The Effect of Health Insurance on Patient Demand for Appropriate Levels of Medical Care*

Jerome Dugan†

WORKING PAPER

April 6, 2015

Abstract

This study investigates the impact of health insurance coverage status on patient demand for appropriate levels of medical care. A discrete choice framework and multinomial logistic regression are used to estimate the effect of different types of health insurance coverage on the probability of a patient scheduling different combinations of medical care following diagnosis/acute event. The study sample consists of adults ages 19 to 64 who have been diagnosed with a disease with a "rapid onset" from the 2008 to 2012 Medical Expenditure Panel Survey. The results show that health insurance coverage is associated with increased use of appropriate levels of physician care, but does not promote increased use of cost-effective routine care among the publicly insured.

Keywords: discrete choice, demand for medical care, health insurance

JEL Codes: I1

*This study was supported in part by the Eunice Kennedy Shriver National Center for Child Health and Human Development grant R24-HD041041, Maryland Population Research Center.

†School of Public Policy, University of Maryland, College Park, 2101 Van Munching Hall, College Park, MD 20742; e-mail: jdugan@umd.edu; website: http://faculty.publicpolicy.umd.edu/dugan/

1 Introduction

The Affordable Care Act (ACA) seeks to reduce health disparities and achieve health equity in the United States by coordinating the enrollment of millions of uninsured Americans into health insurance plans. In order to accomplish this goal, the ACA uses an individual mandate, raises the federal Medicaid eligibility limit, eliminates the pre-existing condition exclusion, and establishes exchanges that sell federally-subsidized insurance plans. The implementation of such design features are especially important for policymakers seeking to bridge the enrollment gaps that lead to lower national health welfare, as the uninsured are the least likely to use preventative medical services, are the most likely to encounter financial barriers to access care, and report the highest rates of preventable hospitalizations (Currie and Gruber, 1996; Ayanian *et al.*, 2000; Card, Dobkin, and Maestas, 2008, 2009; Anderson, Dobkin, and Gross, 2012). To date, over 9.3 million uninsured Americans have benefited from ACA related coverage expansions, lowering the uninsured rate from 20.5% to 15.8% (Carman and Eibner, 2014). For this reason, the ACA has been hailed as the most significant health legislation since the Social Security Amendments of 1965.

Although coverage expansion policies have been effective in addressing wide disparities in health between the insured and uninsured, inequities in health outcomes continue to persist within the insured population itself. For example, a recent analysis of coverage expansions among near-Medicare eligible adults revealed significant disparities in utilization of medical services across socioeconomic and sociodemographic groups (Dugan, Virani, and Ho, 2012). More specifically, Medicare eligibility was associated with a general reduction in financial barriers to access care and an increase in the use of physician services; however, appropriate levels of medical care were not consumed among some groups. In particular, blacks with chronic disease saw a decline in their propensity to utilize appropriate levels of care following their enrollment into Medicare. Other studies document similar disparities in healthcare utilization and outcomes within fully insured populations, without offering clear explanations for their findings (Jha *et al.*, 2003; Peterson *et al.*, 2008; Virani *et al.*, 2011).

There are several potential explanations for the underutilization patterns observed among the insured. First, economic investigations of consumer demand for health insurance suggest that low demand for health insurance may result from credit constraints, which are most often the result of income and health status shocks (Farley and Wilensky, 1984; Nyman, 2003; Delavallade, 2014). Individuals diagnosed with chronic conditions not only face acute health shocks that can drive copayments to unaffordable levels, but they also face income shocks due to lower productivity (Ferrer-i-Carbonell and Van Praag, 2002). Second, as providers can adjust payer-specific marginal costs to reflect payer generosity (Dor and Farley, 1996; Ho, Dugan, and Ku-Goto, 2013), they can offer differential levels of care to patients with the same diagnosis but different insurance status. As a result, patients enrolled in plans with lower reimbursement levels could receive a lower standard of care as compared to patients with plans with more generous reimbursement policies, causing further declines in demand for medical care. Last, differences in the level of cost sharing and supply of network providers could disrupt a patient's use of elective services and procedures (Dor and Farley, 1996; Hullegie and Klein, 2010). Therefore, non-essential services are among the first to be curtailed when patients are enrolled in plans with aggressive cost controls.

Understanding the impact of coverage status on the consumption of medical services has far-reaching impacts for insurers and consumers alike. The performance of accountable care systems, such as Accountable Care Organizations (ACO) and Patient-Centered Medical Homes (PCMH), rely on a consumer's ability to adhere to treatment regimes designed to curb costs and improve overall health outcomes. For patients suffering from chronic disease, their health insurance coverage status can have significant effects on their individual disease management. Despite the importance of health insurance coverage status, little is known about how coverage status influences consumer's tastes for medical treatment.

Assessing whether an individual's demand for medical care varies with their health insurance coverage status is complicated by the fact that the uninsured have different discount rates, risk tolerances, and medical risks than the insured (Anderson, Dobkin, and Gross, 2012). Furthermore, these same factors complicate the examination of the impacts of coverage status among insured individuals with different types of coverage. Studies typically rely on quasi-experimental variation for identification. However, most of these studies only examine Medicare-eligible seniors (Card, Dobkin, and Maestas, 2008, 2009; Dugan, Virani, and Ho, 2012) or Medicaid-eligible adolecences (Dafny and Gruber, 2005; Currie, Decker, and Lin, 2008). Few studies have examined non-elderly adults who have control over their own health insurance decisions (Anderson, Dobkin, and Gross, 2012).

Building on this unresolved question, this paper aims to examine whether a patient's coverage status impacts their demand for medical treatment. A discrete choice random utility maximization framework is used to represent a patient's preferences for medical treatment. In particular, the random utility model describes a patient's choice between rejecting a physician's treatment recommendations and underutilizing the physician service or accepting a physician's recommendations and using an appropriate level of physician service. The patient will select the treatment that maximizes their indirect utility. Data from the Medical Expenditure Panel Survey (MEPS) are used to estimate multinomial logistic models that predict the probability of selecting an alternative medical treatment given a patient's coverage status. To control for the potential endogeneity of health insurance coverage status, the study sample is limited to patients diagnosed with acute diseases with a rapid onset, making it highly unlikely that an individual's insurance status is related to the initial presentation of their health status. The main analysis features patients diagnosed with coronary heart disease and stroke (CHDS), cancer, or diabetes – patient groups whose diagnosis require them to utilize medical care at a particular threshold to ensure that the risk of future acute events is minimized (Geraghty, 2000; Dugan, Virani, and Ho, 2012; ADA, 2014).

The remainder of the paper is organized as follows. Section 2 presents the paper's theoretical framework and Section 3 provides the general estimation equation. Section 4 provides a description of the study sample used in the paper's analysis. The results and discussion are described in Section 5 and the conclusion is presented in Section 6.

2 Economic Framework

An individual's medical consumption decision can be understood by analyzing their decision within a random utility model framework, where individuals are assumed to be utility maximizers (Gertler, Locay, and Sanderson, 1987; Brand, 2006; Tran, 2007). Existing models of demand suggest that having health insurance coverage is associated with increased consumption of medical resources. However, these models do not make considerations for the structure of consumption of medical treatment. This study departs from previous analyses by examining how a consumer's health insurance coverage status impacts their demand for alternative medical treatment bundles - a group of individual medical services that are intended for use together to treat a medical condition. This is accomplished by deriving a discrete choice model that specifically relates a patient's health insurance coverage status to their demand for an appropriate level of medical care following an diagnosis/acute medical event.

2.1 Demand for Medical Care

There are three types of utility maximizing individuals: an individual with public insurance coverage, an individual with private insurance coverage, and an individual with no insurance coverage. Each type of individual, indexed by i, faces a discrete choice decision between J treatment options indexed from $j \in \{OB,\ ER,\ MX\}$: whether to make routine office based visits only (OB), emergency room visits only (ER), or any mixture of routine office based visits and emergency room visits (MX).

Each purchase occasion, an individual uses their income y_i to select a treatment option j that maximizes their utility. The treatment decision is modeled as follows:

$$\max_{j,z} U_i(H, z) \ \text{ s.t. } p_j + p_z z = y_i \ \text{ and } \ H_i = H_i(x_j, \theta_i) \tag{1}$$

where θ represents pre-treatment health state with larger values indicating worse states of health, x_j are characteristics of treatment bundle j, p_j is the price of treatment bundle j, z is an outside option, and p_z is the price of the outside option z. $H_i(\cdot)$ and H_i are the health production function and post-treatment health for individual i, respectively.

As z (denoted $j = 0$) is the non-purchase of any treatment option in J, z can be viewed as a fourth treatment option consisting of no medical visits. The model assumes that $H_i(\cdot)$ is differentiable and that the following initial condition holds:

$$H(0, \theta_i) = -\theta \tag{2}$$

This means that if the consumer does not consume a treatment bundle in J, then their post-treatment health state is equal to their pre-treatment health state (Brand, 2006). Substituting the budget constraint into Equation (1), the individual's problem is now selecting the treatment bundle that gives them the highest conditional indirect utility:

$$\max_j U_{ij}(H_{ij}(x_{ij}, \theta), p_j, p_z, y_i) = V_{ij}(H_{ij}(x_{ij}, \theta), p_j, p_z, y_i) + \epsilon_{ij} \tag{3}$$

where $V_{ij}(\cdot)$ is the indirect utility from all of the observable characteristics and ϵ_{ij} is the unobserved utility that equates $V_{ij}(\cdot)$ to the actual utility of each individual.

3 Econometric Model

Following the discrete choice model of demand for medical treatment derived in Section 2, physician visits are organized into four medical treatment categories and a multinomial logit model is then used to predict the probability of selecting an alternative medical treatment bundle. The multinomial logit model was selected over other models for its ability to better estimate discrete choice decisions when decision makers are utility maximizers and their choice alternatives are highly differentiated (McFadden, 1974; Aldrich and Nelson, 1984).

3.1 Probability of Medical Treatment

The probability that an individual i will choose a medical treatment bundle j over j' lies between 0 and 1. The model assumes that individuals select the medical treatment bundle that maximizes their utility (McFadden, 1974). If we impose linear structure on the conditional indirect utility function of i (Equation 3), the model can be expressed as follows:

$$P_{ij} = \frac{\exp(\beta_j X_i)}{\sum_{j'=0,..,J} \exp(\beta_j X_i)}, \text{ for } j' \neq j \tag{4}$$

where P_{ij} is the probability of choosing routine visits only, emergency room visits only, or any mixture of routine and emergency room visits, with no medical visits as the reference category. J is the number of treatments in the choice set, $j = 0$ is no medical visits, and β_j and X_i are a vector of estimated parameters and independent controls, respectively. If the logit equation above (Equation 4) is rearranged and exponentiated, the multinomial logistic regression equation used to estimate the coefficients is as follows:

$$\ln[\frac{P_{ij}}{1 - P_{ij}}] = b_0 + b_1 x_1 + \cdots + b_k x_k \tag{5}$$

where $\ln[P_{ij}/(1 - P_{ij})]$, the log odds ratio, is a linear function of independent controls, X_i. In this paper, the following independent controls are considered: health insurance coverage status, geographic region, race and ethnicity, age in years, gender, educational attainment, and total out-of-pocket expenditures on medical care.

4 Description of the Data

Empirical analysis of the effects of coverage status on consumer tastes for physician treatment requires the use of data that captures annual measures of individual-level utilization and expenditure on medical services and individual-level information on health status. The Medical Expenditure Panel Survey (MEPS) was selected over other national household surveys, such as the National Health Interview Survey, as the MEPS provides the most current and comprehensive individual-level data for evaluating medical consumption, expenditure, and health status. Moreover, the MEPS details every medical event and the timing of the medical event for each individual during the survey year. In this study, the MEPS data are organized as a cross-sectional panel time-series that spans 5 years. The base year for the study is 2008, the earliest year comprehensive data required for the study are available, and the final year is 2012, the most recent year that comprehensive data are available.

4.1 Determination of the Sample

The sample used to estimate the effects of coverage status on consumer tastes for medical care consists of respondents ages 19 to 64 each survey year. This age group was selected for inclusion in the analysis because respondents under 19 have limited discretion over their health coverage status (Anderson, Dobkin, and Gross, 2012) and individuals aged 65 and older are overwhelmingly enrolled in the Medicare insurance program (Card, Dobkin, and Maestas, 2008; Dugan, Virani, and Ho, 2012). To address the potential endogeneity of health insurance coverage status on utilization, the study sample is limited to respondents diagnosed with a major chronic disease (MCD) with a “sudden” onset and diagnosis. After applying these refinements, the study is left with a pooled sample of 22,873 respondents over the period 2008 to 2012. Table 1 details the sample selection criteria.

4.2 Description of the Sample

4.2.1 Major Chronic Disease Diagnosis

Respondents were identified as having a MCD diagnosis if they reported having heart disease and stroke (CHDS), diabetes, or cancer. Respondents were identified as having cancer or diabetes if they were ever told by a doctor or other health professional that they had cancer or diabetes, respectively. Respondents were identified as having a CHDS diagnosis if they were ever told by a doctor or other health professional that they had angina, coronary heart disease (CHD), a heart attack, any other kind of heart disease or condition, or stroke. CHDS patients are organized into a single diagnosis group because both groups share the same pathophysiology: they have overlapping atherosclerotic disease mechanisms and similar risk prediction algorithms. Therefore, while CHDS are distinct diseases with treatments that vary in their acute phase, they have the same patterns of recommended physician monitoring following an acute event (D'Agustino *et al.*, 2008; Kim and Johnson, 2011; Dugan, Virani, and Ho, 2012). Respondents who did not report having CHDS, diabetes, or cancer were excluded from the study sample. Figure 1 displays the distribution of MCD respondents by each individual diagnosis group.

4.2.2 Medical Treatment Bundles

In order to capture MCD patients' tastes for different patterns of medical treatment, several measures of individual utilization are combined into a single categorical measure of medical treatment. Two or more physician visits per year was chosen as a proxy for the threshold of medical care necessary to routinely monitor risk factors to avoid future acute events (Geraghty, 2000; Dugan, Virani, and Ho, 2012; ADA, 2014). Therefore, the following three treatment bundles are possible: two or more routine office based visits only, two or more emergency room visits only, and any mixture of two or more routine or emergency room visits. Respondents also have the option to make one or less medical visits of either kind. This fourth bundle represents the non-purchase of a treatment bundle capable of mitigating future acute events, and thus represents underutilization of physician services in the study. Figure 2 reports the distribution of treatment bundles in the study sample.

4.2.3 Health Insurance Coverage Status

Respondents were assigned to one of three health insurance coverage status groups: publicly insured, privately insured, and no private or pubic coverage. Respondents were identified as being publicly insured if they were recipients of Medicaid, the state-federal insurance program for low-income and disabled persons, Medicare, the federal insurance program for senior citizens and Social Security Insurance (SSI) and Social Insurance Disability (SSD) recipients, or some other state-federally sponsored insurance plan. As the study sample excludes respondents age 65 and above, only respondents with SSI and SSD are covered by Medicare. Respondents were identified as being privately insured if they obtained their coverage from their employer or a private health insurance marketplace. Respondents who report no private or public insurance coverage were identified as being uninsured. Figure 3 reports the distribution of health insurance coverage by coverage status.

4.2.4 Expenditures on Medical Treatment

Respondent expenditures on medical treatment bundles are measured as out-of-pocket expenditures on routine or emergency room visits instead of overall healthcare expenditures, as out-of-pocket expenditures more accurately assess the economic burden that alternative physician treatment bundles will have on a household. Out-of-pocket expenditures on medical visits are adjusted to reflect 2012 dollars using the U.S. Bureau of Labor Statistics Consumer Price Index (CPI) for Medical Care. Figure 4 reports out-of-pocket expenditures on physician treatment bundles by medical treatment bundle.

4.2.5 Other Control Variables

Individual factors such as age, sex, race/ethnicity, educational attainment, personal income, geographic region, and survey year are included in the regression analysis to control for the socioeconomic and sociodemographic status of respondents. All racial and ethnic groups are controlled for in the regression analysis; however, the subgroup analysis will focus on the three largest racial groups: white non-Hispanic, black non-Hispanic, and Hispanic. The regressions are weighted to adjust for the oversampling or undersampling of responses.

5 Results

5.1 Summary Statistics

The socioeconomic characteristics of respondents who make up the study sample are described in Table 2. The mean age was 49.0 years, and 43.0% (n=9,846) of the population were men. The total out-of-pocket expenditure for respondents was $1,001.1. Respondents with private insurance represent 59.3% (n=13,596) of the sample, respondents with public insurance represent 22.8% (n=5,219) of the sample, and uninsured respondents represent 17.9% (n=4,092) of the sample. All major racial groups are well represented in the sample, with white non-Hispanics, black non-Hispanics, and Hispanics representing 51.2% (n=11,727), 21.4% (n=4,890), and 20.9% (n=4,809), respectively. Most respondents reported having a high school degree (30.8%, n=7,039) or some college experience (51.7%, n=11,835), while 17.5% (n=3,999) report having never completed a high school degree.

The prevalence of medical treatment across respondent socioeconomic characteristics is presented in Table 3. Each of the three columns presents the utilization rate of medical treatment bundles representing appropriate utilization of physician services for a patient with MCD. Medical utilization varies considerably across the socioeconomic distribution. Adults aged 46 to 64 report a higher propensity of making routine visits only (65.8%) than adults aged 18 to 45 (50.2%). Women utilize a mixture of routine and emergency visits at a higher rate (20.0%) than men (15.4%). Insured patients report higher rates of routine visits only and a mixture of visits than uninsured respondents; however, publicly insured respondents report the highest rate of making a mixture of visits (29.1%) than privately insured (15.3%) and uninsured (13.0%) respondents. Whites report the highest propensity of making routine visits only (64.0%) than other racial groups, while blacks report the highest propensity of making a mixture of visits (22.3%). Respondents with some college experience report a rate of routine visits only (64.3%) than respondents with a high school degree (58.0%) or no degree (55.2%). Respondents without at college experience report the highest propensity of making a mixture of visits as compared to respondents with college experience.

5.2 Medical Treatment Regressions

5.2.1 Main Analysis

Table 4 reports the multinomial logistic regression results of routine office based visits only (Column 1, 4), emergency room visits only (Column 2, 5), and a mixture of routine and emergency visits (Column 3, 6), as compared to the underutilization category.[1] The results for the overall sample (Panel A) show that adults with insurance coverage had a higher probability of utilizing routine office based care only than uninsured adults, and the insured had a lower probability of utilizing emergency room based care only than uninsured adults. In particular, private and public insurance holders were 17.3% and 10.9% more likely to utilize routine office based care only than uninsured adults, respectively. Private and public insurance holders were 3.8% and 1.4% less likely than the uninsured to make emergency room visits only, respectively. The analysis of respondent propensity to utilize a mixture of routine and emergency care revealed significant disparities across coverage status. There are statistically significant differences in the way that privately insured and uninsured patients utilize a mixture of routine and emergency care. However, publicly insured respondents are 12.0% more likely than the uninsured to utilize a mixture of routine and emergency care.

Table 4 also presents the medical treatment regression results for individual diseases, focusing on CHDS respondents (Panel B), Cancer respondents (Panel C), and Diabetes respondents (Panel D). The results from the individual disease analysis are consistent with the overall results; however, there were a number of observations worth noting. Privately insured CHDS respondents were 3.8% more likely than the uninsured CHDS respondents to utilize a mixture of visits. On the other hand, privately insured cancer patients were 4.2% less likely than uninsured cancer patients to utilize a mixture of visits. These results

[1] The multinomial logistic regression coefficients in Table 4 and Table 5 have been converted into marginal effects and percentages to improve the interpretability of the multinomial logistic regression models.

suggest that privately insured patients are most likely to schedule their treatment in a routine office-based setting and visit emergency rooms to manage acute events.

5.2.2 Endogeneity

A major assumption of the analysis is that coverage status is not endogenously related to consumer tastes for medical treatment bundles because the analysis is limited to patients diagnosed with acute diseases with a rapid onset, making it highly unlikely that insurance status was selected on. However, this assumption could be violated if MCD patients select their coverage in anticipation of future acute events. To investigate this issue, a sampling approach and quasi-experimental model is employed to reveal how MCD patients react to receiving an unanticipated diagnosis and gaining access to a comprehensive insurance option, respectively. First, the main results are re-estimated using a sample limited to respondents who received their MCD diagnosis within one year of being surveyed (Table 5, Panel A) and a sample limited to respondents who experienced their CHDS event at least one year or more before being surveyed (Table 5, Panel B). The results are robust across both sampling restrictions. Following Dugan *et al.* (2012), an RD model that exploits a sharp increase in coverage resulting from older adults becoming eligible for Medicare at age 65 (Figure 5) is estimated. The results of the RD analysis are consistent with the main results (Table 5, Panel C).[2] These findings support the assumption that coverage status is not endogenous to medical treatment bundle choice.

5.2.3 Redefining Underutilization

In the economic framework of this paper, it was argued that if an individual does not consume a treatment bundle in J, then their post-treatment health state is equal to their pre-treatment health state (Brand, 2006). Due to the mortality risks following an acute

[2] Dugan *et al.* (2012) model compares CHDS patients who are ages ≤ 64 to CHDS patients who are ages ≥ 65, which allows for an examination of the effects of Medicare eligibility (i.e., moving from an insured/uninsured status to a comprehensive public insurance benefit).

event (Henning *et al.*, 1979; Kambara *et al.*, 1993; Tanne *et al.*, 1993), it may be unlikely that emergency only care is enough to limit future events. To address this concern, the main analysis is re-estimated using one less medical treatment bundle, where emergency only care is now incorporated into the underutilization category (Table 5, Panel D). The regression results from this alternative model are similar in sign and magnitude as the regression results of the main model, which suggests that emergency visits only represents an unpopular course of medical treatment.

5.3 Discussion

The medical treatment analysis revealed several important results. First, the main results show that the uninsured utilize emergency services at higher rates than the insured and utilize routine office based services at lower rates than the insured, which is consistent with the literature (Ayanian *et al.*, 2000; Anderson, Dobkin, Gross, 2012). For an uninsured patient, emergency care represents the lowest out-of-pocket cost treatment when facing the full cost of medical care. Unfortunately, emergency rooms are among the most expensive places to seek out care and when this care is uncompensated, the financial pressure on hospitals forces them to shift costs from the uninsured to the insured. Second, the main analysis also reveals that the insured are more likely than the uninsured to consume a threshold of medical care necessary to maintain individual health. This finding not only highlights a clear disparity in the utilization, but potentially explains an important difference in mortality between these two groups (Wilper *et al.*, 2009). Last, the results highlight differences in the way that covered populations consume appropriate levels of medical care. Privately insured patients have the highest propensity to consume routine office based visits, while publicly insured patients have the highest propensity to consume a mixture of routine and emergency care. Since the majority of publicly insured MCD patients under the age of 64 are enrolled in the Medicaid insurance program, their increased propensity of utilizing a mixture of routine and emergency care is likely due to the design of Medicaid cost sharing, which equalizes the direct costs between emergency room and physician office visits (Kangovi *et al.*, 2013).

6 Conclusion

When modeling consumer demand for medical care, studies typically focus their analysis on the effects of individual attributes of health insurance on aggregate measures of health-care utilization (Dor and Farley, 1996; Anderson, Dobkin, Gross, 2012; Card, Dobkin, and Maestas, 2008, 2009; Aron-Dine, Einav, and Finkelstein, 2013). There are two drawbacks to this approach with regard to understanding how coverage status directly influences health disparities and inequities. First, studies that focus on copayment rates or provider generosity typically focus on understanding how these factors impact service intensity and quality. However, modeling differences in service intensity alone will not explain why inequities persist across health status groups. Second, with an exception to emergency situations, an individual's consumption of medical care is voluntary and driven by their diagnosis status. Therefore, an analysis focused on the level of medical service consumed is not enough to determine the appropriate use of care. The treatment of a diagnosis requires that intentional combinations of medical services and procedures be prescribed and consumed.

This paper contributes to the literature by presenting a discrete choice random utility maximization framework that categorizes how an individual's coverage status affects the way they schedule treatment following a diagnosis/acute medical event. The potential endogeneity of coverage status and utilization is addressed by limiting the study sample to patients with diseases with a rapid onset and appropriate utilization is defined using follow-up treatment guidelines, which recommend that patients utilize a particular threshold of physician services following a diagnosis to reduce the odds of future acute events. The model contained within this paper is used to examine the structure of utilization among patients with CHDS, cancer, or diabetes, but can be extended to include any other diagnosis group that requires a well-defined threshold of monitoring following a diagnosis.

In summary, this paper shows that the insured are more likely to use appropriate levels of medical services than the uninsured. Among the insured, privately insured patients report the highest propensity of using cost-effective routine medical care while the publicly insured report the highest propensity to use the least cost effective mixture of medical services. These findings have important implications for the surveillance of inequities in health, understanding the determinants of medical cost growth, and the design of utilization incentives for integrated care.

References

[1] Aron-Dine A, Einav L, and Finkelstein A. The RAND Health Insurance Experiment, Three Decades Later. *Journal of Economic Perspectives* 2013; 27: 197-222.

[2] Aldrich, J.H., Nelson F.E., 1984. Linear Probability, Logit and Probit models, Sage University Paper Series on Quantitative Applications in the Social Sciences, Beverly Hills, California.

[3] American Diabetes Association. Standards of medical care in diabetes. *Diabetes Care* 2014; 37: S14-S80.

[4] Anderson M, Dobkin C, and Gross T. The Effect of Health Insurance Coverage on the Use of Medical Services. *American Economic Journal: Economic Policy* 2012; 4: 1-27.

[5] Ayanian J, Weissman J, Schneider E, et al. Unmet Health Needs of Uninsured Adults in the United States. *Journal of the American Medical Association* 2000; 284: 2061-2069.

[6] Brand K. A Structural model of health plan choice and health care demand in the Medicare managed care program. Working paper, *Federal Trade Commission* 2006.

[7] Carman K and Eibner C. Changes in health insurance enrollment since 2013. Policy Report, *Rand Corporation* 2014.

[8] Card D, Dobkin C, and Maestas N. The Impact of Nearly Universal Insurance Coverage on Health Care Utilization: Evidence from Medicare. *American Economic Review* 2008; 98: 2242-2258.

[9] Card D, Dobkin C, and Maestas N. Does Medicare Save Lives? *Quarterly Journal of Economics* 2009; 124; 597-636.

[10] Currie J and Gruber J. Health insurance eligibility, utilization of medical care, and child health. *Quarterly Journal of Economics* 1996; 111: 431-466.

[11] Czarnecki A, Chong A, Lee D, et al. Association Between Physician Follow-Up and Outcomes of Care After Chest Pain Assessment in High-Risk Patients. *Circulation* 2013; 127: 1386-1394

[12] Dafny L and Gruber J. Public Insurance and Child Hospitalizations: Access and Efficiency Effects. *Journal of Public Economics* 2005; 89: 109-129.

[13] D'Agostino R, Vasan R, Pencina M, et al. General cardiovascular risk profile for use in primary care: the Framingham Heart Study. *Circulation* 2008; 117: 743-753.

[14] Delavallade C. Quality healthcare and health insurance retention: Evidence from a randomized experiment in the Kolkata slums. *International Food Policy Research Institute* 2014.

[15] Dor A and Farley D. Payment Source and the Cost of Hospital Care: Inferences on Quality from a Multiproduct Cost Function. *Journal of Health Economics* 1996; 15: 1-22.

[16] Dugan J, Virani SS, Ho V. Medicare eligibility and physician utilization among adults with coronary heart disease and stroke. *Medical Care* 2012; 50: 547-553.

[17] Dugan J. Trends in managed care cost containment: An analysis of the managed care backlash. *Health Economics* 2014. In Press.

[18] Ferrer-i-Carbonell A and Van Praag B. The subjective costs of health losses due to chronic diseases. An alternative model for monetary appraisal. *Health Economics* 2002; 11: 709-722.

[19] Gertler P, Locay L, Sanderson W. Are User Fees Regressive? The Welfare Implications of Health Care Financing Proposals in Peru. *Journal of Econometrics* 1987; 36: 67-88.

[20] Henning H, Gilpin E, Covell J, et al. Prognosis after acute myocardial infarction: a multivariate analysis of mortality and survival. *Circulation* 1979; 59: 1124-1136.

[21] Ho V, Dugan J, and Ku-Goto M. Why are Hospital Prices Rising? *Health Management, Policy and Innovation* 2013: 1: 1-16.

[22] Hullegie P and Klein T. The effect of private health insurance on medical care utilization and self-assessed health in Germany. *Health Economics* 2010; 19: 1048-1062.

[23] Jha A, Varosy P, Kanaya A, et al. Differences in medical care and disease outcomes among black and white women with heart disease. *Circulation* 2003; 108; 1089-1094.

[24] Kambara H, Nakagawa M, Kinoshita M, et al. Long-term prognosis after myocardial infarction: univariate and multivariate analysis of clinical characteristics in 1,000 patients. Kyoto and Shiga Myocardial Infarction (KYSMI) Study Group. *Clinical Cardiology* 1993; 16: 872-878.

[25] Kangovi S, Barg F, Carter T, *et al.* Understanding why patients of low socioeconomic status prefer hospitals over ambulatory care. *Health Affairs* 2013; 32: 1196-1203.

[26] Kim A and Johnston C. Global variation in the relative burden of stroke and ischemic heart disease. *Circulation* 2011; 124: 314-323.

[27] McFadden, D. Conditional Logit Analysis of Qualitative Choice Behavior. In: Zarembka P (ed), *Economic Theory and Mathematical Economics*. Academic Press, New York

[28] Nyman J. *The Theory of Demand for Health Insurance*. Stanford University Press, 2003.

[29] Peterson E, Shah B, Parsons L, et al. Trends in quality of care for patients with acute myocardial infarction in the National Registry of Myocardial Infarction from 1990 to 2006. *American Heart Journal* 2008; 156; 1045-1055.

[30] Sivers. Follow your heart: optimal care after a heart attack: A guide for you and your patients. *British Journal of Cardiology* 2009; 16: 187-191.

[31] Tanne D, Goldbourt U, Zion M, et al. Frequency and prognosis of stroke/TIA among 4808 survivors of acute myocardial infarction. The SPRINT Study Group. *Stroke* 1993; 24: 1490-1495.

[32] Train K. Discrete Choice Models with Simulation. New York: *Cambridge University Press* 2007.

[33] Virani SS, Woodard L, Landrum C, et al. Institutional, provider, and patient correlates of low-density lipoprotein and non-high-density lipoprotein cholesterol goal attainment according to the Adult Treatment Panel III guidelines. *American Heart Journal* 2011; 161: 1140-1146.

[34] Wilper A, Woolhandler S, Lasser K, *et al.* Health Insurance and Mortality in US Adults. *American Journal of Public Health* 2009; 99: 2289-2295.

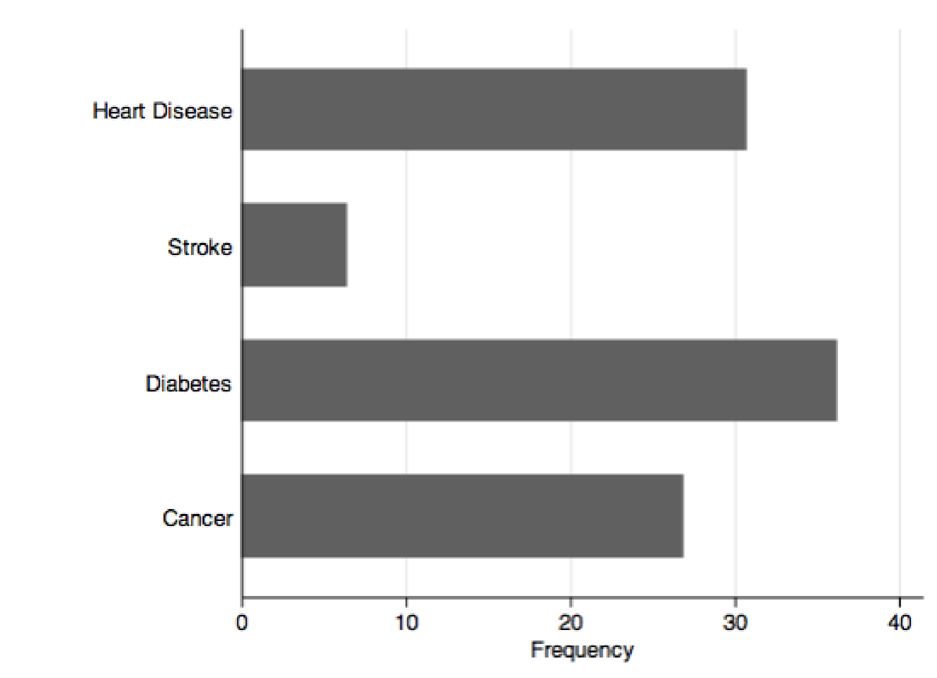

Figure 1: Distribution of Coronary Heart Disease and Stroke Diagnosis

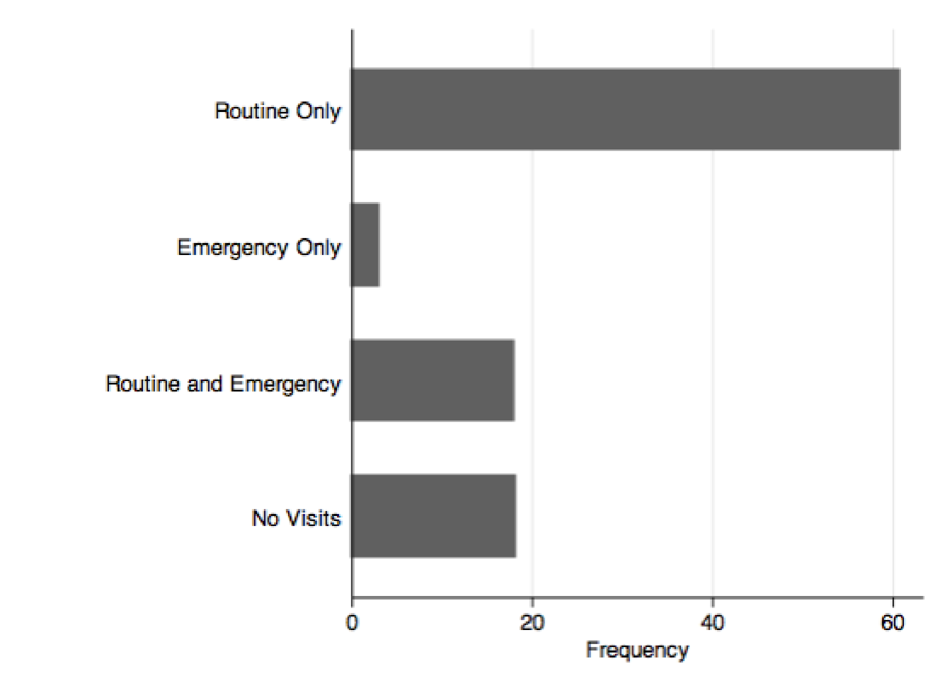

Figure 2: Distribution of Medical Treatment Bundles

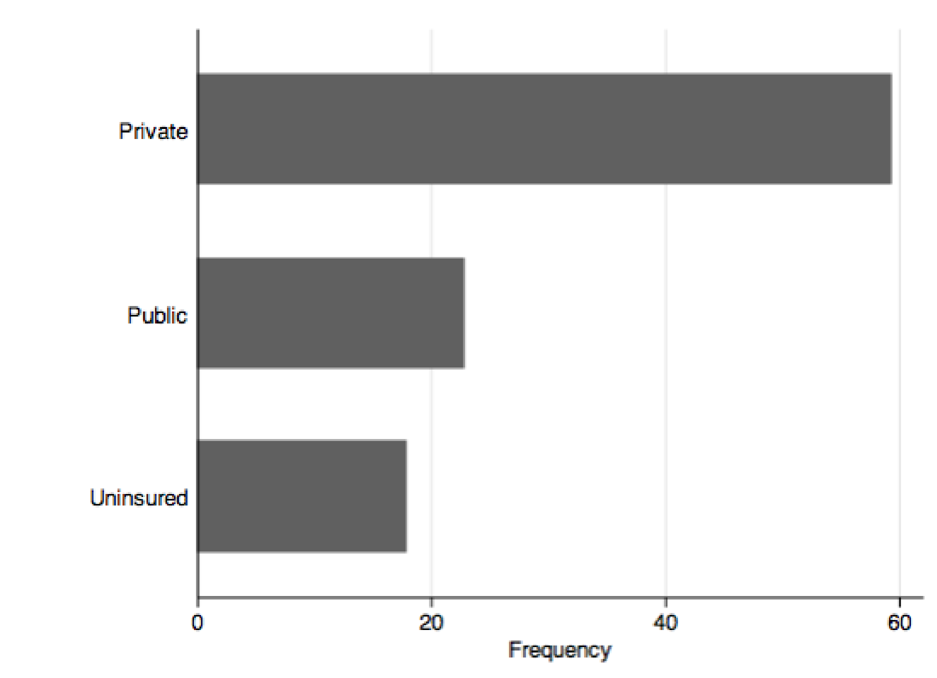

Figure 3: Distribution of Health Insurance Coverage

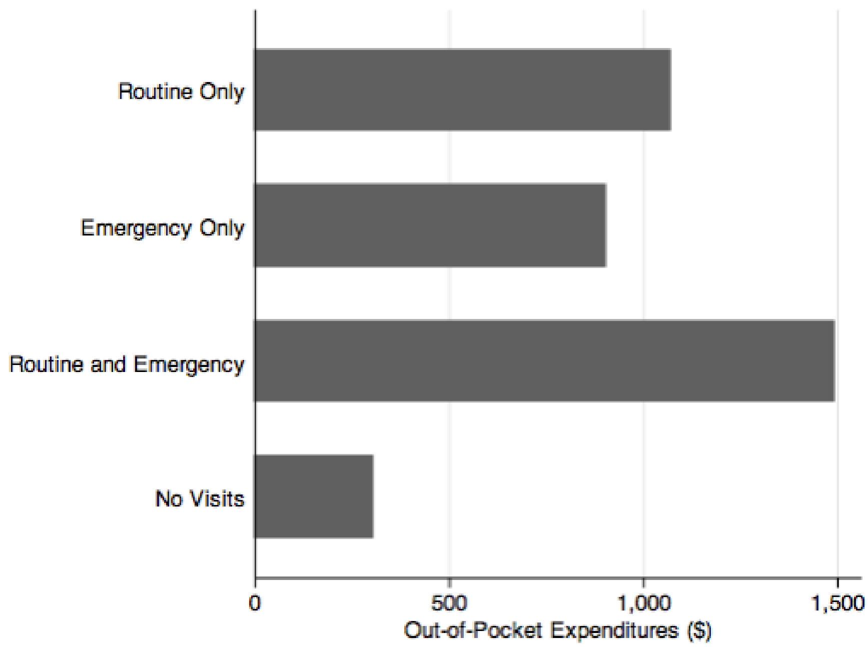

Figure 4: Out of Pocket Expenditures by Medical Treatment Bundle

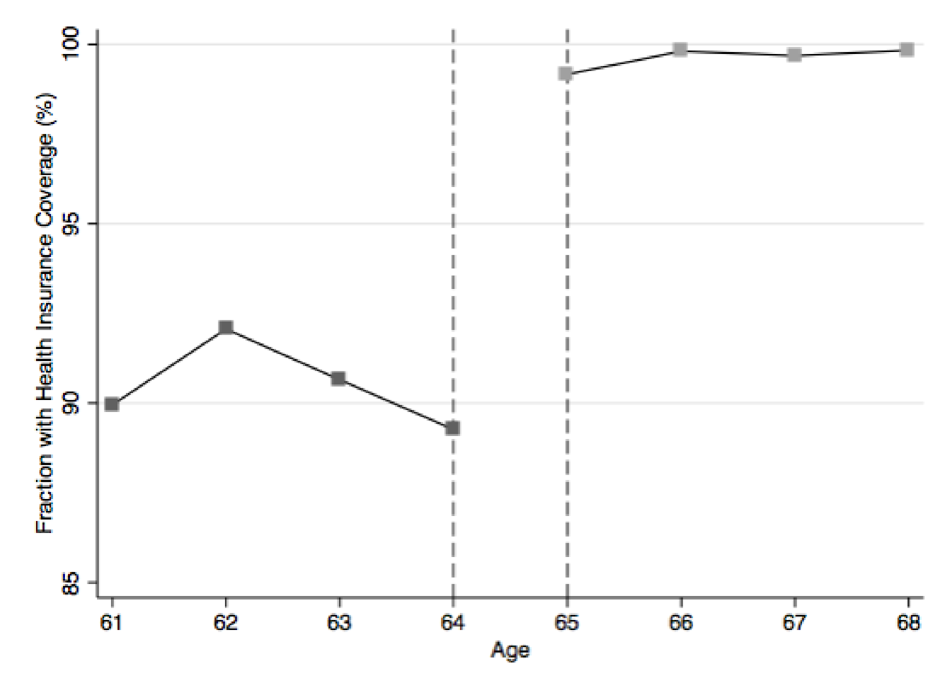

Figure 5: Health Insurance Coverage Rate by Age (Older Population)

Table 1 - Sample Selection Information

Total Number of Observations	212,367
age 19-64	124,333
diagnosed with Cancer, CHDS, or Diabetes	22,907
with valid responses to relevant variables	22,873

Notes: CHDS, Coronary Heart Disease and Stroke.

Table 2 - Distribution of Socioeconomic Characteristics

Variables	*N*	Mean ± S.D.	Percentage
Respondent Age	22,907	49.0 ± 11.4	
Out-of-Pocket Expenditures	22,907	1001.1 ± 2442.7	
Gender			
Male	9,846		43.0
Female	13,061		57.0
Geographic Region			
Northeast	3,488		15.2
Midwest	4,921		21.5
South	9,228		40.3
West	5,270		23.0
Insurance coverage			
Private	13,596		59.3
Public	5,219		22.8
Uninsured	4,092		17.9
Race/Ethnicity			
White Non-Hispanic	11,727		51.2
Black Non-Hispanic	4,890		21.4
Other Non-Hispanic	1,481		6.5
Hispanic	4,809		20.9
Educational Attainment			
No degree	3,999		17.5
High school degree or GED	7,039		30.8
At least some college	11,835		51.7

Notes: SD, Standard Deviation.

Table 3 - Prevalence of Medical Treatment

Variables	Routine Visits Only[a]	Emergency Visits Only[b]	Mixture of Visits[c]
Respondent Age			
18 to 45 years	50.2	5.3	18.6
46 to 64 years	65.8	2.0	17.7
Gender			
Male	59.7	3.1	15.4
Female	61.5	3.1	20.0
Insurance coverage			
Privately insured	67.8	1.6	15.3
Publicly insured	56.0	4.4	29.1
Uninsured	43.1	6.5	13.0
Race/Ethnicity			
White Non-Hispanic	64.0	2.2	17.5
Black Non-Hispanic	55.2	5.0	22.3
Other Non-Hispanic	64.6	2.5	13.4
Hispanic	57.1	3.5	60.6
Educational Attainment			
No degree	55.2	4.9	19.8
High school degree or GED	58.0	3.3	20.2
At least some college	64.3	2.3	16.1

Notes: The numbers reported in the columns are percentages (%).
[a] Routine visits only, 2+ routine office based visits only.
[b] Emergency visits only, 2+ emergency room visits only.
[c] Mixture of visits, 2+ routine and emergency room visits.

Table 4 - Medical Treatment Regressions

Variables	Routine Visits Only[a] (1)	Emergency Visits Only[b] (2)	Mixture of Visits[c] (3)	Routine Visits Only[a] (4)	Emergency Visits Only[b] (5)	Mixture of Visits[c] (6)
	A. Overall Sample (N=22,873)			B. CHDS Respondents (N=8,464)		
Private insurance	17.3***	-3.8***	1.1	19.4***	-5.5***	3.8***
	(0.9)	(0.3)	(0.7)	(1.4)	(0.6)	(1.3)
Public insurance	10.9***	-1.4***	12.0***	12.8***	-1.5***	13.8***
	(1.0)	(0.2)	(0.7)	(1.7)	(0.5)	(1.3)
Uninsured	1†	1†	1†	1†	1†	1†
	C. Cancer Respondents (N=6,139)			D. Diabetes Respondents (N=8,270)		
Private insurance	20.8***	-3.6***	-4.2***	12.7***	-2.1***	2.0
	(1.7)	(0.5)	(1.4)	(1.4)	(0.4)	(1.3)
Public insurance	12.6***	-1.7***	8.8***	8.1***	-1.0***	11.6***
	(2.1)	(0.5)	(1.5)	(1.6)	(0.4)	(1.3)
Uninsured	1†	1†	1†	1†	1†	1†

Notes: The multinomial logistic regression coefficients have been converted into marginal effects to improve interpretability. Numbers in parenthesis are standard errors. All regressions include individual controls, treatment controls, and time trends.

[a] Routine visits only, 2+ routine office based visits only.

[b] Emergency visits only, 2+ emergency room visits only.

[c] Mixture of visits, 2+ routine and emergency room visits.

† The reference category are uninsured respondents.

*** Significant at the 1% confidence level.

** Significant at the 5% confidence level.

* Significant at the 10% confidence level.

Table 5 - Alternative Specifications

Variables	Routine Visits Only[a] (1)	Emergency Visits Only[b] (2)	Mixture of Visits[c] (3)	Routine Visits Only[a] (4)	Emergency Visits Only[b] (5)	Mixture of Visits[c] (6)
	A. Acute Event Occurred Within One Year of the Survey (N=2,587)			B. Acute Event Occurred At Least One Year Before the Survey (N=14,147)		
Privately insured	10.2***	-4.9***	6.7***	17.1***	-3.7***	2.2***
	(2.8)	(1.0)	(2.7)	(1.1)	(0.4)	(0.9)
Publicly insured	-2.4	-3.4***	15.9***	11.9***	-0.9***	12.2***
	(2.8)	(1.0)	(2.8)	(1.2)	(0.3)	(0.9)
Uninsured	1†	1†	1†	1†	1†	1†
	C. Regression Discontinuity at Medicare Eligibility Threshold (N=2,525)[d]			D. Emergency Visits Only Added to Underutilization (N=22,579)		
Privately insured				17.2***		0.9
				(0.9)		(1.1)
Publicly insured				10.1***		11.8***
				(1.0)		(0.8)
Uninsured				1†		1†
RD term (≥ 65)	4.7	-2.7**	-0.3			
	(3.7)	(1.3)	(3.2)			

Notes: The multinomial logistic regression coefficients have been converted into marginal effects to improve interpretability. Numbers in parenthesis are standard errors. All regressions include individual controls, treatment controls, and time trends.
[a] Routine visits only, 2+ routine office based visits only.
[b] Emergency visits only, 2+ emergency room visits only.
[c] Mixture of visits, 2+ routine and emergency room visits.
[d] Regression Discontinuity Window: $64 \leq \text{Age} \leq 66$.
† The reference category are uninsured respondents.
*** Significant at the 1% confidence level.
** Significant at the 5% confidence level.
* Significant at the 10% confidence level.