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What Drives Differences in Health Care Demand? The Role of Health Insurance and Selection Bias

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Abstract This paper employs an econometric model to parse differences in health care utilization attributable to private health insurance and differences due to self-selection into insurance status, with specific interest in selection on unobservable traits such as insurance preference or attitude toward health risks. The model has two components, one component to model insurance outcome, the other to model demand for care measured as the annual number of doctor visits and prescriptions filled. Recognizing the endogeneity of health insurance, the model allows for correlated unobserved heterogeneity by assuming a latent factor structure. Values for these latent factors are drawn through simulation and the model is estimated using maximum simulated likelihood methods. For the observable characteristics that predict need for health services we find evidence of adverse selection. However, we also find evidence of advantageous selection on the unobservable characteristics common to insurance choice and utilization. In other words, unobserved heterogeneity that increases the chances of being uninsured is associated with higher utilization. Given this selection decomposition, there is no inherent conflict in describing the influence of both adverse and advantageous selection in utilization comparisons. After controlling for selection, the insurance incentive effect (ex-post moral hazard) is positive and significant. For the average individual, switching from no coverage to full coverage would result in 2 additional visits to the doctor per year (+160%) and 8 additional prescriptions filled (+207%).

Keywords: Health care; Health insurance; Adverse selection; Treatment effects model, Medical subsidy program

JEL Classification Numbers: I11, D82, C31, H51

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1 Introduction

With passage of the Patient Protection and Affordable Care Act (PPACA) in 2010, the US government expects 32 million individuals to gain insurance coverage by the end of the decade. Of these 32 million, roughly half are expected to gain coverage through private insurers competing in state-based exchanges, with the remaining half to be covered through Medicaid expansions. Disparities in utilization of health care services between the insured and uninsured have been well documented. However, investigating the impact of gaining private health insurance on health care utilization remains challenging for a number of reasons. Chief among these reasons are self-selection into health insurance, the lack of natural experiments with private coverage, and the dynamic nature of insurance coverage. Estimating the importance of unobservable traits in predicting insurance status and demand for care motivates this project, particularly in anticipation of expanding state-based private insurance exchanges due to PPACA reforms.

This paper presents a methodology that takes selection into account and separates the transitionally or temporarily uninsured from the continuously uninsured to measure the effect ("treatment effect", to borrow from the randomized controlled trials lingo) of health insurance on utilization of services. Our model thus provides evidence for the impact of selection decomposed into observable characteristics and unobservable characteristics. The model has two components, one for modeling the decision to insure and the other for modeling utilization decisions. Endogeneity of health insurance is handled by introducing latent factors that allow for correlated unobserved heterogeneity between the two components. Values for latent factors are drawn using simulation and the model is estimated using maximum simulated likelihood methods.

Important measures of access to care are analyzed: office-based physician visits and prescription drugs. These are services that the overwhelming majority of private insurance plans cover. Data for this project was compiled by pooling waves of the Medical Expenditure Panel Survey (MEPS) over the years 1996-2008. MEPS provides a rich set of socioeconomic and demographic variables that serve as observable controls in the insurance choice and utilization components of the model. MEPS also has insurance status by month, facilitating the creation of a temporarily uninsured category to better match insurance status to utilization. The depth of this data allows a thorough dissection of the heterogeneity of responses in terms of utilization after gaining insurance coverage, an important consideration in a treatment-effects model. For observable characteristics strongly associated with health services needs we find evidence of adverse selection. However, we also find strong evidence of advantageous selection on unobservable characteristics. That the model explicitly decomposes the selection effects in this fashion means there is no friction in simultaneously describing the impacts of adverse and advantageous selection on the same group of individuals. After controlling for both selection influences, a random assignment to full insurance coverage from no coverage would result on average in 2 additional doctor visits per year and 8 additional prescriptions filled, increases of 161% and 207% respectively. Temporary coverage does little to mitigate disparities due to insurance coverage. Assignment to full coverage from temporary coverage would still result in 2 additional trips to the doctor and 7 additional prescriptions filled.

Expanding private insurance to approximately 16 million individuals will result in different utilization patterns depending on the individuals themselves. Heterogeneity in treatment response must be considered the rule rather than the exception for studies of insurance expansion. Our paper makes a significant contribution in understanding the heterogeneity of responses to obtaining coverage. Pooling all available years of the MEPS survey yields a sample large enough to drill down into relevant subgroups to provide estimates of how the incentive effects of insurance will affect different groups.

The balance of the paper is structured as follows. Section 2 provides a review of recent literature on the subject matter of this paper. Section 3 describes the data developed for this research. Section 4 details the econometric approach. Section 5 presents results for the full population. Section 6 introduces additional specifications to examine the robustness of the model. Section 7 thoroughly reviews sub-group estimates. Section 8 concludes and discusses future possibilities from this research.

2 Related Literature

Identifying selection bias has defined work in health economics since Kenneth Arrow's seminal article that began the field was published (Arrow, 1963). Individuals have private information about their risk type (e.g. high-risk versus low-risk). High-risk individuals are more likely to purchase insurance and therefore a positive correlation exists between having insurance and the likelihood of the insured event occurring. Rothschild and Stiglitz (1976) provide the canonical model that results in market failure: nonexistence of a pooling equilibrium and predicted under-provision of insurance. Cutler and Zeckhauser (2000) provide a review of adverse selection in practice. Recent research has called into question this presumed positive correlation between likelihood of insurance and likelihood of insured risk.

Chiappori and Salanie (2000) develop a rough test for one of the enduring implications from Rothschild and Stiglitz (1976): within a menu of insurer contracts, more comprehensive coverage is chosen by agents with higher probabilities of insured risk. If insurance choice is independent of insured risk probability after controlling for what insurers observe, however, then adverse selection may not hold. Citing empirical evidence from Cawley and Philipson (1999) showing a negative correlation between likelihood of insurance and insured risk, De Meza and Webb (2001) begin with the assumption that risk preferences are not homogeneous. They posit that more cautious individuals are more likely to buy insurance. In a model with administrative costs, their model predicts a pooling equilibrium where insurance is over-provided. The predominance of more cautious types buying insurance lowers the insurance premium enough to induce more risky types to buy insurance.

Fang et al.(2008) and Finkelstein and McGarry (2006) continue along the lines of De Meza and Webb (2001) in describing private information as multi-dimensional. Individuals have private information about their degree of risk aversion as well as their risk type (among other types of private information). If risk aversion is positively correlated with the decision to insure (or amount of insurance) but negatively correlated with the insured risk, this would result in advantageous or favorable rather than adverse selection. A priori, these authors argue the overall impact of private information on insured risk is unclear. Empirical examples help illustrate this spate of theoretical contributions.

Chiappori and Salanie (2000) use French driving records to test for asymmetric information (adverse selection). French drivers must obtain minimum liability coverage to operate vehicles and also have the option to buy more comprehensive coverage. After controlling for a robust set of observable covariates, the authors do not find significant evidence of a correlation between comprehensive insurance coverage and the insured risk (claims). Cardon and Hendel (2001) similarly find no significant evidence of private information affecting health insurance choices and utilization after controlling for a set of observable characteristics, including insurance prices. Both papers interpretation is that asymmetric information isn't significant, however, both acknowledge that multiple unobservable characteristics may have offsetting impacts.

Finkelstein and McGarry (2006) present two interesting results regarding long-term care health insurance: 1) individuals have residual private information about their risk type (likelihood of nursing home utilization) that is positively correlated with long-term care coverage; 2) despite this positive correlation, overall insurance coverage and risk occurrence are not positively correlated. Such an outcome is reconciled by heterogeneity in preference for insurance. Higher income individuals and individuals exhibiting risk reducing behaviors such as seat-belt use are more likely to purchase insurance but have lower likelihood of the insured risk.

Fang et al.(2008) find strong evidence for favorable selection into Medigap insurance plans. The authors speculate that unobserved cognitive ability may be the pathway impacting the selection process. Higher cognitive ability would lower search costs and increase ability to accurately perceive risks or understand the costs and benefits of insurance. In this setting, higher cognitive ability would increase the likelihood of having insurance while also lowering the insured risk. Cutler and Finkelstein (2008) assess the direction of selection bias for five insurance categories and corresponding risks. They find a consistent relationship between risky behavior (or lack of risk-reducing behavior) and not having insurance. For life insurance and long-term care insurance, individuals less likely to have insurance due to riskier behavior have higher expected claims; interpreted as evidence of advantageous selection. No consistent pattern was found between risky behavior and expected claims for acute health insurance and Medigap plans. Adverse selection was found for annuities; those who live longer were more likely to purchase annuities.

The described efforts to identify the presence and direction of asymmetric information used ex-post observable information to test for correlations between insurance choices and insured risk outcomes. In cases where these observable characteristics were not enough to fully explain insurance choices and insured risk outcomes, observable proxies for relevant unobserved characteristics were analyzed to provide better information about the source of bias, whether adverse or favorable. For the purposes of our research, this literature highlights the importance of having a comprehensive set of observable population characteristics relevant to the insurance outcome process and utilization decisions. However, it is unlikely that observable characteristics are enough to fully account for selection, particularly taking into account the more complex nature of the insurance outcome process when the link between employment and health insurance is considered. Importantly, one of the contributions of this paper is a flexible specification in terms of unobserved information in addition to conditioning on a robust set of observable characteristics related to insurance choice and utilization. This approach allows us to estimate the net impact of selection on observable characteristics and unobservable characteristics, in addition to insurance treatment effects estimates.

Evidence from recent federal health insurance expansion also gives pause with regard to the impact of selection on unobserved traits. Early results are trickling in from the expansion of Medicare to include prescription drug coverage, Medicare Part D. Engelhardt and Gruber (2010) find that public prescription drug expenditures increased by $1,900 per person gaining coverage, a 100% increase over pre-Part D mean spending. Kaestner and Khan (2010) find that gaining prescription drug coverage through Medicare Part D was associated with a 70% increase in the annual number of prescriptions. Levy and Weir (2009) describe those without drug coverage prior to Part D's introduction as having less education, performing worse on cognitive tests, and being in worse health compared to those with coverage prior to implementation of Part D. While far from dispositive, these results are suggestive of favorable selection on unobservable characteristics in terms of drug coverage prior to Part D and worthy of extended study in this regard.

In terms of handling selection on unobservables, this paper adopts the methodology developed in Deb and Trivedi (2006b). Deb et al. (2006) apply this methodology in the context of managed care health insurance plans versus non-managed care plans. They find evidence of advantageous selection on unobservable characteristics into HMO plans. After controlling for selection, health care utilization was found to be higher for those insured in HMO plans versus non-managed care plans. A criticism of this work was the disaggregation of insurance choices among managed care versus non-managed care insurance plans when many employers may not offer a full range of such choices to employees. An advantage of this study is a more straightforward disaggregation of insurance options into private insurance or no coverage. Even this disaggregation is not without criticism as public insurance options exist for those under 65, particularly for individuals at or below the poverty level. Given the differing utilization profiles of Medicaid recipients and greater variation in supply of health care services, we recognize the tradeoffs and focus on private insurance versus no coverage. Mello et al (2002) use a similar approach to handle selection bias and find that while favorable selection explains some portion of the lower utilization of those with HMO insurance plans, the plans themselves do reduce utilization of some services. Both earlier papers analyze choices between different types of private insurance plans to separate the impact of selection on unobservables from changes in utilization due to plan characteristics. This paper is the first to our knowledge to extends this modeling method to the choice framework between no insurance coverage and private coverage.

To gauge the impact of PPACA on utilization, the Congressional Budget Office (CBO) (the official arbiter for the US government in terms of assessing how changes in the health care system will impact demand and spending) would ideally reference an updated version of the RAND Health Insurance Experiment (HIE)that included an uninsured control group. The RAND HIE, conducted in the 1970's, offered estimates of how differing levels of cost sharing associated with insurance plans impacted utilization and outcomes. Such an experiment eliminates the problem of selection on unobservables since insurance plans are randomly assigned. For the individuals that will gain insurance through Medicaid expansions, just such an updated experiment is ongoing. In 2008, the state of Oregon gave a group of low-income residents the chance to apply for Medicaid. Open seats were limited so Oregon was allowed to choose potential recipients by lottery, thereby minimizing the problem of selection bias. Finkelstein et al. (2011) review the results from the first year of the program and find that the likelihood of outpatient visits, prescriptions filled, and hospital admissions all increase significantly for the group that was able to apply for Medicaid slots compared to the group that signed up for the lottery but was not given the chance to apply for insurance.

A random experiment with national coverage dealing with expansions of private insurance isn't feasible. The next stops in search of valid estimates are natural experiments and observational studies that utilize statistical techniques to isolate the impact of insurance on utilization. Buchmueller et al. (2005) assess the existing literature on the impact of gaining insurance on demand for physician visits for adults and find that gaining insurance increases utilization between 60%-100%. Freeman et al. (2008) reviewed 9,701 studies and found only 14 that met the standard for careful handling of the endogeneity of health insurance. Of those 14 studies, gaining insurance increased utilization of outpatient services by between 8%-40%. The majority of the studies cited in these papers focus on natural experiments involving changes in public insurance programs, focus on narrow populations, or lack distinctions between temporary versus continuous lack of insurance coverage. PPACA expects to channel half of the newly insured 32 million into private coverage. The composition of the uninsured likely to enter state-based exchanges skews toward the young and the working poor. Estimates of how gaining coverage will change utilization for this group are scarce.

A more recent study uses a regression discontinuity design to control for selection and capture the treatment effects of insurance. Anderson et al. (2010) focus on 19-year olds that have aged out of their parents coverage. A 10-point drop in the insurance coverage rate among emergency department patients lowers emergency department visits by 4% while a 10-point drop in coverage among hospital patients reduces hospital visits by 6.1%.

Another recent study that focuses on a nationally representative population (Ward et al, 2007), uses Medical Expenditure Panel Survey (MEPS) data from 2000 to 2003 to estimate that obtaining full coverage increases expenditures of the uninsured to the level of those continuously insured. The

CBO (2008) itself adopts a similar approach in establishing a baseline for assessing how gaining insurance affects demand. Using MEPS data from 1997-2005, the CBO found that on average, individuals gaining insurance coverage used between 26%-29% more services than those who were uninsured. A significant drawback to the CBO study is the small number of individuals that experience changes in insurance status, particularly the most relevant change: uninsured to insured. For non-elderly adults, less than 2% of MEPS survey respondents switched from no coverage in survey year 1 to full coverage in year 2. By contrast, more than 50% of the group temporarily covered in year 1 (at least 1 month of insurance coverage) had full coverage in year 2. This clear distinction between temporary versus continuous lack of coverage serves as additional motivation for separating these groups for purposes of modeling the impact of insurance on demand.

3 Data

We use data from the Medical Expenditure Panel Survey (MEPS). MEPS provides a nationally representative sample in addition to rich detail on demographics, individual health status, health spending, and monthly insurance status. Information is collected from individuals through a series of interviews over two years. The final data used in this paper takes advantage of the multiple years of information but only assesses cross-sectional variation for estimation purposes. To form the final dataset, data were collected from individuals starting with the 1996 panel survey and continuing with two-year overlapping panels through 2008. Only individuals with complete observations for the two years were kept to avoid selection bias related to attrition. Subjective health status information was used only from the first year of panel interviews in the insurance choice component of the joint model, recognizing that health status may itself be endogenous in health services usage. All other variables are taken from the second year of the panel interviews unless otherwise noted.

We exclude individuals younger than 18 given different overall health profiles and expected usage patterns compared to adults. Those 65 and older are also excluded since the availability of Medicare obviates the primary insurance decision for almost all US citizens. Individuals that did not have a complete set of socioeconomic and demographic control variables were also excluded from the sample (e.g. missing values for education or age). Finally, only individuals with private insurance were kept in this sample. The focus of this paper is on private insurance, motivated by that insurance channel's portion of PPACA reforms. Further, MEPS publicly available data does not contain information about insurance plan premiums and differences in plan coverage. After exclusions, the final dataset has 82,582 person-year observations.

3.1 Insurance Status

Monthly insurance status observations were gathered from MEPS interviews and consolidated into three annual insurance categories. The three categories of insurance status were developed to dovetail with annualized utilization variables. An individual is termed insured (INSR) if he has private insurance for all 12 months of the year (always observed during the second year for the individual in the panel). Individuals with between 1 and 11 months of insurance are termed temporarily insured/uninsured (TEMPINSR) and those without insurance for any month during the year are termed uninsured (UNINSR). The average number of months without insurance for the TEMPINSR group was 5.2. Insurance status for the full data set breaks down as follows: 55,210 (67% of sample) full-year insured, 8,107 (10%) uninsured for part of the year, and 19,265 (23%) uninsured for the entire year.

3.2 Health Care Demand

Office-based physician visits (OBDOCVIS) and prescription drugs (RXNUM) are the health services analyzed. OBDOCVIS captures the annual number of visits to a physician in an office setting while RXNUM represents the number of prescriptions filled, including refills, during the year. A unit of prescription is a 30-day supply or less if prescribed as such. Table 1 gives a summary of unconditional differences in office-based physician visits and prescription drug usage by insurance status. Compared to those with insurance for the full year, those without any coverage for the year average more than 1.5 fewer physician visits and almost 4 fewer prescriptions filled (p=.05). Temporarily uninsured individuals average about 1 fewer physician visits and just over 3 fewer prescriptions filled compared to the insured (p=.05).

3.3 Health Status

Individual health status is a key differentiating characteristic in decisions regarding insurance and utilization of health services. MEPS provides a range of health status variables that assist in uncovering many of the observable differences among individuals. Survey questions regarding subjective evaluation of personal health are converted to a five point scale: excellent (the omitted variable), very good (VGOOD), good (GOOD), fair (FAIR), and poor (POOR).

An individual's health will impact insurance choice in addition to utilization of health services. To minimize the possibility of endogeneity of health status in the second year decision to insure, we use health status information from the first year of the survey in the insurance component. Second year health status information is then used in the utilization component. This presumes individuals use current health status to forecast future utilization and make insurance decisions accordingly. Realized health status then alters actual utilization as necessary, conditional on the choice of insurance.

MEPS also asks categorical questions that foster a more objective evaluation of health. Individuals are classified based on the total number of chronic conditions present (TOTCHR), the existence of a condition on the priority list (PRIOLST), the existence of ailments that create physical limitations to daily activities (PHYSLIM), and the occurrence of a serious injury (INJRY). A summary of chronic conditions and differences in prevalence of these conditions across insurance status is provided in Table 2. Conditions on the priority list overlap to some degree with the chronic conditions list but also include precursors to diagnosis of chronic conditions such as high blood pressure, high cholesterol, joint pain, and chronic bronchitis, filling in important details on individual health.

Individuals with diabetes, arthritis, and hypertension, the three most prevalent chronic conditions in this sample, are more likely to be continuously insured versus temporarily uninsured or continuously uninsured. Given that utilization is higher for these conditions, this is evidence of adverse selection based on observable health characteristics. Levy and Meltzer (2008) establish that among successful studies demonstrating a causal relationship between health insurance and health outcomes, those with chronic conditions benefit the most in terms of better outcomes from access to insurance.

3.4 Demographic & Socioeconomic Characteristics

Socioeconomic and demographic characteristics play a role in observed disparities in health services usage and decisions to insure. To partial out these observable characteristics and focus on the treatment effect of insurance, we include an appropriate range of socioeconomic and demographic variables in our estimations. Table 3 defines this set of covariates and shows differences by insurance status.

Hispanics are more heavily represented in the continuously uninsured category than their overall population numbers would dictate. To the extent this is cultural, results from this study may overstate the differences in utilization that might result from obtaining insurance. Overall, individuals in the temporarily uninsured and continuously uninsured categories are younger, poorer, less educated, less likely to be married, more likely to be self-employed, and more likely to live in the South and West than individuals with full-year insurance. Selection on these observable characteristics is likely given that almost all show significant differences across insurance categories. Among observable characteristics, the existence of chronic conditions, the occurrence of injury, and conditions that limit daily activities correspond positively with higher utilization and higher probability of being insured; consistent with evidence of adverse selection on observable characteristics.

4 Econometric Model

4.1 Theoretical Background

Estimating health services utilization is complicated by the potential unobserved correlation between the decision to insure and the decision to obtain health services. This correlation can come from family health history, life-style, preference for insurance, or attitudes toward health risks. Given the aggregated utilization and insurance status information used in this paper, a two-stage model for treating the endogeneity of health insurance is not appropriate. Instead, we assume a recursive structure between insurance outcome and utilization outcomes. Individuals make insurance decisions with expected future health needs in mind and then utilization decisions are made based on realized health care needs, conditional on insurance choice. Realized utilization then feeds back into next period's insurance decisions. Such a framework, due originally to Cameron et al.(1988), highlights the focus of this paper on selection rather than simultaneity between insurance choice and utilization outcomes. Both issues can be problematic, but institutional structures in the US insurance industry such as lack of guaranteed issue (insurers aren't forced to provide coverage to an individual that just experienced a negative health shock, e.g.) justify the focus on selection. Coincidentally, PPACA plans to enforce guaranteed issue, thus opening the door for more serious issues of simultaneity in terms of hindering utilization comparisons. Minimum insurance contract periods of one month make the aggregation of a series of monthly insurance and utilization decisions to annual aggregates feasible for our modeling purposes.

4.2 Model Context

Modeling the endogeneity of health insurance has generally taken one of three forms: 1) Longitudinal models, taking advantage of repeated individual observations to eliminate unobservable effects that are time invariant; 2) Instrumental variables (IV), where strong predictors of treatment are used in place of the endogenous treatment variable. This approach is predicated on the assumption that the instruments only influence the likelihood of treatment and do not directly impact utilization behavior; 3) Control functions, an approach that corrects for bias by using error terms from the selection process (insurance choice) in the utilization estimation. The model developed in this paper attacks the endogeneity challenge with a two-component model or joint model that has elements of approaches 2) and 3). The first component specifies the insurance decision and the second component specifies the utilization equation conditional on insurance choice. This joint model of outcomes and treatments can be classified as semi-structural given that we combine a reduced form insurance choice or treatments equation with an outcome equation that contains endogenous insurance status categories. Both observed and unobserved correlations link the two components. A latent factor structure is used to model unobserved correlation. We use instrumental variables for robust identification. What follows is an introduction to the joint model specification; more detail is available to readers in Deb and Trivedi (2006b).

4.3 Insurance Component

Individuals choose an insurance treatment from a set of three choices: Let $d_j,\ j = 0, 1, 2$, be binary variables representing insurance choice, with $j = 0, 1, 2$ corresponding to insured (INSR), temporarily insured (TEMPINSR), and uninsured (UNINSR) respectively. We assume there exists an indirect utility function EV_j^* associated with the jth insurance choice category such that

$$\mathrm{EV}^*_{ji} = \mathbf{z}_i'\boldsymbol{\alpha}_j + \delta_j' l_{ji} + \eta_{ji} \tag{1}$$

where $\mathbf{z}_i$ is a vector of exogenous factors affecting the decision to insure and $\boldsymbol{\alpha}_j$ are the associated parameters. The error term is split into two parts, the random utility term η_{ji}, and the l_{ji}, which capture unobserved factors related to individual $i's$ treatment choice. These factors can be interpreted as private information such as family health history, attitudes toward health risks, or life-style habits. These variables affect both the insurance decision and utilization decisions. We assume l_{ji} are independent of η_{ji}. The δ_j are factor loading parameters associated with the latent factors.

We transform the latent variable equation to the observed insurance choices through a distribution g that posits a multinomial choice model such that

$$\Pr(d_{ji} = 1|\mathbf{z}_i, l_{ji}) = g(\mathbf{z}_i^{'}, l_{ji}),\ j = 0, 1, 2 \tag{2}$$

For the purposes of this data, we assume that the distribution g has a mixed multinomial logit structure conditional on the latent factors, l_{ji}, defined as

$$\Pr[d_{ji} = 1|\mathbf{z}_i, l_{ji}] = \frac{\exp(\mathbf{z}_i^{'}\boldsymbol{\alpha}_j + \delta_j^{'} l_{ji})}{\sum_{k=0}^{J} \exp(\mathbf{z}_i^{'}\boldsymbol{\alpha}_k + \delta_k^{'} l_{ki})} \tag{3}$$

with the normalization restrictions $\boldsymbol{\alpha}_0 = 0$ and $\delta_0 = 0$. Given that $\delta_0 = 0$, it is without loss of generality that we assume $l_{0i} = 0$. Therefore l_{1i} and l_{2i} are interpreted as factors favoring TEMPINSR and UNINSR over INSR.

Adverse selection in this model arises when an individual, expecting a high need for medical services due to private knowledge of future health status, chooses to insure and subsequently uses more health services. Advantageous selection would arise if there were a negative correlation between the private information and the insured risk. An example is if risk aversion is correlated positively with continuous insurance and negatively with demand for care.

4.4 Utilization Component

Let y_i^* denote the value of the latent variable underlying the observed health services utilization values, y_i. The outcome equation is then

$$E(y_i^*) = \mathbf{x}_i^{'}\boldsymbol{\beta} + \gamma_1 d_{1i} + \gamma_2 d_{2i} + \sum_j \lambda_j l_{ji} + \epsilon_i \tag{4}$$

where $\mathbf{x}_i$ is a vector of exogenous covariates and $\boldsymbol{\beta}$ the associated parameters. Coefficients γ_1 and γ_2 gauge the effects of insurance status on health services utilization. Insurance choice is endogenous with respect to utilization since individuals make insurance decisions with future health services needs in mind. Therefore assuming d_1 and d_2 are exogenous in a single equation model would result in inconsistent estimates of γ_1 and γ_2. While such an estimate is biased, it provides useful context to evaluate a model that does handle endogeneity. Estimates from a model that ignores endogeneity are capturing the true health insurance incentive effect plus the impact of unobservable traits. Therefore, in comparison with a model that yields an unbiased estimate of the health insurance incentive effect, an estimate of the magnitude and direction of selection bias is possible.

To isolate the treatment effect of insurance choice on health services utilization latent factors, l_{ij}, are included in the utilization equation. The l_{ij} are the unobserved characteristics that influence both insurance choice and health services usage with λ_j the coefficients or factor loadings associated with the unobserved characteristics. The remainder of the error term is ϵ_i, an independently distributed random error.

Transforming y_i^* into the observed random variable $E(y_i)$ is done through an appropriate distribution function f yielding

$$\Pr[Y_i = y_i|\mathbf{x}_i, d_i, l_i] = f(\mathbf{x}_i^{'} + \gamma_1 d_{1i} + \gamma_2 d_{2i} + \sum_{j=1}^{2} \lambda_j l_{ji} \tag{5}$$

This formulation assumes $l_{0i} = 0$, thus we interpret l_{1i} and l_{2i} as factors favoring TEMPINSR and UNINSR respectively.

Office visits and filled prescriptions are count variables so the negative binomial-2 distribution (NB2) is specified for f. The NB2 distribution accounts for over-dispersion, commonly observed in health services count data, and has been found to be a robust choice of functional form in previous work.

$$f(y_i|\mu_i) = \frac{\Gamma(y_i + \psi)}{\Gamma(\psi)\Gamma(y_i + 1)} \left(\frac{\psi}{\mu_i + \psi}\right)^{\psi} \left(\frac{\mu_i}{\mu_i + \psi}\right)^{y_i} \tag{6}$$

where the conditional mean parameter

$$\mu_i = \exp(\mathbf{x}_i^{'}\boldsymbol{\beta} + \gamma_1 d_{1i} + \gamma_2 d_{2i} + \sum_{j=1}^{2} \lambda_j l_{ji}) \tag{7}$$

denotes the mean component of utilization and $\psi > 0$ is an over-dispersion parameter in the conditional variance function $\mu_i(1 + \psi\mu_i)$.

Given that insurance choice and health care services utilization equations are independent after conditioning on explanatory variables (including the latent factors), the joint probability of an individual choosing a health service y_i times and choosing insurance d_{ji} is the product of conditionally independent probabilities

$$\Pr[Y_i = y_i, d_{ji} = 1|\mathbf{x}_i, \mathbf{z}_i, l_{ji}] = f(\mathbf{x}_i^{'}\boldsymbol{\beta} + \gamma_1 d_{1i} + \gamma_2 d_{2i} + \sum_{j=1}^{2} \lambda_j l_{ji}) \times g(z_i, l_{ji}) \tag{8}$$

4.5 Estimation

The difficulty in estimating the joint probability given in equation (8) stems from the l_{ij} not being observed. If we assume the distribution of the l_{ij}, then their effect, however, can be integrated out of the joint probability function. Let h_j represent the density of l_{ji}. Then,

$$\Pr[Y_i = y_i, d_{ji} = 1|\mathbf{x}_i, \mathbf{z}_i, l_{ji}] = \int \Pr[Y_i = y_i, d_{ji} = 1|\mathbf{x}_i, \mathbf{z}_i, l_{ji}]h_j(l_{ji})dl_{ji} \tag{9}$$

For standard parametric forms for f, g, and h, the integral given in equation (9) does not have a closed form solution. For our purposes, the integral is approximated numerically by extracting S pseudo-random draws, $\tilde{l}_{ji}^{(s)}$ $s = 1, ..., S$, from the density h_j (assumed to follow independent standard normal distributions). After each draw, the simulated values are used in place of the unobserved l_{ji} and then the average of the joint probability is calculated across all simulation draws,

$$\tilde{\Pr}[Y_i = y_i, d_{ji} = 1|\mathbf{x}_i, \mathbf{z}_i] = \frac{1}{S}\sum_{s=1}^{S} \Pr[Y_i = y_i, d_{ji} = 1|\mathbf{x}_i, \mathbf{z}_i, \tilde{l}_{sji}] \tag{10}$$

The log-likelihood function is formed by taking the logarithm of the simulated probability and summing over all observations. We obtain parameter estimates by maximizing the simulated likelihood function (MSL). Variance of the MSL estimates are computed using the robust or sandwich formula. Within STATA, the command **mtreatreg** can be used to efficiently estimate the two component model; Deb and Trivedi (2006a) has details and examples for interested readers.

4.6 Interpretation

The joint model with maximum simulated likelihood (MSL) estimation controls for self-selection on both observables and unobservables allowing us to interpret γ_{TEMPINSR} and γ_{UNINSR} as treatment effects; $\gamma_{\text{TEMPINSR}} > 0$ means an individual randomly assigned to the temporarily uninsured category has higher average utilization of health services than if that individual were assigned to the continuously insured status while $\gamma_{\text{UNINSR}} < 0$ would mean that an individual in the uninsured category has lower average utilization than an individual in the continuously insured category.

Direct interpretation of selection on unobservable characteristics is also possible with the joint model through the factor loadings $\lambda_{\text{TEMPINSR}}$ and λ_{UNINSR}. For example, $\lambda_{\text{UNINSR}} < 0$ would imply that attitude toward health risks (e.g.) that increases the likelihood of uninsured status is associated with lower levels of utilization than those expected under random assignment of insurance status. If healthier individuals are more likely to choose to go without insurance, the insured category (INSR) would suffer from adverse selection. Similarly, $\lambda_{\text{UNINSR}} > 0$, suggests unobserved heterogeneity that increases the likelihood of uninsured status is associated with higher levels of utilization and would be interpreted as favorable selection.

4.7 Identification

While identifying causal parameters through non-linear functional forms is possible, more robust identification is accomplished by using instrumental variables as sources of exogenous variation in insurance status. Instrumental variables need to be highly correlated with insurance choice but uncorrelated with usage of health services. We choose two categories of variables that fit these needs: employment characteristics and marital status changes.

Employment Characteristics

In the U.S., employer sponsored health care plans have favored tax status over individual plans. For large employers, administrative costs can be spread over a much larger number of plan enrollees. Given these advantages, employers in general and large employers in particular tend to offer better and less expensive health insurance plans than often are available on the individual market (Bundorf, 2002). For employees working in firms with 50 or more employees, 98% were offered health insurance while only 64% of employees working for firms with less than 50 employees were offered coverage (Stanton, 2004). We capture this increased likelihood of being insured with two variables: the number of firm employees (FIRMSIZE) and the existence of multiple firm locations (MULTLOC). We assume that health services utilization decisions are uncorrelated with job choice after controlling for a robust set of other observable characteristics. A self-employment indicator (SELFEMP) is also used as an instrument. Previous studies indicate a large negative correlation between self-employment and insurance and self-selection issues between self-employment and health services utilization do not appear significant (Meer and Rosen, 2004). We also include a category to capture what the loss of employment does to available insurance options (LOSTJOB). Job loss is a strong predictor of being covered only temporarily during the year.

Changes in Marital Status

Changes in marital status often change the insurance options available to individuals but a priori should not affect utilization decisions. Getting married (GOTMARRIED) and getting divorced (GOTDIVOR) are used as instrumental variables in this regard. Changes in marital status could influence health, therefore these indicator variables are only feasible as instruments conditional on the health status variables already included in the utilization equation. We note that by construction marital status changes are local instruments as they can only impact the relevant subset of individuals in the population.

5 Results

Given unconditional differences in utilization across insurance categories, we seek to decompose these differences into those attributable to observable and unobservable differences in the populations versus those attributable purely to the effect of different categories of insurance. Differences between continuously uninsured versus temporarily uninsured are analyzed as well as the significant factors affecting insurance choice overall. For comparison versus the joint model, we include results from an estimation of utilization assuming exogenous insurance choice.

In presenting overall results from a treatment-effects model, we recognize that heterogeneity in response to treatments is the rule rather than the exception. To explore such heterogeneity, a thorough evaluation of sub-population estimates is presented in a later section. However, even with noted drawbacks we argue that presenting results from a nationally representative group in this context continues to be vital, particularly in cases where national policy is concerned.

5.1 Insurance Choice

Since results from the insurance choice component of the joint model are very similar between both utilization measures, we present and discuss only the results from office-based physician visits (OBDOCVIS). Table 4 shows coefficient estimates from the mixed multinomial choice model.

Education, marriage, and higher income all decrease the likelihood of being continuously uninsured. Females are less likely to be uninsured while minorities, particularly Hispanics, are more likely to be uninsured. Regionally, compared to living in the South, living in any other region (Northeast, Midwest, West) is associated with a lower likelihood of being uninsured. In terms of the regional comparison, this result fits well with observed insurance trends in the Current Population Survey among those living in the South (Fronstin, 2010). Living in a metropolitan statistical area decreases the probability of being continuously uninsured but does not affect temporary periods without coverage.

Lower subjective ratings of health are associated with a higher probability of being uninsured. Presence of physical limitations to daily activities (PHYSLIM) also increases the likelihood of uninsured status. However, total number of chronic conditions (TOTCHR) and having a condition on the priority list (PRIOLST) both make it significantly less likely that individuals are uninsured. This lack of one-way correlation between different measures of observed health status and continuous insurance illustrates further the importance of pinning down the net impact of both observed and unobserved differences among individuals that affect insurance choice and utilization.

For the employer characteristics used as identifying instruments, FIRMSIZE and MULTLOC, as expected we find higher values decrease the chance of being uninsured. Working for yourself (SELFEMP) increases the likelihood of being uninsured either temporarily or continuously. The category that overwhelmingly predicts temporary uninsured status is losing a job (LOSTJOB). Changes in marital status variables that are also used as instruments, GOTMARRIED and GOTDIVOR, increase the probability of being uninsured. Typically, the act of getting married would be seen to increase the opportunities for health insurance. That this set of results indicates the opposite is worthy of inquiry, albeit left for future work.

5.2 Utilization

Table 5 reports the average marginal effects for office visits (OBDOCVIS) and prescription drugs (RXNUM) from the joint model. As individuals move down the subjective health rating scale from excellent to poor, both the number of office visits and prescription drugs increase. A subjective rating of POOR increases the average number of prescriptions by 9 per year and the number of physician-based office visits by 1.6 per year compared to an individual with a subjective health rating of excellent.

Less subjective health variables are also major drivers of utilization of the medical services analyzed. Injuries (INJRY), physical limitations (PHYSLIM), chronic conditions (TOTCHR), and priority list conditions (PRIOLST) are positive and significant (p=.01) for OBDOCVIS and RXNUM. Particularly for prescription drugs, having a chronic or priority condition is a significant predictor of prescription drug utilization. When combined with a higher likelihood of full insurance coverage, we find evidence of adverse selection based on these observable traits.

Females (FEMALE) have higher usage of medical services than men, while Hispanics (HISPANIC) and Blacks (BLACK) have lower utilization than Whites. Individuals living in regions outside the South have lower utilization of prescription drugs but visit the doctor more often, possibly outlining a different mode of care or differences in availability of physicians in the South.

5.3 Treatment vs Selection

The primary focus of this research is identifying the impact of selection on unobservable traits, thus isolating the impact of insurance status on utilization of health services. Table 6 has results from the joint model for office visits (OBDOCVIS) and Table 7 has results for filled prescriptions (RXNUM). Table 8 provides average marginal effects for both OBDOCVIS and RXNUM. For comparison purposes, unconditional differences are included in addition to marginal effects estimates from a model that ignores the endogeneity of health insurance in explaining utilization. The selection effect is calculated as the treatment effect of the model ignoring endogeneity less the treatment effect of the model capturing endogeneity. This estimate provides the magnitude of the marginal impact of unobservable traits on utilization. A positive selection effect is interpreted as evidence of advantageous selection.

Factor loadings ($\lambda_{\text{TEMPINSR}}$ and λ_{UNINSR}), shown in Tables 6 and 7, show evidence of advantageous selection in the case of both physician visits and prescription drugs. Unobservable characteristics that favor no insurance coverage or only temporary coverage are also associated with HIGHER utilization. Selection effects (Table 8) show that unobservable traits appear more important in explaining utilization of prescription drugs compared to doctor visits and for those temporarily uninsured versus continuously uninsured. Compared to the unconditional means, controlling for observable characteristics lowers the estimated differences in utilization attributable to insurance for OBDOCVIS. This is consistent with evidence of adverse selection; individuals with higher expected health needs based on what we can observe are more likely to be fully insured. Our model therefore yields evidence of both adverse and advantageous selection with no contradiction. Ignoring selection on observables would result in overstating the insurance effect. Selection on unobserved traits, by contrast, is advantageous and results in understating the treatment effect of insurance. After controlling for all self-selection, an individual continuously uninsured has 2 fewer trips to the doctor per year and 8 fewer prescriptions filled, respectively.

For the continuously uninsured, these results suggest that all else equal, a switch to full coverage would increase utilization of physician visits by 161% and prescription drugs by 207%. At these higher levels of utilization, the formerly uninsured would be right on par with the continuously insured for physician visits (113% of insured utilization) and would actually exceed the average utilization of insured individuals in prescription drugs usage (156% of insured utilization). Temporary coverage does not appear to mitigate disparities to a significant extent. Being randomly assigned to full coverage from temporary coverage would result in 2 additional trips to the doctor and 7 additional prescriptions filled.

For robustness analysis, we evaluate an alternative model specification and estimate the joint model for a series of sub-populations to gauge the sensitivity of these results, with particular interest in heterogeneity in response to changes in insurance status.

6 Robustness Analysis

6.1 Generalized Method of Moments (GMM)

As a validity check to the simulated maximum likelihood estimation, we use a generalized method of moments (GMM) specification to handle the endogeneity of health insurance in the health care utilization estimations. This specification is far less stringent in functional form assumptions as compared to the maximum likelihood specification.

Let y_i denote the dependent count variable, allowing the conditional mean to be specified as

$$E(y_i|\mathbf{x}_i) = \mu_i = exp(\mathbf{x}_i^{'}\boldsymbol{\beta}) \tag{11}$$

where $\mathbf{x}_i$ is a k-dimensional vector of explanatory variables and $\boldsymbol{\beta}$ a k-dimensional vector of parameters.

The conditional mean specification of (11) implicitly defines a regression model

$$y_i = exp(\mathbf{x}_i^{'}\boldsymbol{\beta}) + \epsilon_i \tag{12}$$

where ϵ_i are the additive error terms reflecting unobserved heterogeneity between individuals. If some elements of x_i are endogenous, the Poisson estimator will be inconsistent as $E(\epsilon_i|\mathbf{x}_i \neq 0)$.

GMM techniques are applicable if there exists a set of instruments, $\mathbf{z}_i$, that are orthogonal to the error term. Estimation under these circumstances is then based on the single moment condition

$$E[\mathbf{z}_i\{y_i - exp(\mathbf{x}_i^{'}\boldsymbol{\beta})\}] = 0 \tag{13}$$

where $\mathbf{x}_i$ includes two endogenous dummy variables for health insurance status (TEMPINSR, UNINSR). We estimate this model using two different sets of instruments.

For the first specification (GMM 1), we include as instruments the employment and marital status indicators used in identifying the joint model: employer size characteristics (FIRMSIZE, MULTLOC), a self-employment indicator (SELFEMP), and marital status changes (GOTDIVOR). Getting married (GOTMARRIED) was rejected as a weak instrument in the OBDOCVIS estimate, although the same instrument was not rejected in the RXNUM estimate. Given the insignificant differences in coefficients and standard errors, we report GMM 1 results without (GOTMARRIED) as an instrument. For the second GMM estimate (GMM 2), we use predicted probabilities of insurance choice from a multinomial choice estimation as instruments. These instruments can be thought of as non-linear combinations of the exogenous variables used to explain insurance choice.

Results

Insurance status coefficients from GMM 1 and GMM 2 are included alongside previous insurance status coefficients for doctor visits (OBDOCVIS) in Table 9 and filled prescriptions (RXNUM) in Table 10. Tests of overidentification were rejected for GMM 1 and are unavailable for GMM 2 as it is a just-identified model.

For both OBDOCVIS and RXNUM, random assignment to the continuously uninsured status lowers utilization compared to being assigned to full-year insured status. Both coefficients are significant (p=.01). Results from the GMM 2 specification for OBDOCVIS correspond very closely to the joint model results. Both illustrate that a model that ignores endogeneity UNDERSTATES the impact that obtaining insurance will have on utilization of doctor visits –evidence of advantageous selection.

GMM results for temporary lack of coverage yield a more complex picture. This model indicates that average utilization outcomes are not significantly different for individuals continuously insured or only temporarily insured during the year. Maximum likelihood estimates, by contrast, present evidence that temporary coverage leads to fewer prescriptions filled. An interpretation favorable to the maximum likelihood specification is that unobserved characteristics that the joint model takes into account play a key role in sorting differences between continuously versus temporarily insured. Overall, GMM results compare favorably to the results from the joint model, providing credibility to the assumptions underlying that model.

7 Sub-population Analysis

Heterogeneity is multi-dimensional in assessing the impact of health insurance outcomes on health services utilization. This paper evaluates multiple treatments to provide a better explanation of utilization behavior and it is important to note that the treatments themselves are heterogeneous in terms of plan costs and benefits. A limitation of this study is the lack of insurance plan details (premiums, co-pays, out-of-pocket prices, etc.), allowing only a statement about the average insurance plan's impact on utilization. An additional layer of heterogeneity arises in responses to treatments. Individuals respond differently to gaining or losing health insurance and these responses could be driven by interactions among explanatory variables that differ by observable categories (e.g. gender, ethnicity, education level). Averaging responses to a treatment over a large population of individuals may obscure vital differences, perhaps even masking the sign of response to a treatment among some individuals. To gauge this brand of heterogeneity, a thorough analysis of sub-populations is performed in lieu of an extensive set of interactions among the key explanatory characteristics.

We review estimates from a series of sub-populations that isolate important demographic and socioeconomic cross-sections of the US population. Relevant angles of this review include: 1) Comparing differences in selection on both observable and unobservable characteristics between utilization categories and across sub-populations; 2) Identifying groups that experience the largest declines in utilization due to lack of insurance; 3) Evaluating differences in temporary versus continuous lack of insurance coverage between sub-groups. Differences on these levels may reflect different priorities while uninsured. For vulnerable sub-groups such as those with chronic conditions, skipping doctor visits may be preferable to not filling prescriptions, e.g. Alternatively, individuals expecting a period without coverage may shift or "time" utilization to coincide with periods of coverage.

Table 11 allows a comparison of insurance status across sub-populations. Differences in continuously insured versus continuously uninsured dominate changes in the temporarily uninsured category. For example, the stark differential between those at or below poverty level (21% insured, 68% uninsured) and those at the highest income level (85% insured, 8% uninsured) dwarfs the difference between the temporarily uninsured in the two categories (11% and 7%, respectively). Such a finding further validates distinguishing between temporary versus continuous lack of coverage in evaluating disparities in utilization.

Percentages of individuals continuously insured rises monotonically as age, education level, and income increase. Hispanics are far more likely to be continuously uninsured compared to either Blacks or Whites (47% vs. 27% and 23%, respectively). Men are only slightly more likely to be continuously uninsured than women. Individuals with chronic conditions (arthritis, diabetes, hypertension) are less likely to be without coverage, either temporarily or continuously. Unemployed and self-employed individuals find themselves without health insurance far more frequently than the broader category of employed individuals. Employees in a unionized workforce only rarely enter the ranks of the uninsured (92% continuously insured). The following sections delve more deeply into the criteria identified above by sub-population. Tables 12 and 13 detail unconditional usage by sub-groups across insurance status. Tables 14-20 reprise the treatment and selection effects estimates for sub-groups first presented in Table 8 for the full population. Figures 1a-7b offer visual insight into the heterogeneity of responses to being assigned to full coverage from continuous lack of coverage. Each

7.1 Gender

Women have higher utilization of doctor visits and prescription drugs across all insurance categories. Continuously insured women have 75% more trips to the doctor annually and 58% more prescriptions filled compared to men. The gender utilization gap is more pronounced for the uninsured; continuously uninsured women have 98% more trips to the doctor and 78% more prescriptions filled compared to continuously uninsured men. For women temporarily insured during the year the difference in utilization widens further: temporarily insured women have 102% more trips to the doctor and 114% more prescriptions filled compared to temporarily insured men. Such disparities may reflect different elasticities between men and women with respect to medical services. In the case of temporary insurance, the increased gap between men and women suggests women may also be more likely to engage in utilization "timing", where doctor visits or prescriptions are either delayed or accelerated to take advantage of an insured period. As the MEPS data used in this study do not include insurance status with utilization episodes, establishing firmer evidence of "timing" behavior is left for future work.

Advantageous selection on unobserved characteristics is found for both men and women. Unobserved traits such as attitudes toward health risks that increase the likelihood of being without coverage also increase utilization. This effect is significant across temporary and continuous lack of coverage, across gender and across utilization category. Treatment effects of being without coverage (detailed in Tables 14a and 14b) are negative and significant across gender and utilization category.

While women have higher levels of absolute utilization, estimates indicate that upon assignment to continuous coverage men would experience a larger percentage increase in utilization compared to women. This result is consistent with men being more price sensitive with respect to medical services. Figures 1a and 1b provide a sense of the heterogeneity across gender in response to being assigned to no insurance coverage from full coverage. The leftmost bar in each grouping represents the average marginal treatment effect from a model ignoring the endogeneity of health insurance. The scale on y-axis is the number of doctor visits or prescriptions filled. Full coverage is the control group so each bar represents the change in utilization as a result of being assigned to the uninsured category. Negative values mean lower utilization. Bars 2 and 3 decompose the biased treatment effect from the model treating health insurance as exogenous into the true average marginal treatment effect due to being assigned to no coverage (bar 2) and the impact of unobserved traits on utilization (bar 3). Positive values for this selection effect are interpreted as evidence of advantageous selection. Women suffer slightly more than men in terms of fewer trips to the doctor and prescriptions filled but the magnitude of differences in treatment response are small.

7.2 Age Group

For the youngest age group (Tables 15a,15b), we find evidence of adverse selection on unobservable traits (with the exception of doctor visits for the temporarily insured). Unobservable characteristics associated with higher likelihood of being without coverage are also associated with lower utilization. Figures 2a and 2b illustrate that assignment to no coverage does not appear to result in significantly fewer trips to the doctor or prescriptions filled for this group of individuals. Treatment effects for uninsured compared to the continuously insured are minimal in magnitude and statistically insignificant. For each successive age cohort above 18-24 we find advantageous selection on unobservables into TEMPINSR and UNINSR for both doctor visits and prescription drugs. Heterogeneity in response to continuous lack of coverage is significant across age cohorts, particularly for prescriptions. Lack of coverage translates to 3.4 fewer prescriptions filled for those 25-34 but almost 10.5 fewer for those between 55 and 64.

Given higher incidence of chronic illness and overall poorer subjective health, the near elderly cohort (55-64) may be the most vulnerable to periods without insurance coverage. Even the magnitude of the differences in treatment response do not capture the overall impact. This study does not accommodate for differences in the importance of any individual trip to the doctor or prescription. Any decline in care may be more harmful to health for the near-elderly but is outside the scope of this study.

7.3 Ethnic Group

Hispanics as a group are significantly more likely to be without insurance coverage compared to Blacks or Whites, either temporarily or continuously. Patterns of utilization differ among Hispanics as well. While Hispanics visit the doctor at close to the same frequency as Blacks (both have fewer visits than Whites regardless of insurance status), Hispanics have significantly lower prescription drug usage. Figure 3b provides the visual evidence of differences across ethnic groups in response to continuous lack of coverage in terms of fewer prescriptions. Cultural differences or differences in patterns of care may play a role in explaining such heterogeneity. Results from the maximum simulated likelihood estimation (Tables 16a,16b) further identify unique patterns for Hispanics. Selection on unobservable characteristics into UNINSR is not significant for doctor visits or prescriptions filled. Selection on unobservables making TEMPINSR more likely, however, leads to more trips to the doctor and fewer prescriptions filled, while the treatment effect of TEMPINSR compared to INSR runs the reverse: those temporarily uninsured use more prescriptions but have fewer trips to the doctor after controlling for selection.

For Blacks and Whites advantageous selection on unobserved traits is found for both the temporary and continuously uninsured. In terms of magnitude, the impact of selection on unobservables is stronger for prescription drugs than for doctor visits. The evidence also suggests that lack of insurance leads to large gaps in usage of prescription drugs. For Blacks, after controlling for selection, being assigned to continuous coverage would increase prescriptions by 7.62 (+195%) for those in temporarily uninsured and 8.17 (190%) for those continuously uninsured. The corresponding figures for Whites are 7.17 (144%) for temporarily uninsured and 8.01 (200%) for continuously uninsured.

7.4 Education Level

Level of completed education emerges as a strong predictor of insurance status. For those with less than a high school education, 47% find themselves without coverage, while for those with at least a bachelor's degree, the rate is only 8%. Completing a high school education brings a large jump in the ranks of the insured, from 42% for those without a high school degree to 65% for those with a high school diploma. Finishing a four-year degree brings another 20 point increase in the ranks of the insured.

Hispanics make up more than 50% of those without high school diplomas and not surprisingly, the selection and treatment effects pattern found among Hispanics are similar to those found in this education category (Tables 17a,17b). Selection on unobservables into UNINSR is not significant at all for doctor visits and has very little impact for prescription drugs. Treatment effects comparing assignment of UNINSR to INSR are negative and significant for doctor visits and prescription drugs. Selection on unobservables plays a very small role for this group. For TEMPINSR, however, the treatment effect for prescription drugs is positive while the impact of selection on unobservables is negative. In effect, this outcome suggests individuals would fill more prescriptions while only temporarily insured compared to the same individual with full insurance coverage. More detailed breakdowns of utilization and insurance coverage are needed to explain this pattern, including an assessment of differences in the selection and utilization process among Hispanics.

Selection on unobservables and treatment effect patterns are consistent for those with at least a high school education. Selection on unobservables is significant and advantageous for prescription drugs and doctor visits. For individuals with at least a high school degree, unobservable characteristics that lead to lack of coverage are associated with higher utilization. Treatment effects for TEMPINSR and UNINSR in comparison to INSR are negative and significant. After controlling for selection, disparities in utilization are starker than they appear when comparing unconditional differences across insurance categories. Such evidence of advantageous selection on unobserved traits among those completing higher levels of education tends to give circumstantial support to an ability threshold in making insurance choices described in Fang et al. (2008).

We observe the largest relative gains in utilization and the biggest jump in gains for those completing high school (Figures 4a,4b). Assignment to full coverage from no coverage increases trips to the doctor by 200% and prescriptions filled by 256%. Given the well documented income disparities between those with a college education versus only a high school degree, it is not surprising to find evidence of a greater sensitivity to gains or losses in coverage among those with only a high school degree.

7.5 Income Group

To compare utilization and insurance effects by income, we separate the population into five different groups based on income as a percentage of the Federal Poverty Level (FPL): Poor ($\leq$ 100% of FPL), Near Poor (100-125% of FPL), Low Income (125%-200% of FPL), Middle Income (200%-400% of FPL, High Income ($\geq$ 400% of FPL). Among the insured poor, we find utilization levels on par with insured high income individuals. A significant driver of this pattern is the 18% of the poor reporting their health status as fair or poor compared to only 6% for high income individuals. Lack of insurance also results in larger declines in utilization for the poor, reinforcing the motives of health insurance reformers to target this high risk group.

Selection on unobserved traits into TEMPINSR and UNINSR (Tables 18a,18b) for middle income and high income individuals (approximately 75% of the sample) is significant and favorable, a consistent result from this analysis that may appear to run contrary to conventional wisdom. However, there is no contradiction in the typical adverse selection story and our findings when selection is decomposed. That our model separates selection into observable and unobservable components is an important contribution in making sense of disparities in utilization. Figures 5a and 5b highlight the heterogeneity in response to continuous lack of coverage. Middle and high income groups suffer significantly larger drops in utilization of both doctor visits and prescriptions filled in comparison with lower income groups (excepting the poorest group that shows treatment responses similar to the higher income groups).

For individuals making less then 200% of FPL, results are less consistent and closely resemble results found among Hispanics and individuals with less than a high school education. We find evidence of adverse selection on unobservables into TEMPINSR, particularly significant in magnitude for prescription drug utilization. Treatment effects for TEMPINSR are positive for prescription drugs. Effectively this evidence means assigning an individual to temporary insurance from continuous coverage results in HIGHER utilization of prescription drugs. Such a counter intuitive result calls for further investigation of plausible explanations including "timing" of utilization to coincide with covered periods and substitution of prescription drugs for other modes of care. Nothing in the data collected for this study allows utilization episodes to be categorized as occurring during an insured or uninsured period. Demographics must also be considered, as Hispanics make up 40% of the bottom three income categories but only 16% of the top two income categories and we have already noted the distinct utilization pattern among Hispanics.

7.6 Employment Status

With insurance outcomes so closely tied to employment for many Americans, breaking down results from the maximum simulated likelihood estimation by employment status is an important exercise. Here we compare the employed versus those not employed, those working for themselves, and those with a union job.

Beginning with the implications of continuous lack of insurance coverage on outcomes, we find very consistent results (Tables 19a,19b, Figures 6a,6b). Treatment effects for UNINSR are negative and significant across all employment categories. Selection on unobservables, however, depends on the employment category. For union members and those employed generally, selection on unobserved traits is advantageous and significant for both doctor visits and prescriptions filled. By contrast, unobserved characteristics increasing the likelihood of being without coverage also lead to lower utilization (adverse selection) for those not employed or self-employed. These differences suggest that different unobservable characteristics are driving insurance and utilization outcomes across these groups. Whatever unobserved factors are pushing employed individuals into the ranks of the uninsured also result in higher utilization. Meanwhile, for self-employed or unemployed individuals the opposite is true: unobserved factors that increase the likelihood of continuous or temporary periods without coverage also lead to lower utilization levels.

For self-employed or unemployed individuals not eligible for Medicaid, obtaining insurance coverage is likely to come through a spouse or through the purchase of non-group policies. Therefore, these outcomes suggest positive action on the part of the individual to obtain coverage. That adverse selection on unobserved traits such as risk preference is present in such circumstances is consistent with the notion of individuals knowing their type (risk averse, e.g.) and making coverage decisions accordingly. The filter into insured or uninsured for those employed is more likely to come from the size of the employer or firm mechanisms for sorting employees into (or out of) insurance plans. Smaller employers are less likely to provide coverage to employees, particularly in cases where one sick employee could drastically raise the expected costs of coverage. That we find positive correlation between poor self-reported health and working for smaller companies adds weight to this conjecture. If more risk averse and healthier individuals work for larger companies, thus making insurance coverage more likely, then evidence of favorable selection on attitudes toward risk is quite plausible.

Results for TEMPINSR in the employment comparisons push further for more comprehensive evaluation of utilization patterns and periods of coverage. For the self-employed and unemployed, selection on unobservables largely reflect adverse selection, consistent with results for UNINSR. Treatment effects, however, are positive for prescription drugs for both groups and positive for doctor visits for the self-employed. Self-employed individuals are less likely to identify as Hispanic than the full population so cultural explanations are not as viable for the utilization pattern in this instance. Exploring “timing” behavior and substitution patterns in use of medical services for this subgroup is left to future research.

7.7 Chronic Conditions

Previous research has suggested that individuals with chronic conditions stand to gain the most from obtaining health insurance (Levy and Meltzer, 2008). We estimate our model for individuals with diabetes and hypertension and also for a group with no reported chronic conditions. Each condition is associated with higher utilization of services, particularly prescription drugs. Diabetics with continuous insurance coverage fill almost 300% more prescriptions than the insured population average. The utilization gap is even larger comparing continuously uninsured diabetics to the overall population of uninsured. Diabetics without any coverage use almost 500% more prescriptions than the uninsured population average. Uninsured diabetics have utilization patterns that are closer to their insured counterparts than the general uninsured population. This pattern persists for those with hypertension.

After controlling for observable and unobservable characteristics, we find treatment effects for UNINSR that correspond closely to the overall findings from the full population (Tables 20a,20b). Assigning an uninsured individual with diabetes (hypertension) to INSR would result in 1.5 (3.0) additional trips to the doctor and almost 7 (6.6) additional prescriptions filled. Figures 7a and 7b highlight the heterogeneity in treatment response of chronic condition sufferers in comparison to the group without a reported chronic condition. It bears repeating that trips to the doctor and filled prescriptions are not all created equal and thus comparisons of disparities are left wanting in this sense. Also unanswered in this research is the impact that lack of insurance has on out-of-pocket costs for diabetics (and other chronic condition sufferers) when filling needed prescriptions and visiting specialists.

Selection on unobservables does not appear to play a significant role in comparing utilization of those continuously uninsured versus insured. In the case of chronic condition sufferers, observable characteristics explain differences in utilization. Paired with evidence that advantageous selection has featured prominently for other sub-populations, the fact that selection on unobservables is negligible and overall rates of coverage are higher for those with chronic conditions is an informative piece of evidence. When weighting the impact of insurance expansion on utilization, our results suggest that unobserved traits making individuals more likely to be without coverage prior to reform are also associated with heavier use of services compared to the case of full insurance coverage. That differences in utilization are driven by unobservable characteristics further elucidates the note of caution regarding a priori assumptions of adverse selection. Our model shows that both adverse selection and advantageous selection can coexist and the magnitude of each factor will determine the net effect. Private information is not only multi-dimensional but the weight of that information in impacting insurance and utilization outcomes will undoubtedly vary depending on what cross-section of the population is being observed.

8 Discussion

In this paper we set out to explain differences in utilization of health care services due to selection on unobservables and differences due to the insurance or treatment effect. To provide a better categorization of the uninsured, we separated those who lack coverage for less than a year from those who lack coverage for a full year or more. We introduced an innovative two-part model estimated using maximum simulated likelihood methods to handle the endogeneity of health insurance in demand for services.

Results from this effort suggest that unobserved traits play a significant role in explaining differences in utilization of doctor visits and prescription drugs. Evidence from the full representative population points strongly in the direction of advantageous selection. We also find evidence of adverse selection on observable traits such as chronic conditions. That the magnitude of advantageous selection results in understating the impact of gaining continuous insurance coverage on utilization is an important piece of evidence for PPACA reforms via the private insurance channel.

A thorough review of sub-populations yields subtle distinctions in selection effects. At the lower end of the socioeconomic spectrum there is more evidence supporting adverse selection on unobservables. Higher up on the socioeconomic ladder we find advantageous selection. Anecdotally, this is consistent with recent research reiterating the importance of multi-dimensional private information, particularly the possibility that cognitive ability is positively associated with continuous insurance coverage and negatively associated with insured risk or utilization. Additional work to disaggregate the impact of private information is warranted from these results. Finding proxies for typically unobserved traits would be particularly useful for pinning down the mechanism driving selection into insurance and utilization decisions. Hispanics as a group are also worthy of additional attention in the literature given noted differences in insurance coverage rates and utilization.

Evidence on the impact of gaining continuous health insurance coverage is overwhelming: assignment to full coverage from no coverage leads to significantly higher utilization of doctor visits and prescription drugs. Sub-populations exhibit variation in the overall magnitude of the treatment effect but the significance and direction of the effect are consistent. Heterogeneity in treatment responses is most significant in comparisons across age groups and income groups. Diabetics and hypertension sufferers also exhibit significantly stronger responses to treatments versus those with no chronic conditions.

Being without coverage only temporarily appears to ameliorate differences in utilization between the insured and uninsured only slightly. We also find the magnitude of selection on unobserved characteristics to be stronger among those temporarily uninsured. However, the definition of temporary insurance coverage used for our purposes cannot definitively correlate the utilization episode with insurance status. Therefore, it is possible that “timing” of expected losses or gains in coverage could play a role in utilization for this group.

Data limitations in this research open the door for future contributions. Publicly available MEPS data do not contain consistent individual information on premiums, deductibles, co-pays, etc. More detailed plan data would result in a model more aptly described as behavioral with attendant predictive capacity with respect to specific plan characteristics. Further, this paper did not delineate doctor visits based on practice type or specialty type. An area for future research is categorizing office-based physician visits by specialists and generalists. Lack of coverage may yield more pronounced differences when examining access to more expensive specialty care or technology. Particularly for those with chronic conditions, all visits to the doctor are not equivalent. Finally, this effort did not pay heed to “hot spotters” or “frequent fliers”, terms given to the individuals that are extensive users of the medical system and whose utilization may have an outsized impact on average treatment effects due to insurance.

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Table 1. Mean Utilization by Insurance Status

Service	Definition	INSR Mean	TEMPINSR Mean	UNINSR Mean
OBDOCVIS	Office-based doctor visits	3.06	1.99**	1.32**
RXNUM	Prescription drugs	7.90	4.74**	4.02**
ERVIS	Emergency room visits	0.12	0.17**	0.15**

** Significantly different from Insured category (p=.05)

Table 2. Chronic Conditions by Insurance Category

Variable	Definition	INSR Mean	TEMPUNI Mean	UNINSR Mean
Cancer	1 if has cancer	3.7%	2.0%**	1.6%**
Diabetes	1 if has diabetes	5.0%	3.5%**	4.2%**
Arthritis	1 if has arthritis	9.9%	6.9%**	7.0%**
Hypertension	1 if has high blood pressure	14.6%	8.7%**	9.1**
Heart	1 if has heart disease	1.1%	0.7%**	0.8%**
Asthma	1 if has asthma	3.8%	4.0%	2.6%**
Mental	1 if mental health problems	6.4%	6.5%	6.0%

** Significantly different from INSR category (p=.05)

Table 3. Characteristics by Insurance Category&

Variable	Definition	67% INSR Mean	10% TEMPINSR Mean	23% UNINSR Mean
Demographic/Socioeconomic				
Age	Age divided by 10	4.15	3.51**	3.75**
Female	1 if Female	0.51	0.49**	0.43**
Black	1 if Black	0.09	0.12**	0.14**
Hispanic	1 if Hispanic	0.08	0.13**	.28**
Educ	Years of education	13.71	13.05**	11.71**
Income	Income (000's)	39.43	26.36**	18.69**
Famsize	Number of persons in family unit	2.86	2.67**	2.89
Married	1 if married	0.63	0.42**	0.39**
Employed	1 if employed	0.86	0.82**	0.68**
Self-employed	1 if self-employed	0.09	0.10**	0.16**
Region				
Noreast	1 if live in Northeast Region	0.20	0.16**	0.13**
Midwest	1 if live in Midwest Region	0.25	0.21**	0.17**
South	1 if live in South Region	0.33	0.38**	0.44**
West	1 if live in West Region	0.22	0.25**	0.26**
Health Status				
Injry	1 if injured during the year	0.21	0.23**	0.20
Physlim	1 if health limits physical activity	0.14	0.14	0.18**
Poor	1 if rated health poor	0.01	0.01	0.03**
Fair	1 if rated health fair	0.05	0.07**	0.10**
Good	1 if rated health good	0.25	0.26**	0.31**
Vgood	1 if rated health very good	0.32	0.31	0.26**
Excellent	1 if rated health excellent	0.37	0.36	0.30**
Priolst	1 if has condition on priority list	0.45	0.39**	0.35**
Totchr	Number of chronic conditions	0.62	0.47**	0.46**

** Significantly different from INSR category (p=.05)

& Calculated using MEPS person weights

Table 4. Insurance Choice Coefficients (OBDOCVIS)

Variable	**TEMPINSR**	STD ERROR	**UNINSR**	STD ERROR
Demographic/Socioeconomic				
Age	-0.091	0.033	1.304***	0.069
Age Sq	-0.003***	0.000	-0.002***	0.000
Female	-0.137***	0.006	-0.473***	0.024
Black	0.101	0.066	0.241***	0.059
Hispanic	0.348***	0.038	1.312***	0.030
Education	-0.043***	0.006	-0.162***	0.005
Income	-0.013***	0.001	-0.028***	0.001
Famsize	-0.088***	0.009	-0.011	0.007
Married	-0.522***	0.036	-1.202***	0.030
Got Married[#]	0.152***	0.045	0.148***	0.040
Got Divorced[#]	0.217***	0.166	0.204***	0.064
Employment				
Employed	0.511***	0.051	-0.138***	0.039
Self-employed[#]	0.303***	0.053	0.890***	0.042
Firm Size[#]	-0.015***	0.001	-0.035***	0.001
Multiple Firm Locations[#]	-0.232***	0.034	-0.731***	0.030
Lost Job[#]	0.848***	0.068	0.291***	0.051
Region				
Noreast	-0.389***	0.043	-0.745***	0.038
Midwest	-0.315***	0.038	-0.626***	0.033
West	-0.074***	0.036	-0.292***	0.030
Health Status				
Poor1	0.249***	0.116	0.879***	0.083
Fair1	0.274***	0.057	0.569***	0.046
Good1	0.111***	0.037	0.345***	0.031
Vgood1	0.016	0.034	0.030	0.030
Injry	0.106***	0.035	0.039	0.031
Physlim	0.091***	0.041	0.213***	0.034
Priolst	-0.028	0.036	-0.300***	0.032
Totchr	0.024	0.022	-0.130***	0.020

***,**,* Significant at p = .01, .05, and .10, respectively

Identifying instruments

Table 5. Utilization Marginal Effects Estimates

Variable	**OBDOCVIS**	STD ERROR	**RXNUM**	STD ERROR
Demographic/Socioeconomic				
Age	-0.457***	0.067	-1.741***	0.282
Age Sq	0.001***	0.000	0.003***	0.000
Female	1.350***	0.026	5.594***	0.119
Black	-0.174***	0.057	-0.466***	0.253
Hispanic	-0.188***	0.043	-2.878***	0.019
Education	0.069***	0.006	0.196***	0.020
Income	0.002***	0.000	0.005***	0.002
Famsize	0.094***	0.008	-0.496***	0.033
Married	0.400***	0.030	1.063***	0.117
Employed	-0.205***	0.043	-0.365***	0.141
Region				
Noreast	0.175***	0.033	-1.683***	0.145
Midwest	-0.119***	0.031	-0.784***	0.124
West	-0.159***	0.030	-1.914***	0.130
Health Status				
Poor	1.637***	0.083	8.996***	0.368
Fair	1.095***	0.048	6.429***	0.209
Good	0.546***	0.031	3.837***	0.138
Vgood	0.288***	0.028	1.977***	0.126
Injry	0.867***	0.029	0.841***	0.112
Physlim	0.638***	0.032	1.924***	0.134
Priolst	0.910***	0.028	6.739***	0.123
Totchr	0.685***	0.016	4.378***	0.092

***,**,* Significant at p = .01, .05, and .10 respectively

Table 6. Utilization Estimates: Insurance Status and Selection Coefficients (OBDOCVIS)#

n = 82,852	Assume Ins Exogenous		MLE Joint Model	
	Coeff.	Std. Error	Coeff	Std. Error
TEMPINSR	-0.276***	0.021	-1.057***	0.041
UNINSR	-0.673***	0.020	-1.048***	0.072
λ-TEMPINSR			0.867***	0.042
λ-UNINSR			0.322***	0.094

Identifying instruments: FIRMSIZE, MULTLOC, SELFEMP, LOSTJOB, GOTMARRIED, GOTDIVOR
***,**,* Significant at p = .01, .05, and .10 respectively

Table 7. Utilization Estimates: Insurance Status and Selection Coefficients (RXNUM)#

n = 82,852	Assume Ins Exogenous		MLE Joint Model	
	Coeff.	Std. Error	Coeff.	Std. Error
TEMPINSR	-0.269***	0.021	-.912***	0.037
UNINSR	-0.614***	0.020	-1.070***	0.040
λ-TEMPINSR			0.698***	0.033
λ-UNINSR			0.403***	0.046

Identifying instruments: FIRMSIZE, MULTLOC, SELFEMP, LOSTJOB, GOTMARRIED, GOTDIVOR
***,**,* Significant at p = .01, .05, and .10 respectively

Table 8. Treatment And Selection Effects vs. INSR

(n=82,852)	***OBDOCVIS***		***RXNUM***	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-1.07**	-1.74**	-3.16**	-3.88**
Observables: Assumes Insurance Exogenous#	-0.68***	-1.48***	-1.98***	-4.13***
Observables & Unobservables: Assumes Insurance Endogenous#	-2.15***	-2.13***	-7.10***	-8.33***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	1.47	0.65	5.12	4.20

Calculated using Average Marginal Effects

***,**,* Significant at p = .01, .05, and .10 respectively

Table 9. Insurance Status and Selection Coefficients (OBDOCVIS)

n = 82,852	Assume Ins. Exogenous		MLE Joint Model#		GMM (1)		GMM (2)	
	Coeff.	Std. Error	Coeff	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
TEMPINSR	-0.276***	0.021	-1.057***	0.041	-0.482	0.393	-1.307**	0.536
UNINSR	-0.673***	0.020	-1.048***	0.072	-1.688***	0.384	-0.872***	0.067
λ-TEMPINSR			0.867***	0.042				
λ-UNINSR			0.322***	0.094				
Test of OID (Hansen's J-statistic)					5.58		(n/a)	
					(p=.13)		(n/a)	

Identifying instruments: FIRMSIZE, MULTLOC, SELFEMP, LOSTJOB, GOTMARRIED, GOTDIVOR
(1) Instruments: FIRMSIZE, MULTLOC, SELFEMP, LOSTJOB, GOTDIVOR
(2) Instruments: PRTEMPINSR, PRUNINSR
***,**,* Significant at p = .01, .05, and .10 respectively

Table 10. Insurance Status and Selection Coefficients (RXNUM)

n = 82,852	Assume Ins. Exogenous		MLE Joint Model#		GMM (1)		GMM (2)	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
TEMPINSR	-0.269***	0.021	-.912***	0.037	-0.372	0.375	-0.076	0.185
UNINSR	-0.614***	0.020	-1.070***	0.040	-0.830***	0.179	-0.610***	0.061
λ-TEMPINSR			0.698***	0.033				
λ-UNINSR			0.403***	0.046				
Test of OID (Hansen's J-statistic)					1.24		(n/a)	
					(p=.74)		(n/a)	

Identifying instruments: FIRMSIZE, MULTLOC, SELFEMP, LOSTJOB, GOTMARRIED, GOTDIVOR
(1) Instruments: FIRMSIZE, MULTLOC, SELFEMP, LOSTJOB, GOTDIVOR
(2) Instruments: PRTEMPINSR, PRUNINSR
***,**,* Significant at p = .01, .05, and .10 respectively

Table 11. Subgroup Characteristics by Insurance Category

	INSURANCE STATUS		
	INSR	**TEMPINSR**	**UNINSR**
Variable	**%**	**%**	**%**
Gender			
Male	65%	10%	25%
Female	69%	10%	21%
Age Group			
18-24	50%	17%	33%
25-34	59%	13%	28%
35-44	70%	9%	21%
45-54	75%	6%	19%
55-64	75%	6%	19%
Ethnicity			
Hispanic	43%	10%	47%
Black	61%	12%	27%
White	68%	9%	23%
Education			
Less than H.S. (< 11)	42%	11%	47%
H.S. (12)	65%	10%	25%
Some College (13-15)	73%	11%	16%
Bachelors+(>=16)	85%	7%	8%
Income			
Poor	21%	11%	68%
Near Poor	32%	13%	55%
Low Income	44%	13%	43%
Middle Income	68%	12%	20%
High Income	85%	7%	8%
Employment Status			
Not Employed	49%	10%	41%
Self-Employed	58%	9%	32%
Union Job	92%	5%	3%
Employed	71%	10%	19%
Chronic Condition			
No Chronic	63%	11%	26%
Diabetes	72%	7%	21%
Hypertension	77%	7%	17%

Table 12. Subgroup Characteristics by Insurance Category

	OBDOCVIS		
	INSR	**TEMPINSR**	**UNINSR**
Variable	**Mean**	**Mean**	**Mean**
Gender			
Male	2.20	1.31**	0.90**
Female	3.83	2.65**	1.78**
Age Group			
18-24	1.74	1.31**	0.67**
25-34	2.55	1.62**	0.86**
35-44	2.67	1.96**	1.10**
45-54	3.38	2.67**	1.94**
55-64	4.54	3.85**	2.77**
Ethnicity			
Hispanic	2.50	1.55**	0.98**
Black	2.47	1.57**	1.20**
White	3.19	2.09**	1.35**
Education			
Less than H.S. (< 11 yrs)	2.51	1.63**	1.11**
H.S. (12)	2.93	1.82**	1.23**
Some College (13-15)	3.13	2.18**	1.69**
Bachelor's + (>=16)	3.38	2.45**	1.96**
Income			
Poor	3.11	1.80**	1.30**
Near Poor	3.08	1.95**	1.15**
Low Income	2.63	1.82**	1.19**
Middle Income	2.88	1.86**	1.24**
High Income	3.25	2.34**	1.85**
Employment Status			
Not Employed	4.03	2.26**	1.68**
Self-Employed	2.73	1.86**	1.24**
Union Job	3.36	1.85**	2.52**
Employed	2.89	1.92**	1.12**
Chronic Condition			
No Chronic	1.85	1.19**	0.63**
Diabetes	5.94	4.46**	4.38**
Hypertension	5.10	4.38**	3.48**

** Significantly different from INSR category (p=.05)

Table 13. Subgroup Characteristics by Insurance Category

	RXNUM		
	INSR	TEMPINSR	UNINSR
Variable	Mean	Mean	Mean
Gender			
Male	6.05	3.19**	2.93**
Female	9.56	6.26**	5.22**
Age Group			
18-24	2.83	2.26**	1.09**
25-34	4.02	2.73**	1.49**
35-44	5.52	4.04**	2.59**
45-54	10.08	8.17**	6.85**
55-64	15.56	13.72**	12.32**
Ethnicity			
Hispanic	5.20	2.82**	2.23**
Black	7.09	3.91**	4.29**
White	8.20	4.97**	4.01**
Education			
Less than H.S. (< 11 yrs)	6.84	3.81**	3.37**
H.S. (12)	8.28	4.63**	4.03**
Some College (13-15)	8.21	5.04**	4.91**
Bachelor's + (>=16)	7.72	5.66**	5.51**
Income			
Poor	8.30	4.41**	4.40**
Near Poor	6.53	4.74**	3.80**
Low Income	6.92	4.33**	3.54**
Middle Income	7.56	4.32**	3.59**
High Income	8.31	5.74**	5.19**
Employment Status			
Not Employed	10.92	5.75**	5.72**
Self-Employed	7.41	5.57**	3.74**
Union Job	7.98	3.98**	4.80**
Employed	7.37	4.48**	3.05**
Chronic Condition			
No Chronic	3.13	1.87**	1.10**
Diabetes	29.48	22.91**	23.96**
Hypertension	21.96	17.57**	19.20**

** Significantly different from INSR category (p=.05)

Table 14a. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: GENDER

	OFFICEVIS			
	MEN (n=40,301)		***WOMEN*** (n=42,281)	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-0.89**	-1.30**	-1.18**	-2.05**
Observables: Assumes Insurance Exogenous#	-0.54***	-1.46***	-0.91***	-2.12***
Observables & Unobservables: Assumes Insurance Endogenous#	-1.53***	-1.59***	-2.70***	-2.38***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	0.99	0.13	1.79	0.26

Calculated using Average Marginal Effects

***,**,* Significant at p = .01, .05, and .10 respectively

Table 14b. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: GENDER

	RXNUM			
	MEN (n=40,301)		***WOMEN*** (n=42,281)	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-2.86**	-3.12**	-3.30**	-4.34**
Observables: Assumes Insurance Exogenous#	-2.01***	-4.33***	-2.14***	-5.19***
Observables & Unobservables: Assumes Insurance Endogenous#	-6.42***	-6.97***	-5.25***	-7.51***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	4.41	2.64	3.11	2.32

Calculated using Average Marginal Effects

***,**,* Significant at p = .01, .05, and .10 respectively

Table 15a. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: AGE GROUP

	OFFICEVIS									
	***Ages 18-24* (n=11,479)**		***Ages 25-34* (n=18,010)**		***Ages 35-44* (n=21,038)**		***Ages 45-54* (n=19,270)**		***Ages 55-64* (n=12,785)**	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-0.43**	-1.07**	-0.93**	-1.69**	-0.71**	-1.57**	-0.71**	-1.44**	-0.69**	-1.77**
Observables: Assumes Insurance Exogenous#	-0.76***	-1.32***	-0.62***	-1.29***	-0.64***	-1.46***	-0.70***	-1.50***	-0.55***	-1.57***
Observables & Unobservables: Assumes Insurance Endogenous#	-1.26***	-0.19	-1.79***	-1.15***	-1.80***	-2.32***	-2.38***	-2.32***	-2.87***	-1.87***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	0.50	-1.13	1.17	-0.14	1.16	0.86	1.68	0.82	2.32	0.30

Differences calculated using Average Marginal Effects

***,**,* Significant at p = .01, .05, and .10 respectively

Table 15b. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: AGE GROUP

	RXNUM									
	***Ages 18-24* (n=11,479)**		***Ages 25-34* (n=18,010)**		***Ages 35-44* (n=21,038)**		***Ages 45-54* (n=19,270)**		***Ages 55-64* (n=12,785)**	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-0.57**	-1.74**	-1.29**	-2.53**	-1.48**	-2.93**	-1.91**	-3.23**	-1.84**	-3.24**
Observables: Assumes Insurance Exogenous#	-0.25***	-0.71***	-0.97***	-1.99***	-1.46***	-3.00***	-2.51***	-4.56***	-2.47***	-4.96***
Observables & Unobservables: Assumes Insurance Endogenous#	0.10	-0.08	-3.17***	-3.43***	-4.47***	-6.24***	-8.42***	-9.37***	-8.52***	-10.47***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	-0.35	-0.63	2.2	1.44	3.01	3.24	5.91	4.81	6.05	5.51

Differences calculated using Average Marginal Effects

***,**,* Significant at p = .01, .05, and .10 respectively

Table 16a. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: ETHNICITY

	OFFICEVIS					
	HISPANIC (n=18,205)		***BLACK*** (n=10,540)		***WHITE*** (n=66,973)	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-0.95**	-1.52**	-0.90**	-1.27**	-1.10**	-1.84**
Observables: Assumes Insurance Exogenous#	-0.61***	-1.44***	-0.54***	-1.44***	-0.80***	-1.91***
Observables & Unobservables: Assumes Insurance Endogenous#	-1.63***	-1.22***	-1.70***	-1.46***	-2.29***	-2.11***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	1.02	-0.22	1.16	0.02	1.49	0.20

Calculated using Average Marginal Effects
***,**,* Significant at p = .01, .05, and .10 respectively

Table 16b. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: ETHNICITY

	RXNUM					
	HISPANIC (n=18,205)		***BLACK*** (n=10,540)		***WHITE*** (n=66,973)	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-2.38**	-2.97**	-3.18**	-2.80**	-3.23**	-4.19**
Observables: Assumes Insurance Exogenous#	-1.94***	-3.59***	-2.33***	-5.03***	-2.23***	-5.10***
Observables & Unobservables: Assumes Insurance Endogenous#	2.46***	-3.37***	-7.62***	-8.17***	-7.17***	-8.01***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	-4.40	-0.22	5.29	3.14	4.94	2.91

Calculated using Average Marginal Effects
***,**,* Significant at p = .01, .05, and .10 respectively

Table 17a. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: EDUCATION LEVEL

	OFFICEVIS							
	Less than H.S. **(n=17,350)**		***H.S.*** **(n=25,931)**		***Some College*** **(n=19,183)**		***Bachelors+*** **(n=20,118)**	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-0.88**	-1.40**	-1.11**	-1.70**	-0.95**	-1.44**	-0.93**	-1.42**
Observables: Assumes Insurance Exogenous#	-0.50***	-1.29***	-0.70***	-1.53***	-0.62***	-1.44***	-0.82***	-1.36***
Observables & Unobservables: Assumes Insurance Endogenous#	-1.74***	-1.35***	-1.99***	-2.48***	-1.82***	-2.68***	-2.32***	-2.46***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	1.24	0.06	1.29	0.95	1.20	1.24	1.50	1.10

Differences calculated using Average Marginal Effects

***,**,* Significant at p = .01, .05, and .10 respectively

Table 17b. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: EDUCATION LEVEL

	RXNUM							
	Less than H.S. **(n=17,350)**		***H.S.*** **(n=25,931)**		***Some College*** **(n=19,183)**		***Bachelors+*** **(n=20,118)**	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-3.03**	-3.47**	-3.65**	-4.25**	-3.17**	-3.30**	-2.06**	-2.21**
Observables: Assumes Insurance Exogenous#	-2.01***	-4.31***	-2.24***	-4.65***	-1.79***	-3.76***	-1.74***	-3.28***
Observables & Unobservables: Assumes Insurance Endogenous#	3.87***	-4.07***	-7.68***	-10.31***	-6.09***	-7.86***	-4.60***	-6.79***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	-5.88	-0.24	5.44	5.66	4.30	4.10	2.86	3.51

Differences calculated using Average Marginal Effects

***,**,* Significant at p = .01, .05, and .10 respectively

Table 18a. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: INCOME GROUP

	OFFICEVIS									
	Poor **(n=7,119)**		***Near Poor*** **(n=3,060)**		***Low Income*** **(n=10,975)**		***Middle Income*** **(n=27,666)**		***High Income*** **(n=33,762)**	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-1.31**	-1.81**	-1.13**	-1.93**	-0.81**	-1.44**	-1.02**	-1.64**	-0.91**	-1.40**
Observables: Assumes Insurance Exogenous#	-0.62***	-1.57***	-0.96***	-2.03***	-0.48***	-1.23***	-0.62***	-1.41***	-0.68***	-1.22***
Observables & Unobservables: Assumes Insurance Endogenous#	-0.56***	-3.02***	-1.43***	-0.46***	0.72***	-0.41***	-1.86***	-2.50***	-1.85***	-2.58***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	-0.06	1.45	0.47	-1.57	-1.20	-0.82	1.24	1.09	1.17	1.36

Differences calculated using Average Marginal Effects
***,**,* Significant at p = .01, .05, and .10 respectively

Table 18b. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: INCOME GROUP

	RXNUM									
	Poor **(n=7,119)**		***Near Poor*** **(n=3,060)**		***Low Income*** **(n=10,975)**		***Middle Income*** **(n=27,666)**		***High Income*** **(n=33,762)**	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-3.89**	-3.90**	-1.79**	-2.73**	-2.59**	-3.38**	-3.24**	-3.97**	-2.57**	-3.12**
Observables: Assumes Insurance Exogenous#	-1.93***	-5.04***	-2.40***	-4.43***	-1.38***	-3.61***	-1.94***	-3.94***	-1.68***	-3.33***
Observables & Unobservables: Assumes Insurance Endogenous#	3.81***	-6.56***	2.54*	-3.13*	3.70***	-3.26***	-6.74***	-8.78***	-5.64***	-6.96***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	-5.74	1.52	-4.94	-1.30	-5.08	-0.35	4.80	4.84	3.96	3.63

Differences calculated using Average Marginal Effects
***,**,* Significant at p = .01, .05, and .10 respectively

Table 19a. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: EMPLOYMENT STATUS

	OFFICEVIS							
	NOT EMPLOYED (n=16,749)		***SELF-EMPLOYED*** (n=7.805)		***UNION JOB*** (n=7,687)		***EMPLOYED*** (n=65,833)	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-1.77**	-2.25**	-0.87**	-1.49**	-1.51**	-0.84	-0.97**	-1.77**
Observables: Assumes Insurance Exogenous#	-1.17***	-2.02***	-0.52***	-1.39***	-1.25***	-0.89***	-0.67***	-1.79***
Observables & Unobservables: Assumes Insurance Endogenous#	-2.83***	-1.34***	0.99***	-1.19***	-2.33***	-2.25***	-2.04***	-1.71***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	1.66	-0.68	-1.51	-0.20	1.08	1.36	1.37	-0.08

Calculated using Average Marginal Effects

***,**,* Significant at p = .01, .05, and .10 respectively

Table 19b. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: EMPLOYMENT STATUS

	RXNUM							
	NOT EMPLOYED (n=16,749)		***SELF-EMPLOYED*** (n=7.805)		***UNION JOB*** (n=7,687)		***EMPLOYED*** (n=65,833)	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means	-5.17**	-5.20**	-1.84**	-3.67**	-4.00**	-3.18**	-2.89**	-4.32**
Observables: Assumes Insurance Exogenous#	-4.25***	-6.63***	-1.19***	-3.63***	-2.43***	-4.80***	-1.78***	-4.69***
Observables & Unobservables: Assumes Insurance Endogenous#	3.58***	-6.35***	4.06***	-4.21***	-5.65***	-8.40***	-5.38***	-8.15***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	-7.83	-0.28	-5.25	0.58	3.22	3.60	3.60	3.46

Calculated using Average Marginal Effects

***,**,* Significant at p = .01, .05, and .10 respectively

Table 20a. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: CHRONIC CONDITION

	OFFICEVIS					
	***NO CHRONIC* (n=51,371)**		***DIABETIC* (n=3,835)**		***HYPERTENSIVE* (n=10,492)**	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means			-1.48**	-1.56**	-0.72**	-1.62**
Observables: Assumes Insurance Exogenous#	-0.47***	-1.26***	-1.10***	-1.44***	-0.67***	-1.80***
Observables & Unobservables: Assumes Insurance Endogenous#	-1.15***	-1.46***	-3.69***	-1.56***	-2.72***	-2.98***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	0.68	0.20	2.59	0.12	2.05	1.18

Calculated using Average Marginal Effects
***,**,* Significant at p = .01, .05, and .10 respectively

Table 20b. Subgroup Analysis: Treatment And Selection Effects vs. INSR
BY: CHRONIC CONDITION

	RXNUM					
	***NO CHRONIC* (n=51,371)**		***DIABETIC* (n=3,835)**		***HYPERTENSIVE* (n=10,492)**	
TREATMENT EFFECTS CONTROLLING FOR:	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**	**TEMPINSR**	**UNINSR**
Nothing: Unconditional Means			-6.57**	-5.53**	-4.39**	-2.77**
Observables: Assumes Insurance Exogenous#	-0.92***	-2.03***	-4.02***	-5.33***	-4.09***	-5.30***
Observables & Unobservables: Assumes Insurance Endogenous#	-2.31***	-2.79***	-4.51***	-6.93***	-5.42***	-6.56***
SELECTION EFFECT (TE_{EXOG} - TE_{ENDOG})	1.39	0.76	0.49	1.60	1.33	1.26

Calculated using Average Marginal Effects
***,**,* Significant at p = .01, .05, and .10 respectively

Treatment and Selection Effects Comparison: Uninsured versus Insured

Figure 1a

By Gender (OBDOCVIS)

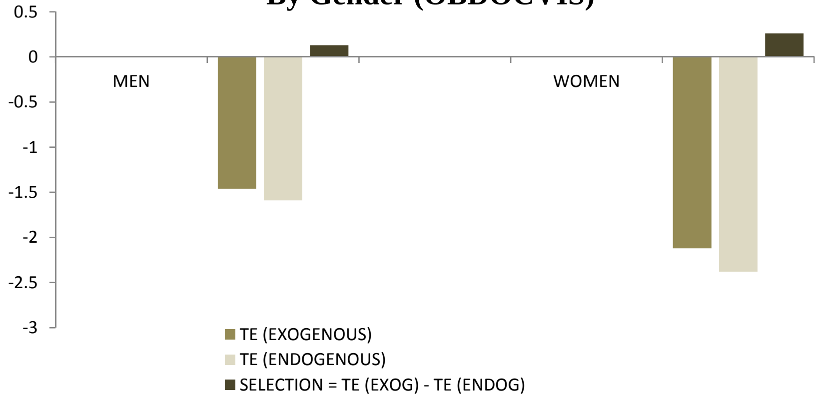


Figure 2a

By Age (OBDOCVIS)

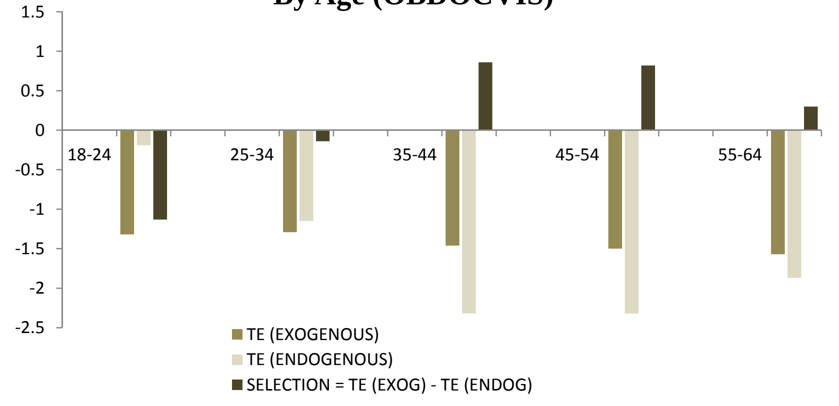


Figure 1b

By Gender (RXNUM)

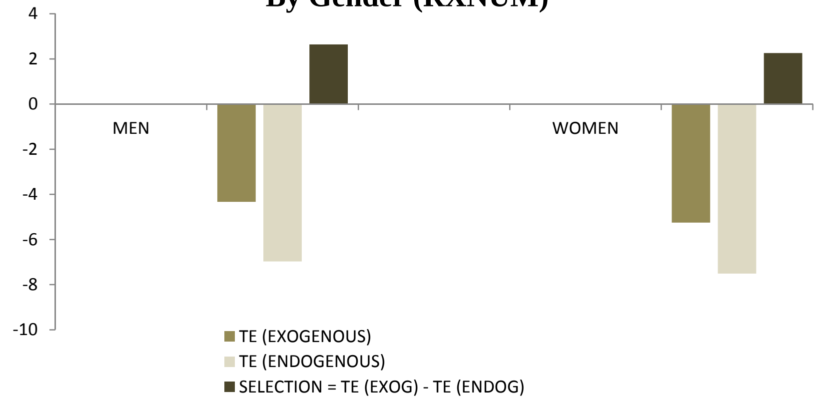
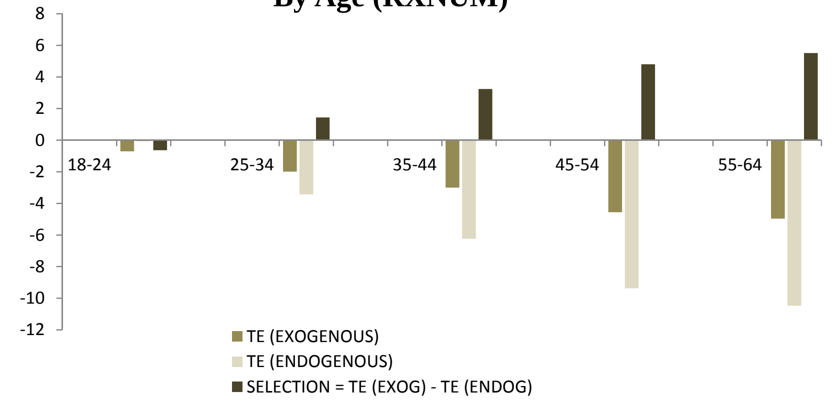


Figure 2b

By Age (RXNUM)



Treatment and Selection Effects Comparison: Uninsured versus Insured

Figure 3a

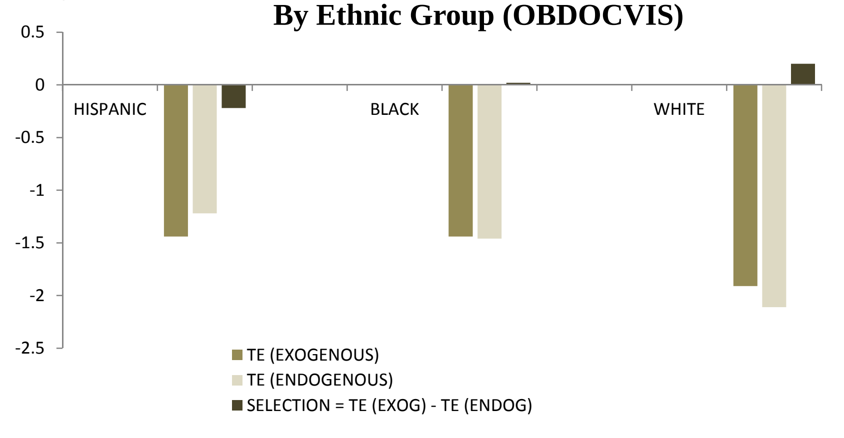


Figure 4a

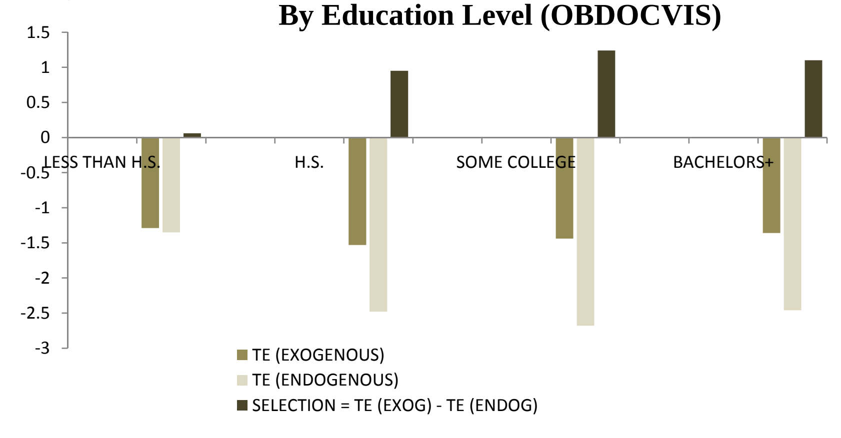


Figure 3b

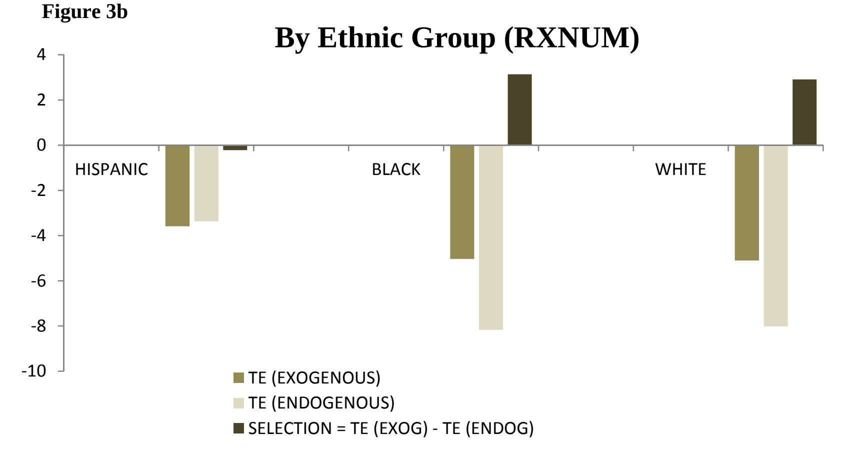
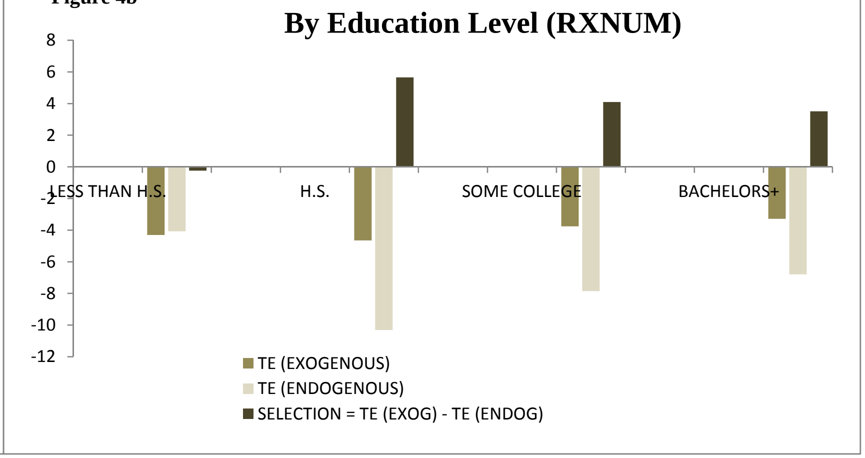
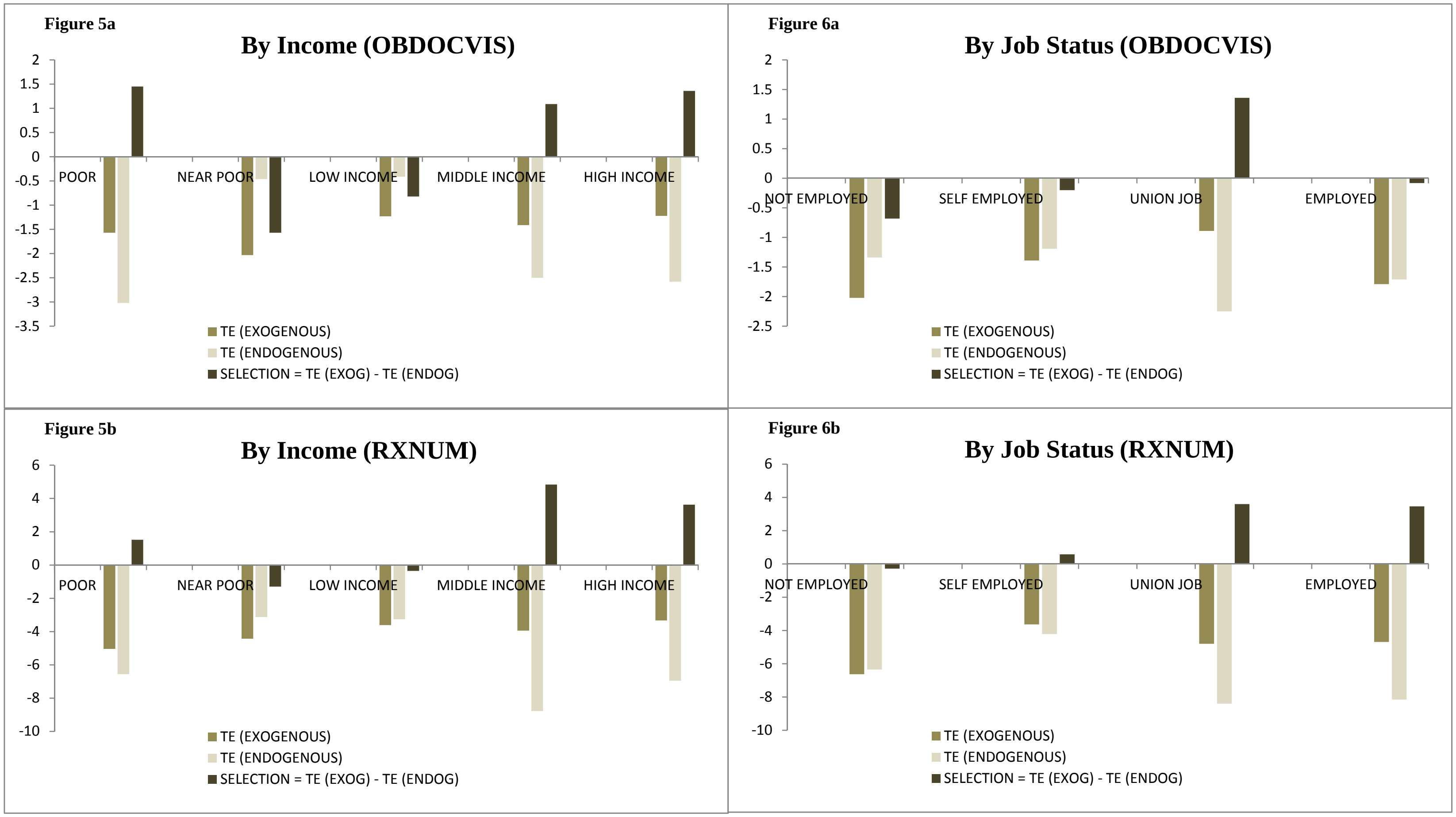


Figure 4b



Treatment and Selection Effects Comparison: Uninsured versus Insured



Treatment and Selection Effects Comparison: Uninsured versus Insured

Figure 7a

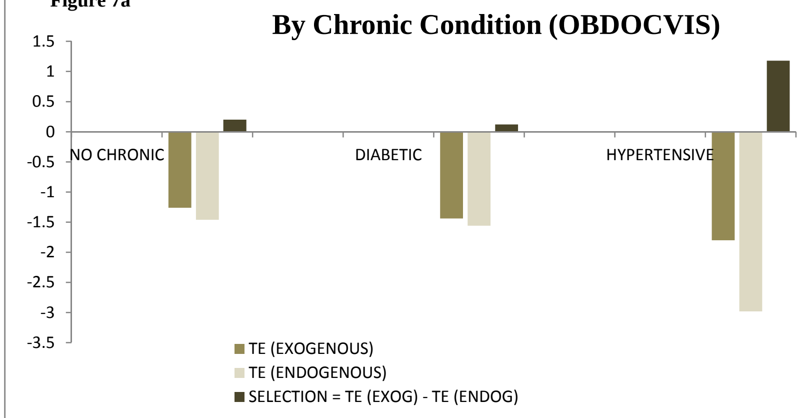


Figure 7b