		-7.718
		(33.924)		(308.593)		(0.456)		(11.298)
Local participation rate			0.095	0.154**			0.175***	0.163***
(First-stage)			(0.073)	(0.067)			(0.039)	(0.040)
N of obs.	580	648	580	648	8,151	8,329	8,151	8,329
Adj. / Centered R2	0.188	0.166	0.780	0.735	0.763	0.761	0.853	0.850
Cragg-Donald Wald F stat.	–	–	3.02	9.86	–	–	75.28	65.48

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.7 Estimation results for health care utilization (age cohort between 40 and 64)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-0.961		-7.172		0.680***		-2.435	
	(0.692)		(7.854)		(0.217)		(2.733)	
Health checkup (-1)		-0.913		-15.994*		.0360		-1.142
		(0.906)		(9.251)		(0.251)		(4.179)
Local participation rate			0.138***	0.136***			0.138***	0.136***
(First-stage)			(0.031)	(0.032)			(0.031)	(0.032)
N of obs.	14,673	14,323	14,673	14,323	14,673	14,323	14,673	14,323
Adj. / Centered R2	0.775	0.771	0.844	0.836	0.804	0.772	0.864	0.843
Cragg-Donald Wald F stat.	–	–	89.19	86.01	–	–	89.19	86.01

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-9.907		123.057		0.786**		-2.407	
	(11.888)		(213.239)		(0.376)		(3.849)	
Health checkup (-1)		-2.754		-206.758		0.562		-0.780
		(17.402)		(175.616)		(0.412)		(6.385)
Local participation rate			0.095	0.154**			0.175***	0.163***
(First-stage)			(0.073)	(0.067)			(0.039)	(0.040)
N of obs.	580	648	580	648	8,147	8,326	8,147	8,326
Adj. / Centered R2	0.560	0.507	0.866	0.820	0.771	0.743	0.857	0.840
Cragg-Donald Wald F stat.	–	–	3.02	9.86	–	–	75.42	65.37

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.8 Estimation results for health care expenditures (age cohort between 65 and 74)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-2.871**		7.668		-1.166***		2.672	
	(1.147)		(22.616)		(0.373)		(7.833)	
Health checkup (-1)		4.590***		-42.323		-0.699		18.410*
		(1.641)		(29.296)		(0.536)		(10.476)
Local participation rate			0.118***	0.115***			0.118***	0.115***
(First-stage)			(0.019)	(0.019)			(0.019)	(0.019)
N of obs.	22,470	21,655	22,470	21,655	22,470	21,655	22,470	21,655
Adj. / Centered R2	0.348	0.280	0.530	0.460	0.509	0.502	0.646	0.622
Cragg-Donald Wald F stat.	–	–	86.82	80.65	–	–	86.82	80.65

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-13.910		-489.153		-1.360***		1.122	
	(16.723)		(908.791)		(0.453)		(9.368)	
Health checkup (-1)		19.306		-264.889		-0.811		18.435
		(20.219)		(224.336)		(0.634)		(12.131)
Local participation rate			0.045	0.191***			0.117***	0.120***
(First-stage)			(0.061)	(0.071)			(0.022)	(0.022)
N of obs.	1,035	1,158	1,035	1,158	17,673	17,365	17,673	17,365
Adj. / Centered R2	-0.161	-0.499	0.482	0.495	0.529	0.526	0.672	0.652
Cragg-Donald Wald F stat.	–	–	0.96	15.60	–	–	66.42	70.20

Note: ****p*<0.01, ***p*<0.05, **p*<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.9 Estimation results for health care utilization (age cohort between 65 and 74)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-0.801***		-6.435		-0.291		-0.002	
	(0.263)		(6.148)		(0.218)		(3.352)	
Health checkup (-1)		0.727**		-9.698		-0.204		4.996
		(0.347)		(6.444)		(0.217)		(3.927)
Local participation rate			0.118***	0.115***			0.118***	0.115***
(First-stage)			(0.019)	(0.019)			(0.019)	(0.019)
N of obs.	22,470	21,655	22,470	21,655	22,470	21,655	22,470	21,655
Adj. / Centered R2	0.720	0.652	0.796	0.744	0.651	0.631	0.749	0.728
Cragg-Donald Wald F stat.	–	–	86.82	80.65	–	–	86.82	80.65

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-6.487*		-198.514		-0.472*		0.057	
	(3.464)		(294.955)		(0.267)		(4.133)	
Health checkup (-1)		0.841		-72.593		-0.390		4.971
		(4.070)		(56.866)		(0.261)		(4.548)
Local participation rate			0.045	0.191***			0.117***	0.120***
(First-stage)			(0.061)	(0.071)			(0.022)	(0.022)
N of obs.	1,035	1,158	1,035	1,158	17,673	17,363	17,673	17,363
Adj. / Centered R2	0.694	0.425	0.803	0.814	0.619	0.608	0.735	0.719
Cragg-Donald Wald F stat.	–	–	0.96	15.60	–	–	66.42	70.18

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.10 Estimation results for health care expenditures (males)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-4.111***		31.455*		-0.434		3.578	
	(1.373)		(18.686)		(0.499)		(7.087)	
Health checkup (-1)		3.070		-8.252		-1.067		10.958
		(2.152)		(22.099)		(0.751)		(9.379)
Local participation rate			0.151***	0.149***			0.151***	0.149***
(First-stage)			(0.022)	(0.022)			(0.022)	(0.022)
N of obs.	17,128	16,571	17,128	16,571	17,128	16,571	17,128	16,571
Adj. / Centered R2	0.468	0.403	0.603	0.569	0.638	0.637	0.738	0.734
Cragg-Donald Wald F stat.	—	—	117.00	110.85	—	—	117.00	110.85

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-23.968		538.368		-0.847		3.667	
	(20.592)		(658.190)		(0.738)		(9.667)	
Health checkup (-1)		26.119		-307.257		-1.451		8.827
		(25.081)		(216.397)		(1.037)		(11.541)
Local participation rate			0.059	0.180***			0.159***	0.177***
(First-stage)			(0.053)	(0.060)			(0.026)	(0.027)
N of obs.	943	1,089	943	1,089	11,582	11,523	11,582	11,523
Adj. / Centered R2	-0.059	-0.292	0.534	0.558	0.622	0.638	0.743	0.752
Cragg-Donald Wald F stat.	—	—	1.81	16.54	—	—	83.30	104.61

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.11 Estimation results for health care utilization (males)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-1.311***		7.773		0.227		-1.963	
	(0.448)		(5.634)		(0.250)		(2.671)	
Health checkup (-1)		-0.120		-0.945		-0.253		1.702
		(0.611)		(6.678)		(0.251)		(3.583)
Local participation rate			0.151***	0.149***			0.151***	0.149***
(First-stage)			(0.022)	(0.022)			(0.022)	(0.022)
N of obs.	17,128	16,571	17,128	16,571	17,128	16,571	17,128	16,571
Adj. / Centered R2	0.756	0.722	0.820	0.800	0.769	0.749	0.832	0.819
Cragg-Donald Wald F stat.	—	—	117.00	110.85	—	—	117.00	110.85

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-8.873		243.638		-0.053		-2.076	
	(6.789)		(281.468)		(0.350)		(3.711)	
Health checkup (-1)		-4.516		-86.511		-0.425		1.027
		(6.244)		(74.831)		(0.337)		(4.412)
Local participation rate			0.059	0.180***			0.159***	0.177***
(First-stage)			(0.053)	(0.060)			(0.026)	(0.027)
N of obs.	943	1,089	943	1,089	11,578	11,519	11,578	11,519
Adj. / Centered R2	0.591	0.489	0.773	0.840	0.740	0.726	0.823	0.814
Cragg-Donald Wald F stat.	—	—	1.81	16.54	—	—	83.26	104.44

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.12 Estimation results for health care expenditures (females)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-2.160**		-27.759		-0.779**		1.684	
	(0.916)		(21.271)		(0.306)		(6.018)	
Health checkup (-1)		1.435		-30.467		0.311		-1.386
		(1.037)		(25.192)		(0.358)		(8.392)
Local participation rate			0.116***	0.115***			0.116***	0.115***
(First-stage)			(0.020)	(0.020)			(0.020)	(0.020)
N of obs.	20,856	20,250	20,856	20,250	20,856	20,250	20,856	20,250
Adj. / Centered R2	0.472	0.447	0.601	0.581	0.678	0.593	0.763	0.702
Cragg-Donald Wald F stat.	—	—	79.84	76.48	—	—	79.84	76.48

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-7.747		-724.964		-1.033**		0.953	
	(17.391)		(739.419)		(0.407)		(7.520)	
Health checkup (-1)		-9.571		-193.534		0.415		-1.483
		(23.613)		(253.906)		(0.447)		(11.139)
Local participation rate			0.085	0.153**			0.132***	0.120***
(First-stage)			(0.068)	(0.075)			(0.023)	(0.023)
N of obs.	752	826	752	826	14,988	14,919	14,988	14,919
Adj. / Centered R2	0.135	-0.079	0.382	0.675	0.701	0.627	0.792	0.740
Cragg-Donald Wald F stat.	—	—	2.31	9.37	—	—	71.09	59.12

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.13 Estimation results for health care utilization (females)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-0.599*		-17.215**		-0.051		1.257	
	(0.308)		(8.253)		(0.200)		(3.039)	
Health checkup (-1)		0.172		-17.358**		0.284		3.076
		(0.341)		(7.688)		(0.215)		(3.865)
Local participation rate			0.116***	0.115***			0.116***	0.115***
(First-stage)			(0.020)	(0.020)			(0.020)	(0.020)
N of obs.	20,856	20,250	20,856	20,250	20,856	20,250	20,856	20,250
Adj. / Centered R2	0.750	0.729	0.799	0.784	0.683	0.633	0.767	0.729
Cragg-Donald Wald F stat.	–	–	79.84	76.48	–	–	79.84	76.48

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-7.655		-215.403		-0.210		0.718	
	(7.405)		(229.993)		(0.261)		(3.637)	
Health checkup (-1)		-1.515		-116.123		0.140		4.327
		(8.279)		(98.556)		(0.276)		(5.002)
Local participation rate			0.085	0.153**			0.132***	0.120***
(First-stage)			(0.068)	(0.075)			(0.023)	(0.023)
N of obs.	752	826	752	826	14,988	14,919	14,988	14,919
Adj. / Centered R2	0.700	0.525	0.842	0.842	0.656	0.604	0.761	0.719
Cragg-Donald Wald F stat.	–	–	2.31	9.37	–	–	71.09	59.12

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.14 Estimation results for health care expenditures (below 50% of the median income)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-4.212**		15.060		0.031		16.220	
	(2.033)		(32.952)		(0.515)		(17.076)	
Health checkup (-1)		1.050		-24.168		1.366**		-13.944
		(3.001)		(41.911)		(0.678)		(20.740)
Local participation rate			0.101**	0.098**			0.101**	0.098**
(First-stage)			(0.040)	(0.041)			(0.040)	(0.041)
N of obs.	10,233	9,944	10,233	9,944	10,233	9,944	10,233	9,944
Adj. / Centered R2	0.681	0.643	0.781	0.755	0.8239	0.767	0.872	0.836
Cragg-Donald Wald F stat.	—	—	33.66	31.61	—	—	33.66	31.61

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-22.368		-720.267		-0.058		22.390	
	(26.910)		(2043.715)		(0.763)		(22.636)	
Health checkup (-1)		-13.605		-406.946		1.874*		-23.787
		(31.595)		(623.097)		(0.996)		(28.924)
Local participation rate			0.017	0.067*			0.131**	0.126**
(First-stage)			(0.037)	(0.040)			(0.051)	(0.051)
N of obs.	623	652	623	652	6,434	6,472	6,434	6,472
Adj. / Centered R2	0.352	0.322	0.617	0.713	0.811	0.753	0.868	0.830
Cragg-Donald Wald F stat.	—	—	0.16	2.56	—	—	30.61	28.61

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.15 Estimation results for health care utilization (below 50% of the median income)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-1.994*		0.621		0.589		-0.199	
	(1.046)		(14.911)		(0.382)		(6.294)	
Health checkup (-1)		-0.436		-21.950		0.990**		1.025
		(1.611)		(17.496)		(0.444)		(8.067)
Local participation rate			0.101**	0.098**			0.101**	0.098**
(First-stage)			(0.040)	(0.041)			(0.040)	(0.041)
N of obs.	10,233	9,944	10,233	9,944	10,233	9,944	10,233	9,944
Adj. / Centered R2	0.835	0.828	0.888	0.877	0.790	0.755		0.834
Cragg-Donald Wald F stat.	–	–	33.66	31.61	–	–	33.66	31.61

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-17.875		156.315		0.576		1.945	
	(16.395)		(800.613)		(0.551)		(8.153)	
Health checkup (-1)		-17.727		-243.770		1.145*		-0.547
		(19.807)		(294.993)		(0.618)		(10.837)
Local participation rate			0.017	0.067*			0.131**	0.125**
(First-stage)			(0.037)	(0.040)			(0.051)	(0.051)
N of obs.	623	652	623	652	6,430	6,470	6,430	6,470
Adj. / Centered R2	0.727	0.671	0.888	0.850	0.763	0.730	0.848	0.827
Cragg-Donald Wald F stat.	–	–	0.16	2.56	–	–	30.59	28.46

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.16 Estimation results for health care expenditures (over 50% of the median income)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-2.735***		3.721		-0.808***		-1.030	
	(0.893)		(14.627)		(0.308)		(4.642)	
Health checkup (-1)		2.768**		-17.305		-0.633		8.635
		(1.247)		(19.333)		(0.457)		(6.461)
Local participation rate			0.144***	0.142***			0.144***	0.142***
(First-stage)			(0.019)	(0.019)			(0.019)	(0.019)
N of obs.	26,480	25,641	26,480	25,641	26,480	25,641	26,480	25,641
Adj. / Centered R2	0.279	0.270	0.472	0.461	0.561	0.519	0.679	0.644
Cragg-Donald Wald F stat.	–	–	153.32	145.82	–	–	153.32	145.82

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-11.220		340.024		-1.161***		-3.051	
	(16.795)		(944.318)		(0.421)		(6.123)	
Health checkup (-1)		28.046		-156.624		-0.732		8.248
		(20.826)		(184.811)		(0.569)		(7.748)
Local participation rate			0.042	0.212***			0.145***	0.156***
(First-stage)			(0.066)	(0.076)			(0.021)	(0.022)
N of obs.	981	1,133	981	1,133	19,238	19,102	19,238	19,102
Adj. / Centered R2	-0.465	-0.687	0.541	0.545	0.576	0.551	0.703	0.681
Cragg-Donald Wald F stat.	–	–	0.70	19.12	–	–	112.52	128.92

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Table 3.17 Estimation results for health care utilization (over 50% of the median income)

Full sample	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-0.632***		-3.888		-0.089		-0.514	
	(0.193)		(4.153)		(0.174)		(2.129)	
Health checkup (-1)		0.233		-4.206		-0.165		2.959
		(0.279)		(4.706)		(0.182)		(2.718)
Local participation rate			0.144***	0.142***			0.144***	0.142***
(First-stage)			(0.019)	(0.019)			(0.019)	(0.019)
N of obs.	26,480	25,641	26,480	25,641	26,480	25,641	26,480	25,641
Adj. / Centered R2	0.461	0.417	0.604	0.572	0.680	0.636	0.766	0.731
Cragg-Donald Wald F stat.	–	–	153.32	145.82	–	–	153.32	145.82

Sample with positive outcomes	Inpatient care				Outpatient care			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Health checkup	-5.467		184.294		-0.369		-1.095	
	(4.306)		(375.395)		(0.235)		(2.825)	
Health checkup (-1)		2.751		-57.533		-0.331		3.182
		(5.327)		(54.608)		(0.233)		(3.286)
Local participation rate			0.042	0.212***			0.145***	0.156***
(First-stage)			(0.066)	(0.076)			(0.021)	(0.022)
N of obs.	981	1,133	981	1,133	19,238	19,100	19,238	19,100
Adj. / Centered R2	0.143	-0.144	0.583	0.688	0.649	0.608	0.754	0.721
Cragg-Donald Wald F stat.	–	–	0.70	19.12	–	–	112.52	128.90

Note: ***p<0.01, **p<0.05, *p<0.1. Robust standard errors reported in parentheses are clustered at the individual and local community levels.

Conclusion

This thesis consists of three chapters that analyze health care activities from an economic perspective, focusing on the efficiency of health care delivery, income-related inequalities in health care consumption, and the causal impacts of health checkups on health care. The first chapter evaluates the efficiency and productivity of surgical treatments across surgical specialties in a high-volume Japanese teaching hospital. The second chapter examines income-related inequalities in health care utilization and spending under universal coverage in a long-term perspective for the case of the Republic of Korea. The third chapter investigates the causal relationship between participation in health checkups and health care expenses or use under the Japanese healthcare system.

Chapter one evaluates the efficiency and productivity of surgical treatments across surgical specialties in a high-volume Japanese university hospital. Japan's healthcare expenditures, which are largely publicly funded, have been growing dramatically due to the rapid aging of the population as well as the innovation and diffusion of new medical technologies. The efficiency and productivity of healthcare providers is a critical issue to maintain or improve the existing quality of health care under the constraint of tight government financial resources. In particular, a large amount of hospital resources are utilized in surgical procedures in the inpatient care setting; annual costs for surgical treatments are estimated to be approximately USD 20 billion. Using unique longitudinal clinical data at the individual surgeon level, this chapter aims to estimate the technical efficiency of surgical treatments across surgical specialties in a high-volume Japanese teaching hospital by employing stochastic frontier analysis (SFA) with production frontier models. We simultaneously examine the impacts of potential determinants that are likely to affect inefficiency in operating rooms. Our empirical results show a relatively high average technical efficiency of surgical production, with modest disparity across surgical specialties. This might reveal one of the characteristics of Japanese high-volume teaching hospitals, in the sense that clinical management and resource utilization tend to be well organized. Nevertheless, we suggest that there is room to reorganize and improve resource utilization in the operating rooms of surgical specialties that show lower technical efficiency; that is to say, to attain higher surgical efficiency in higher specialties with average technical efficiency. We also demonstrate that an increase in the number of operations performed by a surgeon significantly reduces operating room inefficiency, whereas the revision of the fee-for-service schedule for surgical treatments does not have a significant impact on inefficiency. It is reasonable to think that surgical volume which represents the surgical proficiency and technical capability of surgeons would be a determinant of technical efficiency in operating rooms, since clinical practice guidelines often recommend that patients undergo operations at healthcare facilities where surgical volume is large enough to ensure clinical safety. In addition, we find higher technical efficiency among surgeons who perform multiple daily surgeries than those who perform a single operation in a day. This is consistent with the fact that surgeons who perform multiple daily surgeries would be forced to exercise strict time management. We suggest that it is important for hospital management to retain efficient surgeons and physicians and provide efficient healthcare services given the competitive Japanese healthcare market. The importance of efficiently operating teaching hospitals is also growing, as they are not only expected to produce skillful and efficient surgeons through advanced medical training, but they are also expected to help improve fee schedules so that they adequately reflect surgical efficiency and motivate other medical facilities to reorganize their clinical management and resource utilization for efficiency.

Chapter two considers income-related inequality in health care under universal coverage from a long-run perspective in the case of the Republic of Korea. Many countries have sought to promote well-being for their entire populations through the implementation of universal health coverage (UHC). To identify the extent to which UHC has been attained, it is necessary to evaluate equity of access to use of needed care and the cost burden of health services for the country's entire population. Exploiting longitudinal data from a nationally representative health survey from 2008 to 2018, this chapter investigates how income-related inequalities in health care use and spending in Korea have varied over time and examines the extent to which need and non-need factors contribute those inequalities, using an in-depth decomposition analysis, allowing for heterogeneous responses across income groups. The empirical results show that overall health care utilization is disproportionately concentrated among the poor over both the short and long run. Income-group differences and household characteristics, such as marital status, make larger pro-poor contributions to inequality in inpatient care use, while chronic disease prevalence greatly pushes outpatient care utilization in a pro-poor direction. These considerations suggest that it is important for health care policy in Korea to focus on improvements in the health status and well-being of low-income groups, as poor people are likely to be in poorer health. The results regarding inpatient care expenses indicate a similar pattern of pro-poor bias, demonstrating that the direct effect of income-group differences and non-need determinants contribute to most of the income-related inequality. This implies that higher spending on inpatient care may be a heavier financial burden for low-income people. Thus, additional financially supportive measures should be provided for them to mitigate their heavy burden of inpatient care spending and prevent them from suffering economic hardship. This may also lead to institutional issues in terms of the charging of inpatient care services. On the other hand, long-run inequality favors the better-off in terms of outpatient care expenses, where the contribution of income-group differences has the largest impact. People in high-income groups may spend most on costly services in outpatient care, including uninsured services, with the help of additional private health insurance. This currently brings about a policy debate on how to regulate uninsured health care services and the growing market for private health insurance. These findings obtained from the Korean healthcare system may provide a thoughtful policy implication for Japan in considering the expansion of the scope of mixed treatments partially covered by public health insurance and the corresponding growth of private health insurance, as the sustainability of health financing in Japan under UNC has been called into question because of the Japanese government's huge fiscal debt and the dynamic demographic change due to rapid population aging.

Chapter three investigates the causal relationship between participation in health checkups and health care under the Japanese healthcare system. There exists a globally growing concern regarding the prevention and control of non-communicable diseases (NCDs), and Japan is no exception wherein lifestyle-related NCDs have a significant impact on public health. To prevent the prevalence of metabolic syndrome and control the rising healthcare costs, the Japanese government initiated a novel annual health checkup initiative, known as the Specific Health Checkups (SHC) and Specific Health Guidance (SHG), which targets individuals aged 40-74 years in April 2008. Utilizing distinctive longitudinal administrative data at the individual enrollee level for the periods between fiscal year (FY) 2011 and FY 2016, graciously provided by a local municipality (identified as city X) in Japan, this chapter examines the causal impacts of taking the SHC on their health care expenditures and utilization for inpatient and outpatient care services.

We employ an instrumental variable (IV) estimation that relies on regional variation in peer effects as a determinant in the individual's decision, allowing for a deeper investigation into the heterogenous impacts with specific demographic groups. Our IV estimation for the entire sample demonstrates little significant effects of the SHC participation on health care expenses and use in both the same and the subsequent FYs at the intensive margin, given that it proves to be a sufficiently strong instrument. We only find that it may have a small possibility of reducing inpatient care utilization in the following FY. This suggests that implementing the SHC in city X may not be cost-effective, as it does not lead to an overall reduction in health care expenditures and use. It prompts a reevaluation of the intervention or promotion approach from a public health policy perspective, especially considering the relatively lower participation rate in city X. However, our stratification analysis uncovers distinct patterns. Individuals under the age of 65 years may decrease their inpatient care utilization in in the subsequent FY, while the elderly over 65 years of age are inclined to raise their annual expenses for physician visits in the year following the SHC participation. Additionally, males tend to increase their annual expenditures for hospital admission soon after participating in the SHC. Conversely, females are more likely to reduce their use of hospitalization through the SHC participation. These findings emphasize the necessity of providing the SHC participants with tailor-made follow-up care, beyond the SHG, considering the heterogenous causal effects within different demographic groups. Moreover, differential intervention approaches to the targeted population according to their frequency and pattern of the SHC participation may also be worth considering, as different patterns of the SHC participation are usually observed across demographic groups.

There remain numerous limitations in this dissertation, which are described in detail in each chapter. However, this thesis would add to the literature on health care in health economics and provide valuable policy implications for the Japanese and Korean healthcare systems.

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