THE RELATIONSHIP BETWEEN HEALTH INSURANCE CHARACTERISTICS AND THE USE OF BEHAVIORAL HEALTH TREATMENT SERVICES

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A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Health Policy and Administration, School of Public Health

Chapel Hill
2006

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ABSTRACT

Laura J. Dunlap: The Relationship Between Health Insurance Characteristics and the Use of Behavioral Health Treatment Services
(Under the direction of Edward C. Norton, Ph.D.)

Rationale: Many people delay health care treatment and some never seek care from the formal health care system. It is estimated that 28 percent of the U.S. adult population in any year has a diagnosable mental or addictive disorder, and yet less than one-third of these individuals seek treatment. **Objective:** The objective of this study is to estimate the effect of health insurance characteristics on mental health and substance use (MH/SA) treatment utilization for privately-insured employees and their dependents. **Methodology:** Using a two-part model, I estimate the effect of MH/SA health insurance characteristics on the decision to use MH/SA services and, conditional on use, the number of treatment days. Probability of use is modeled using a random-effects logit model and the number of treatment days is modeled using a random-effects negative binomial model. Data used are private insurance enrollment and claims data for 1997-1998 from MEDSTAT's Marketscan® database. **Results:** Individuals are found to respond to expected out-of-pocket expenses for outpatient MH care, but this response is very small. Furthermore, MH/SA health characteristics appear to have little or no effect on SA treatment utilization for spouses and other dependents. My models show that the effect of MH/SA health insurance varies for individuals by their relationship to the policy (i.e., primary beneficiary versus spouse or other dependent). Primary beneficiaries are found to be more responsive to these characteristics than spouses and other dependents. When significant, the requirement of precertification by an employee assistance program (EAP) has a negative effect on MH/SA utilization.

Conclusions: My findings suggest that the response to cost-sharing for MH care demand is similar to general medical care and brings into question previous arguments against parity for MH/SA treatment. Finally, the role of an EAP is not straightforward. Rather than facilitating treatment access, EAP precertification may create an obstacle to treatment and discourage utilization. However, it is also possible that EAP precertification may decrease formal utilization by providing some brief MH/SA services to individuals with milder conditions.

ACKNOWLEDGEMENTS

I am grateful for this opportunity to thank those whose guidance, questions, and examples enabled me to write this dissertation. I owe a special thanks to my advisor Edward Norton. His patience with me, knowledge of health services and econometrics, and enthusiasm for learning have given me an education that I will always value. I would also like to thank my committee, Marisa Domino, Michael French, Joseph Morrissey, and Gary Zarkin, all of whom provided valuable insights and sound advice to help me achieve this goal.

I was very fortunate to be granted use of the Marketscan® claims and enrollment data through the MEDSTAT MarketScan Dissertation Support Program. I would especially like to thank Stella Chang, a senior manager in pharmaceutical operations at Thomson Medstat, for her help in resolving data issues. RTI International was instrumental in the completion of my dissertation. As a researcher at RTI, I have benefited from outstanding resources including tuition support, computer and publications support, and intellectually challenging colleagues, many of whom over the years donated their own time to discuss my research and provided valuable suggestions. My supervisors, Allen Miedema and Gary Zarkin, provide a wonderful environment at RTI that fosters confidence, scientific collaboration, and innovation. Being able to work in this environment while completing my dissertation made the journey much more rewarding.

On a more personal note, I would also like to thank Gary Zarkin for his years of mentorship and emotional support as I worked toward this goal. His inspiration, enthusiasm, and knowledge have helped me to continue to grow as a researcher and a person. I would also like to thank the "sixth man" of my committee, Jeremy Bray of RTI. Jeremy was always available to provide practical and methodological advice, and working with him is a great pleasure.

Most importantly, I could not have accomplished this without the continuing encouragement of my family and friends. My family was always ready to help me and thankfully understood all those missed family gatherings because I had one more analysis to run. I especially want to thank Susan Reif and Paula Groulx. Their encouragement and friendship kept me mentally and emotionally healthy over the years. We discussed everything in our lives except how my research was proceeding and for that I am extremely grateful.

TABLE OF CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

CHAPTER I: BACKGROUND AND SIGNIFICANCE

Mental health and substance abuse (MH/SA) disorders are an enormous problem in the United States, affecting many aspects of society including health care, crime, and employment. Approximately 30 percent of the population experiences some diagnosable MH/SA disorder in a given year (Kessler et al., 1994). In 1997, the U.S. spent almost $71 billion for the direct treatment of mental disorders (Mark et al, 1998. In addition, indirect costs of mental disorders were estimated in 1990 at $78.6 billion (Rice & Miller, 1996)—a conservative estimate because it does not include some measure of the pain, suffering, disruption, and reduced productivity that are not reflected in earnings. Substance abuse disorders are also associated with high societal costs. In 1998, the direct costs of alcohol and drug use were estimated to be about $91 billion, and the indirect costs, including costs associated with crime and productivity losses due to premature death and disability, accounted for about $233 billion (Office of National Drug Policy [ONDCP], 2004). These estimates show that mental illness and substance abuse are comparable to many high-profile medical conditions including cardiovascular disease ($351.8 billion in 2003; NHLBI, 2003), cancer ($189.5 billion in 2003; NHLBI; 2003), diabetes ($132 billion in 2003; Hogan, Dall, and Nikolov, 2003), and obesity ($99.2 billion in 1995; Wolf and Colditz, 1998). Even if we only compare the direct costs of MH/SA, it still must be considered one of the more costly health problems in the nation (ONDCP, 2004).

With MH/SA disorders placing such a large burden on society, it might be expected that treatment would be readily available and used by those individuals suffering from these disorders. However, only one-third of individuals with a diagnosable mental disorder or substance use problem receive treatment in a given year (DHHS, 1999). The reasons for low treatment utilization among individuals in need vary. Some individuals simply may not want treatment because they do not perceive they have a problem. Others may recognize their problem and want treatment but they are not able to receive it because of financial and/or other barriers. For example, the 2003 National Survey on Drug Use and Health (NSDUH) found that 33 percent of the individuals in need who sought drug or alcohol treatment did not receive it because of the cost (SAMHSA, 2004).

Much of the research on MH/SA treatment utilization, especially for substance use treatment, has focused on uninsured or publicly-insured individuals who access treatment through public funding. Although this population is extremely important and deserves the attention of researchers and policymakers, understanding the relationship between economic variables and MH/SA utilization is also important for insured individuals. Depending on the generosity and structure of an individual's health plan, an insured individual may find their access to MH/SA treatment and their treatment choices quite limited. Furthermore, insured individuals may not have the same access to publicly-funded treatment because of their employment and/or insurance status. With the ongoing changes to the financing and delivery of MH/SA treatment services, it is important to understand how the out-of-pocket expenses faced by insured individuals may affect their likelihood to seek treatment and to remain in treatment through its completion. Furthermore, studies of the help-seeking behavior of privately insured individuals may help guide policy makers about public insurance entities such as Medicaid and Medicare.

Private Insurance Coverage for MH/SA Treatment Services

Major insurance coverage for outpatient MH services began in the 1950s in the form of fee-for-service (indemnity) plans, which were the most common form of health insurance at the time. Initial coverage options for MH care were quite generous and often comparable to coverage for medical services (Wells et al., 1982). However, insurers' initial experience was high costs for intensive MH treatment used by relatively few patients, prompting them to limit coverage for MH services making it less generous than general medical care. According to Bureau of Labor Statistics reports, 58 percent of adults who had employer-provided health coverage in 1981 had inpatient coverage for mental illness comparable to that for physical illness, and 10 percent had comparable outpatient coverage. By 1993 these percentages had decreased to 16 percent and 4 percent (Otten, 1998).

In the following years, insurance coverage for both general medical care and MH/SA services underwent significant changes, although MH/SA continue to have substandard coverage compared to general medical care. Insurers justified the unequal treatment of MH/SA services as a way to control unnecessary costs based on the belief that MH/SA demand is more responsive to health coverage than general medical care resulting in a greater welfare loss from coverage due to moral hazard (Frank and McGuire, 2000). Standard economic efficiency criteria (Ramsey pricing rules) suggest that insurance coverage should be greatest for those services where market distortion due to moral hazard is least (Deb and Homes, 1998).

Today, most individuals obtain health insurance through their employers and these plans offer some coverage for MH/SA services, although this coverage may not be adequate, especially for SA services (Rogowski, 1992). It is still common for MH/SA coverage to have limits on annual number of visits or length of treatment episode or to require higher levels of cost-sharing per visit for the individual. For example, private insurance may limit the number of MH/SA outpatient visits to between 20 and 30 visits per year and inpatient days to 30 days per year. Thus, MH/SA coverage provides some coverage for low ranges of spending but leaves individuals unprotected against more expensive treatment (Frank and McGuire, 2000). For insured individuals in need of MH/SA services, the range of covered benefits and the level of cost-sharing imposed on them may significantly influence whether they will use MH/SA services or, if used, whether they will receive the appropriate amount of care. If MH/SA treatment demand has greater price responsiveness than general medical care, then the optimal insurance literature would indicate that higher MH/SA cost-sharing is appropriate (Ellis and McGuire, 1993). However, if MH/SA demand response is comparable to general medical care, then the lack of parity in coverage for MH/SA may not be justified.

In addition to cost-sharing, health plans may use other mechanisms to help control utilization of services. For example, some plans may require prior authorization or precertification for MH/SA services to be covered. Under these mechanisms, plans may require authorization for MH/SA services be given by a primary care physician or a worksite employee assistance program (EAP) prior to the individual initiating service use in the formal healthcare system. Procedures to gain prior authorization may vary across health plans and may range from calling a phone center for automatic authorization to undergoing a clinical screening by a trained health professional (Horgan et al., 2003).

At first glance, the use of the EAP as the gatekeeper to MH/SA services seems a natural and attractive arrangement. After all, EAPs are work-based programs designed to help in the early identification and resolution of employee problems that may impair job performance such as stress, emotional problems, and substance use (Horgan et al., 2003; Reynolds and Lehman, 2003). However, willingness to contact an EAP may be affected by fears of job loss or social stigma perceptions. Therefore, requiring employees and their dependents to contact the workplace EAP to obtain authorization for MH/SA service use in the formal healthcare system may create unintended obstacles for those individuals in need of services.

In the 1990s, two critical changes in the coverage of MH/SA services took place which suggests that continued research in this area is needed. Mental health and substance abuse coverage experienced a dramatic increase in behavioral health care carve-out arrangements. Under carve-out contracts, a health insurance purchaser carves out certain types of benefits from a general medical plan and these conditions are managed by a separate contract or administrator (Sturm and McCulloch, 1998; Frank and McGuire, 2000). Carve-outs have long been the standard for dental or vision care, but their use in MH/SA services was not common prior to 1990.

In 1996, President Clinton passed legislation enacting the Mental Health Parity Act (MHPA). Although the MHPA was heralded as a great advancement for mental health care, its scope was quite limited. The MHPA did not require employers to offer mental health coverage, only that dollar limits on coverage be equal to dollar limits on medical benefits if mental health coverage is offered. The MHPA did not impose any mandates on deductibles, copayments, limits on days or visits, or require coverage for substance abuse (Sturm and

McCulloch, 1998). The debates leading to the MHPA highlighted the uncertainty surrounding the impact of insurance cost-containment mechanisms on MH/SA utilization (Sturm and McCulloch, 1998).

As noted above, failure to get treatment not only affects the individual and their family, but has high costs for society in general. Consequently, over the last few decades researchers and policy makers have grappled with questions regarding the responsiveness of individuals to MH/SA cost-sharing arrangements. Given the recent and ongoing changes in the marketplace (e.g., the growth of carve-out companies), the policy debates surrounding the financing of MH/SA treatment and the need for information continues today.

Previous Studies of Behavioral Health Care Demand

Early studies of mental health care demand have focused on response to cost-sharing. Although the magnitudes of the price responses vary considerably, the consistent finding across studies is that mental health care demand is more responsive to cost-sharing than demand for general medical care. The primary policy implication of these early empirical findings is that there may be an efficiency rationale for outpatient MH treatment to be covered at a higher level of cost sharing than other types of outpatient health care (Frank and McGuire, 2000).

Probably the best known study of the effect of health insurance on health care demand is the RAND Health Insurance Experiment (HIE). During the mid-1970s, researchers at RAND randomly assigned families to one of 14 health insurance plans offered by RAND in the role as a third party payer. Using this design, researchers were able to directly observe the use of health care services and the prices charged and paid rather than relying on self-reports from individuals, providers, and payers.

Numerous studies have been published using the RAND HIE data and several of these studies have focused on the relationship between health insurance and use of mental health services (e.g., Keeler, Manning, and Wells, 1988; Keeler et al., 1986; Manning and Wells, 1987; Manning, et al. 1984; Manning et al., 1986; Wells et al., 1986a; Wells et al., 1986b; Wells, et al, 1982). These studies examined different measures of mental health services (e.g., the number of ambulatory visits, expenditures on care, and the use of formal care versus informal care) and employed various multivariate regression techniques (e.g., probit and logistic models for dichotomous measures of probability of use, negative binomial for counts of the number of visits or services, and linear regression for continuous measures of expenditures). In each of these studies, use of outpatient mental health care was found to be more responsive to cost sharing mechanisms than medical care with estimated elasticities ranging from –0.17 to –1.00. Participants with less cost sharing were more likely to use mental health services and incur higher overall mental health expenditures.

For example, using RAND HIE data Wells et al. (1982) and Manning et al. (1984) both found that the coinsurance rate had a strong impact on MH care expenditures. Wells and colleagues found that the probability of any use of ambulatory mental health services doubled from a plan with 95 percent coinsurance rate to a free plan (zero percent coinsurance). Ambulatory MH expenditures per enrollee rose by three-quarters on the same plans when coinsurance went from 95 percent to zero percent (free plan). However, small deductibles ($150 per person for ambulatory care followed by free care) had a statistically insignificant effect on expenses compared to free care. They estimated a price elasticity of –0.17 for outpatient MH care demand relative to price. Similarly, Manning and colleagues found that expenditures on mental health care in the 95-percent coinsurance plan were only

53 percent of expenditures in the free plan. However, compared to general medical care, they did not find that the response to psychotherapy services cost sharing was significantly larger, suggesting that arguments against parity for mental health coverage may not be true.

Keeler et al. (1986) examined demand for episodes of mental health care and found that individuals with no insurance coverage (i.e., 100 percent coinsurance) spent one-quarter as much on mental health care as individuals with free care. Individuals in plans with a 50-percent coinsurance rate and no additional limits had two-fifths the expenditures as individuals in the free care plan. In a comparison of prepaid plans and fee-for-service plans using the RAND HIE data from the Seattle group, Wells et al. (1986b) found that enrollees in the prepaid groups had significantly more mental health problems in a given year than those in fee-for-service plans, but they had two-thirds less number of visits per enrollee per year to formally trained mental health specialists compared to enrollees in the free and individual fee-for-service plans.

Ellis and McGuire (1986) examined demand responsiveness of outpatient mental health care using an increasing block price (no deductible, cost sharing up to a limit on outpatient spending) to derive an expected end-of-year price. They estimated a price elasticity (for level of use) of –0.37.

The RAND health study is the only large-scale study of health insurance to use randomization. Findings from this study provided a substantial contribution to the knowledge of medical and mental health care utilization. However, most of the RAND studies did not examine utilization of SA treatment separate from MH care (one exception is Wells et al. (1982) who found that increasing the copayment for SA treatment decreased the probability of using treatment services). Furthermore, the RAND study results are limited in their generalizability because their sample included families from only 6 cities in the U.S. and some researchers have questioned whether the cap placed on total expenditures for families as part of the study design may have biased the results. In response to this last criticism, Keeler, Manning, and Wells (1988) examined demand only for those users in the RAND sample who were not near the dollar limit on total out-of-pocket expenses when they began use of MH care. They still found MH care to be more responsive than general medical care, with individuals in the free care plan using about four times more outpatient MH care than those in the 95-percent coinsurance plan.

In addition to the RAND studies, there have been numerous observational studies that use cross sectional survey data and claims data from purposively sampled insurers/employers to estimate the relationship between the use of ambulatory mental health services and cost-sharing provisions in health insurance. The findings from these studies have been inconsistent. Some studies have shown that insurance increases the probability of treatment and the number of visits, while higher out-of-pocket payments are associated with lower utilization (e.g., McGuire, 1981; Horgan, 1986; Taube et al. 1986; Watts, Scheffler, and Jewel, 1986; Simon et al., 1996; Deb and Holmes, 1998) while others have found only limited association or none at all (e.g., Scheffler and Miller, 1989). In most of these studies, the annual number of ambulatory mental health visits is the key outcome of interest and it was assumed that individuals faced a constant price that was usually derived as the average price for the year. The most common econometric approach employed in these studies was the two-part model. The first part estimating the effect of health insurance cost-sharing on the probability of use and the second part estimating the effect of health insurance cost-sharing on level of use conditional on any use occurring.

McGuire (1981) used data from the 1973 Joint Information Service Survey of office-based psychiatrists to determine the effect of out-of-pocket costs on the number of visits among outpatient MH care users. He found that expected use was responsive to price and that the degree of responsiveness varied by income with higher income individuals being more responsive to price. He estimated a price elasticity of –1.00 indicating a negative constant elasticity for mental health care demand.

Taube et al. (1986) used data from the National Medical Care Utilization and Expenditure Survey (NMCUES) to estimate adult's use of mental health care services in both the specialty sector and general medical care. Using the average percentage of expenses paid out-of-pocket by the individual per MH visit for their price measure, they estimated a price elasticity of –0.54 suggesting that a 10 percent increase in the price would lead to a 5.4 percent decrease in annual number of visits. This estimate was about 4 times larger than their estimated price elasticity for medical care (–0.13) leading them to conclude that mental health care use is much more responsive to price. Taube and colleagues also found that price elasticity varied by income; however contrary to McGuire's findings, they found that low income (<$10,000) and mid-income ($10,000 and $24,000) individuals were more responsive (elasticity = –0.43) than higher income individuals (>$25,000; elasticity = 0.02).

Similar elasticity estimates for mental health care were estimated by Horgan et al. (1986) who used the National Medical Care Expenditure Survey to estimate an elasticity of –0.44, which was 2.75 times that of their estimate for general medical care (–0.16). Wallen, Roddy, and Meyers (1986) used claims data from the United Mine Workers of America to estimate the effect of coinsurance rates on MH expenditures. They estimated a price elasticity of –0.32 for outpatient MH care, and they also found that men are more sensitive than women to changes in the price of MH care. The estimated price elasticities were –0.50 and –0.31 for men and women, respectively. In a study of the Blue Cross/Blue Shield Federal Employee Health Benefits Plan, Scheffler and Miller (1989) found no effect of price of the probability of using outpatient or inpatient care or on the level of use of inpatient care. They did, however, find that price had a negative effect on days of outpatient care with an estimated elasticity of –0.27.

In a more recent study, Deb and Holmes (1998) used data from the National Medical Expenditure Survey to study the extent to which patients may substitute physician and non-physician outpatient mental health services in response to insurance coverage which differs by provider type. Their results indicated that insurance coverage significantly affects the choice of provider from whom care is sought and, for individuals who seek care from both provider types. They estimated own-price elasticities of about –0.70 and cross-price elasticities of about +0.50 which suggests that physician and non-physician services are substitutes.

The studies of SA treatment utilization have not been as abundant as MH care utilization studies, but in recent years several studies have examined the effect of insurance on SA treatment utilization (e.g., Schmidt and Weisner, 2005; Ciemins, 2004; Weisner et al., 2002; Garcia et al., 1999; Friedman et al., 2001; Green-Hennessy, 2002; Wu, Hoven, and Fuller, 2003) and the specific effect of insurance co-payment amounts or coinsurance rates on the level of substance use treatment services used by individuals in treatment (e.g., Stein et al., 2000; Lo Sasso and Lyons, 2002; Stein and Zhang, 2003; Lo Sasso and Lyons, 2004; Schoenbaum, Zhang, and Sturm, 1998; Goodman et al, 1999). The findings from these studies are inconsistent and do not provide a consensus view of the effect that insurance may have on individuals' decisions regarding use of SA services.

Garcia and colleagues (1999) used data from a SA treatment program in southern Florida to examine factors associated with completing SA treatment. They found that the likelihood of completing treatment among insured users was 1.34 times that of uninsured users ($p<0.05$) suggesting that insurance facilitates receipt of appropriate levels of SA treatment services.

However, Friedman, Lemon, and Stein (2001) found the opposite result when they looked at factors affecting retention in outpatient methadone maintenance treatment and in outpatient drug-free treatment. Using data from the Drug Abuse Treatment Outcomes Study (1991–1993), they examined the probability of staying in treatment for at least the minimum number of days most often cited as necessary for successful treatment (at least 365 days for methadone treatment and at least 90 days for outpatient drug-free). They found that type of insurance (private, public, uninsured) had no significant effect on treatment stay for methadone treatment. However, privately-insured patients in outpatient drug-free treatment were less likely to stay in treatment for at least 90 days (Odds Ratio = 0.72) compared to uninsured patients.

Green-Hennessy (2002) found no insurance effect when she examined factors that affect use of MH/SA services among adults with substance dependence that participated in the 1995 and 1996 National Household Survey on Drug Abuse (NHSDA) surveys. Factors that were found to be statistically significant included being female, having an income greater than $75,000, having contact with the criminal justice system, being depressed, and perceived need for treatment. In fact, high income and perceived need for treatment were the two strongest predictors of any use.

Studies that examined the effect of copayment levels specifically found that copayment levels had a significant negative effect on utilization of substance use treatment. Lo Sasso and Lyons (2004) estimated elasticities ranging from –0.17 to –0.27 for days of outpatient SA treatment and –0.017 for days of inpatient treatment.

As with studies of MH utilization, these studies have advanced our knowledge of the effect of insurance on substance use treatment utilization. However, they have several limitations that reveal the need for more studies in this area. One limitation of these studies is that they either focus on a crude measure of insurance or they focus on only one aspect of the insurance design—the copayment. Another limitation is that most of these studies are only able to examine utilization for a population of individuals already in treatment. Their data did not contain information on enrollees who did not utilize SA treatment services and, therefore, did not allow examination of the probability of any treatment service use.

To my knowledge, no studies have examined the specific effect of requiring EAP precertification for MH/SA services on the utilization of such services. However, some studies have examined the effect that an EAP per se has on service utilization. For example, Reynolds and Lehman (2003) studied a random sample of municipal employees in the southwestern U.S. and found that overall substance abusers were less willing to use the EAP than nonusers. However, substance users who were aware of the EAP and who had favorable attitudes about workplace policy were as willing to use the EAP as nonusers. They concluded that creating awareness of and favorability for the EAP might help buffer substance abusers' reluctance to seek help through the EAP.

In a study of employees of a large midwestern employer, Zarkin, Bray, and Qi (2000) examined the effect of the EAP on health care utilization including both general medical care and MH/SA services. They found that going to an EAP substantially increased both the probability of an MH/SA service claim and the number of MH/SA claims in the same quarter as EAP contact. They concluded that the EAP is able to identify MH/SA problems that may affect workplace performance and prompt EAP users to access formal MH/SA services through their healthcare plan.

Significance

This study provides insights into the economic behavior of individuals related to the demand for MH and SA treatment services. Given the ongoing debate on mental health parity coupled with the dire consequences associated with untreated MH and SA disorders, understanding the effect that insurer's utilization-control mechanisms have on MH and SA treatment demand is essential. Results from this study could be used to inform policy debate on future MH/SA coverage mandates and on the role that employee assistance programs may play in MH/SA treatment access. Although previous studies have examined MH and SA treatment demand response relative to cost-sharing, this study fills an important gap and adds to the research field in several ways:

1. I examine the effect of cost-sharing on both the probability of use and on the amount of services received by using a recent national database of claims data which contains detailed plan information on both service users and non-using enrollees. With these data, I am able to estimate the incremental effect of cost-sharing on MH and SA treatment demand and to investigate how demand response differs between the two stages of the treatment decision—any use and extent of use. Many of the previous health utilization

studies that use either claims data or self-reported survey data have been limited to examining levels of use among users because they do not have data on non-using enrollees.

2. I examine MH care and SA treatment utilization separately which allows me to investigate whether users of MH and SA services have differential demand response relative to cost-sharing. Until recently, much of the previous behavioral health utilization research has focused solely on either mental health or substance abuse without making any comparisons. Furthermore, for each type of care, I also examine inpatient and outpatient services separately allowing me to compare responsiveness by service modality.
3. Because of the detailed plan information available in my data, I am able to examine the possibility of cross-price effects between inpatient and outpatient care as well as between in-network and out-of-network services. Previous behavioral health utilization studies have tended to focus on the effect of a single price variable (e.g., outpatient coinsurance rate or average out-of-pocket expense). To my knowledge, only a few studies have examined cross-price effects (e.g., LoSasso and Lyons , 2004).
4. Again, because of the plan information available in my data, I am able to examine insurer's containment mechanisms beyond cost-sharing. Specifically, I examine the effect that an EAP precertification requirement for MH/SA services has on the demand for these services. To my knowledge, no study has examined this effect in combination with coinsurance rates.

5. Finally, my study examines demand responsiveness for children as well as adults. Previous studies that estimated demand responsiveness relative to price typically include only adults in their sample.

CHAPTER 2: CONCEPTUAL FRAMEWORK

The decision to seek health care has been shown to be a complex process (Furnham et al, 1995; Sussman, Robins, and Earl, 1987). As numerous studies have demonstrated, need for care does not always result in a visit to a health care provider (Suchman, 1965; Zola, 1972, 1973). Many people delay treatment, some never seek care from the formal health care system, and others who do seek treatment may not obtain the appropriate amount of services. This seems especially true for mental health care and substance abuse (MH/SA) treatment services in which it is estimated that 28 percent of the US adult population in any year has a diagnosable mental or addictive disorder, yet only 8 percent seeks treatment (Klick and Markowitz, 2006; DHHS, 1999).

Although numerous factors play a role in utilizing health care services, there are three basic factors that largely drive this demand—need, the ability to pay for services, and having access to services. The latter two factors are clearly interrelated because access can be thought of in different ways. Access typically refers to whether treatment is available to an individual upon demand. For example, does the location of treatment providers make them geographically accessible to the individual? Is the supply of providers sufficient so that treatment slots are available and the individual does not need to be unduly waitlisted for treatment? If the answer to either of these questions is no, then the individual lacks access to treatment. However, even if treatment is physically available, if an individual is unable to afford the cost of the service (either as self-pay or through the aid of insurance) then, in effect, they have no access to treatment; that is, they lack financial access to care.

Most health plans offer some level of access to MH/SA services, but they still require varying levels of cost-sharing by the individual in the form of copayments, coinsurance, and deductibles. In most cases, an insured individual has access to services as long as they can afford their out-of-pocket share of expenses that result from the cost-sharing structure. Thus, the price that the individual faces is an important determinant in the individual's decisions regarding use of MH/SA services.

In this chapter I describe a two-stage model of decision-making for MH/SA service utilization based on the work of Pohlmeier and Ulrich (1995). In executing this two-stage model, I present an economic model of health care demand (e.g., Newhouse and Phelps, 1974; Phelps and Newhouse, 1973; Phelps and Newhouse, 1974; Grossman, 1972) which portrays choices about health care utilization in a utility-maximizing framework. Next, I describe non-economic variables included in my empirical models that may affect the utilization decision. Finally, I present hypotheses drawn from the demand equation for health services and from previous research findings. I conclude the chapter with a brief discussion of the job and health plan choice and their effect on the relationship between health care utilization and health insurance.

Demand for Mental Health Care and Substance Abuse Treatment Services

The decision to seek health care can be conceptualized as a two-stage decision process. In the first stage, the individual makes the decision to contact a health care provider about treatment. In the next stage, the individual working with the provider determines the amount of treatment services to use. This conceptualization of the decision-making process recognizes that, although the individual makes the initial decision to make the first contact with a health care provider, the decision regarding intensity of treatment involves both the individual and the provider (e.g., Pohlmeier and Ulrich, 1995; Charles, Gafni, and Whelan, 1999; Charles, Gafni, and Whelan, 1997; Bissell, May, and Noyce, 2004; Singh, Cuttler, and Silvers, 2004). The level of involvement for the health care provider can vary. One extreme is that the individual entrusts the provider to make all decisions regarding intensity of use. The other extreme is that the health care provider only imparts technical information and treatment recommendations, and the individual still assumes sole decision-making power. It is this latter model that I apply in my framework, and which is illustrated in Figure 1. Because of the nature of this decision process it makes sense to estimate it using the two-part model which mirrors the decision process by separating the estimation into two distinct, yet related, regression equations for probability of any use and level of use among health care users.

As shown in Figure 1 (located at end of chapter) , the decision to seek treatment is influenced by the 3 previously mentioned utilization drivers—individual's perceived need, their ability to pay for services, and their access to services (i.e., enabling factors). In addition, predisposing characteristics may affect their utilization decisions (Anderson, 1995; Aday and Anderson, 1974; Anderson and Newman, 1973). Predisposing factors may include demographic variables, health beliefs, and social structure. These factors may affect an individual's health status, their ability to evaluate health, and their ability to cope with health conditions (Chi, 1998). Although some of these variables such as age and gender are directly controlled for in my empirical model, other predisposing factors are unobserved and, therefore, represented in the error term.

As indicated by the arrows in Figure 1, not only do these sets of factors affect health care utilization but the variables within each set of factors may affect variables in the other set of factors. For example, it is not unreasonable to expect that age or gender (both predisposing factors) may affect an individual's response to health insurance characteristics (enabling factors), a relationship which I formally test in my empirical analysis.

Models of utility-maximization for health demand such as those developed by Newhouse and Phelps (1972, 1973) and Grossman (1972) provide a useful framework by which the two-stage decision-making process for health care utilization can be modeled. In this framework, both decision stages are driven by utility-maximization based on the individual's preferences and budget constraints. The only difference between the two stages is the individual's information regarding health care service options and prices. This is the primary reason I view this as a two-stage process. If individuals had full information at the very beginning on all their service options and associated prices, they could maximize a single-stage utility problem. However, most individuals need input from a health care provider regarding treatment options and price, and with this information they can make choices to maximize the next stage utility problem.

Utility-Maximization

A large amount of research has been done on the demand for general medical care. Much of this work is based on economic models that represent the demand for health care within a utility-maximization framework in which health is one of several arguments in the utility function (e.g., Ruhm, 1995; Cameron et al., 1988; Wagstaff, 1986). As noted above, early examples of these types of models include Newhouse and Phelps (1974), Phelps and Newhouse (1973, 1974) and Grossman (1972). These economic models recognize that people do not consume health care services per se, but rather as inputs into the production of health. In this context, the use of health services is a derived demand that is generated from an individual's desire to be healthy and avoid illness.

An important feature of Grossman-type models for health care demand is that they clearly demonstrate that the derived demand for health care services is negatively associated with the price of services. In the basic Grossman model, an individual derives utility from the function $U = U_t(H_t, Z_t)$ in which H_t is the stock of health capital and Z_t is the consumption of other goods. Healthy days bring utility to the individual and individuals produce health using market inputs such as medical services and time inputs.

Grossman-type models yield a reduced-form individual demand equation for medical care services (M_t) as a function of wage (w_t), price of medical care (P_{mt}), age (t) and human capital (E), which can be presented in logarithmic form as:

$$\ln(M_t) = \beta_0 + \beta_1 \ln(w_t) - \beta_2 \ln(P_{mt}) + \beta_3 t - \beta_4 E + u_t$$

The βs are parameters to be estimated and u_t represents unobserved characteristics unrelated to the three main explanatory factors and random noise. From this equation, hypotheses can be drawn about the relationship between the demand for medical care services and the specific explanatory variables.

Mental Health Care Utilization

The simplest way to introduce mental health care into the demand for health care framework is to recognize that health stock can also denote mental health stock. Thus, higher mental health stock implies better mental health, and individuals derive utility from days of good mental health and disutility from days of bad mental health. In this way, days of bad mental health is analogous to sick days in the basic Grossman model.

Similar to physical health, mental health may affect an individual's productivity and budget constraints. For example, mental health factors such as depression, anxiety, and emotional stress are often reported as a cause for absence from work, which can result in less time for market production and lower earnings. Investing in mental health increases the number of good mental health days that an individual achieves and thereby increases their utility and improves their efficiency at producing non-market and market goods. In this framework, individuals produce mental health with both time inputs and mental health care services. Thus, the demand for mental health care services is still a derived demand as an input in the production for days of good mental health. I should still expect to obtain the same reduced-form equation for health care services demand which indicates a negative relationship between demand and price for mental health care.

There are some caveats that should be noted regarding this interpretation of the health demand utility model. First, using a utility framework assumes that individuals with mental health disorders are rational decision makers—simply put, even with a mental health disorder they are able to rank preferences and consistently maximize their utility over time. Some have argued that the assumption of rational behavior is not reasonable for mental health. However, I believe that economic rationality is a reasonable assumption especially for my sample where the majority of individuals do not have severe mental illness. These individuals are employed (or in the household of an employed individual), have access to private insurance, and most likely are able to choose treatment rather than be involuntarily committed to treatment. Although, more severe disorders (e.g., schizophrenia, manic depression, psychotic afflictions) may reduce an individual's ability to function in the consumer role, for this sample it is likely that rational decisions would then be made by a caregiver or proxy decision-maker within the household (Frank and McGuire, 2000).

Another point that should be recognized is that the basic Grossman model is a pure-investment model in which health care services are investment goods and individuals do not receive direct utility from them. However, individuals may get direct utility from receiving mental health care (Williams and Doessel, 2003). For example, they may get utility simply because they enjoy talking to someone. Under this scenario, I no longer have a pure-investment model. Instead, it is a mixed model of investment and consumption. However, this should not change expectations about the negative relationship between service demand and its price. For example, Muurinen (1982) developed demand equations for the Grossman model for a pure consumption model, and although the equation of derived demand for health care services yielded slightly different coefficients for the equation variables, the relationship between health care service demand and its price was still found to be negative.

Furthermore, unlike medical care, perceived stigma may have a large effect on use of mental health care services (Sirey et al., 2001; Dinos et al., 2004; DHHS, 1999; Cooper-Patrick et al., 1997). Studies have shown that adults tend to stigmatize individuals with mental health or substance use disorders more harshly than those with other health conditions (Corrigan, et al. 2005; Glozier, 1998). Stigma has been shown to be an important barrier to treatment seeking and to treatment adherence (Lindrooth, Lo Sasso, and Lurie, 2005; Cooper-Patrick et al., 1997). Therefore, not only may stigma be associated with not using treatment services among persons in need, but it may also be associated with not receiving the appropriate amount of care even once treatment is sought. Stigma can be viewed as part of the full social cost of using MH/SA services. Individuals with greater fear of stigmatization for using MH/SA services may view these services as more costly. Unfortunately, given that I use claims data in my study, I do not have any measures of perceived stigma. If available, I would include these variables in both parts of my two-part model with the expectation that individuals with greater fear of stigmatization would be less likely to seek treatment services even when in need, and would have lower levels of use once treatment is sought.

Finally, I am examining three different samples. Primary beneficiaries and spouses mostly contain adults over the age of 18. However, my dependent sample primarily consists of adolescents and young children. The situation of children who use mental health care services is different from that of adults. Children rarely seek treatment on their own, relying instead on their parents to make decisions. Therefore, parents' characteristics and their beliefs and stigmas about mental health and mental health care may be a strong factor in treatment utilization decisions for children and adolescents.

Hypotheses/Expectations for Mental Health Care Models

Main Explanatory Variables

Cost-sharing for Mental Health Care Services

The level of cost-sharing that the individual faces for mental health care services is the main variable of interest in my empirical models of mental health care utilization. I represent this cost-sharing with 3 variables that measure applicable coinsurance rates. The 3 coinsurance variables are all measured as the percentage of costs for the service that must be paid by the individual. For my outpatient mental health care services models, the included coinsurance rates are:

1. Coinsurance rate for outpatient mental health care provided by in-network providers;
2. Coinsurance rate for outpatient mental health care provided by out-of-network providers; and
3. Coinsurance rate for inpatient mental health care provided by in-network providers.

The first two measures represent the cost-sharing faced by the individual for the outpatient mental health service. I cannot distinguish between in-network and out-of-network services in my data, and therefore I include the coinsurance rates for both of these types of services. In making decisions about overall utilization, it seems reasonable to expect that both prices will affect not only whether the individual uses any services but where they will go for these services. In all cases, the in-network price is always lower than the out-of-network price so I might expect that the individual would always choose in-network care. However, other factors may influence the individual—such as quality or convenience—which may lead them to choose an out-of-network provider.

The third cost-sharing measure represents the level of cost-sharing for the alternative inpatient mental health care service that the individual could choose to use. I expect that, all else equal, an increase in the level of cost-sharing for outpatient mental health care (represented by the first two variables listed above) will be associated with a decrease in the demand for that service. However, I expect that, all else equal, an increase in the level of cost-sharing for inpatient mental health care will be associated with an increase in the demand for outpatient health care. That is, as the level of cost-sharing for inpatient care that individuals face increases relative to outpatient care, individuals may substitute outpatient care for inpatient care, and vice versa.

For my inpatient mental health care services models, the included coinsurance rates are:

1. Coinsurance rate for inpatient mental health care provided by in-network providers;
2. Coinsurance rate for inpatient mental health care provided by out-of-network providers; and
3. Coinsurance rate for outpatient mental health care provided by in-network providers.

These coinsurance rates are defined as above except that the mode of care to which they apply is reversed—inpatient instead of outpatient for the first 2 rates and outpatient instead of inpatient for the last rate.

In addition, I also include a variable indicating whether precertification by the EAP for service use is required. This variable is included in both the outpatient and inpatient mental health care models. I expect that required EAP precertification will have a negative association with utilization of mental health care services. There are several different ways in which EAP precertification may affect mental health care utilization. First, EAP precertification increases the time price associated with mental health care by requiring the individual to spend more time gaining access to formal mental health care services. Second, some individuals may feel uncomfortable contacting the EAP because of its association with their workplace even though EAPs promise confidentiality. Individuals may fear that they will suffer adverse work consequences resulting from stigma if their mental health condition was made known to others in the workplace. Third, EAP precertification may decrease utilization through the formal health care system by providing employees' and their dependents with some mental health care services. Individuals with milder conditions may receive an adequate dose of services through the EAP and, therefore, not need additional services. Each of these three scenarios should indicate a negative association between utilization of mental health care services in the formal health care system and EAP precertification. However, a fourth possibility is that EAP precertification may increase mental health care utilization by helping individuals in need navigate a complicated health care system. Under this last scenario, I would expect a positive association between utilization in the formal health care system and EAP precertification. However, I believe that this fourth scenario is less likely. I believe that individuals are more likely to view this precertification requirement more as an additional obstacle to treatment.

Other Explanatory Variables

<u>Age</u>

In Grossman's model, the pure age effect (assuming that wage and health stock are independent of age) is captured through the depreciation rate of the health stock. As people age, this depreciation rate may increase which leads to an increase in the costs of health and a decrease in demand for health. On the other hand, as the depreciation rate increases the health being produced for a fixed investment level is falling. Therefore more health care may be demanded as inputs to maintain the same level of health.

However, unlike physical health, the expectation of depreciating mental health with age is less certain. For example, several studies have found that older persons do not appear unhappier than middle-aged or younger persons, despite declines in physical health, deaths of peers or spouses, and other objective rigors that accompany aging (e.g., Staudinger, Fleeson, and Baltes, 1999; Brandtstadter and Greve, 1994). Others even suggest that well-being may improve with age (e.g., Carstensen, 1995; Carstensen and Turk-Charles, 1994; Lawton, 1996). Several studies have found that the prevalence of depression disorders increases up to a certain age and then decreases (Kessler et al., 2005; Bland et al., 1988; Fichter et al., 1996). Furthermore, the age of onset for most mental disorders is usually below 30 years. For example, in their recent study of age-of-onset distributions in the National Comorbidity Survey Replication, Kessler et al. found that half of all lifetime cases start by age 14 years and three-fourths by age 24 years. Prevalence of disorders tends to increase up to about 44 years of age and then declines (Kessler et al., 2005). On the other hand, stress-related mental health conditions may increase with age due to increasing career and family demands that may lead to increased use of mental health care.

Related to age, studies have found that treatment utilization is often delayed after onset of a mental disorder. Kessler, Olfson, and Berglund (1998) found that first treatment contact for depression in a nationally representative sample of people with a lifetime history of depression had a median delay of 7 years. Wang et al. (2004) found the median delay from onset to treatment utilization to be 11 years. In their study, Wang et al. found that patients whose first onsets occurred as children have significantly longer delays in seeking treatment than individuals whose first onsets occurred as adults. Taken together, these studies suggest that use of mental health care most likely will increase with age up to a point and then decline. Thus, for primary beneficiaries and spouses, I expect that mental health care use will be greater in younger age cohorts (16 to 30 years and 31 to 45 years) and less in the older age cohort (46 to 64 years).

The relationship between age and mental health care use among adolescents and children is similar to my expectations for the adult samples. Some studies suggest that very young children in need of mental health care are much less likely to receive help for mental health disorders unless they are associated with disruptive or aggressive behavior (Pihlakoski et al., 2004; Lavigne, et al., 1998). In addition, other studies find that young adults (greater than 17 years) are much less likely to use services than adolescents and children (Cohen and Hesselbart, 1993). Given the pattern of disorder onset and the delay in treatment seeking, I would expect greater mental health care use among young children (6-11 years) and adolescents (12 to 17 years) than among very young children (0-5 years) or young adults (>17 years).

Age is included in my models as spline variables. For the adult samples, there are 3 age splines for ages 16 to 30, 31 to 45, and 46 to 64. In all the models, I exclude adults aged 65 and older because these individuals are most likely to have additional coverage other than the employer-based plans (e.g., Medicare). For youths and young adult dependents, the age splines represent 0 (newborn) to 5, 6 to 11, 12 to 17, and greater than 17 years.

Gender

Numerous studies have found that women are more likely to use mental health services than men (Frieman, 1998; Sturm et al., 1995; Leaf and Bruce, 1987). Some studies have found that women are more likely to seek early help for mental health disorders compared to men and this treatment is usually sought from a non-specialty health care physician (Holbeck and Segal, 2005; Prior, 1999; Smith, 1992). However, it is less likely that non-specialty physicians will correctly identify mental health care needs in women (Holbeck and Segal, 2005). Thus, women may be more likely to use any mental health care services, but may use fewer subsequent services (i.e., have lower treatment intensity) if their mental health care problem is not correctly identified. The opposite is true for men. Men typically seek treatment later in the course of their mental disorder and, therefore, may be more severe upon presenting. This suggests that in a given year, we may see fewer men with any use of mental health care, but for men that do use services the intensity of use may be greater because of more severe problems. Therefore, I hypothesize that for my adult samples (primary beneficiaries and spouses) any use of mental health care services will be positively associated with being female. Among those that use services, I hypothesize that days of use will be positively associated with being male.

Research findings have been inconsistent on the effect that gender has in predicting use of mental health care services among adolescents and children. For example, Zimmerman (2005) and Haines et al. (2002) both found that girls are less likely to use mental health care than boys. One possible explanation for this differential use is the greater likelihood of aggressive behavior among boys. Studies suggest that among adolescents and young children, disruptive disorders and aggressive behavior are much more likely to lead to mental health treatment than other disorders such as depression. Since girls are more likely to experience depression and less likely to engage in aggressive or disruptive behavior, it suggests that girls will have less mental health care use compared to boys. However, Cohen and Hesselbart (1993) and Cuffe et al. (1995) found no gender differences in use of mental health care or in the actual prevalence of disorders. Despite the lack of significant findings in some previous studies, I hypothesize that mental health care use will be greater among boys in my dependent sample compared to girls.

Marital Status

Married clients may have less severe emotional and behavioral disorders than those who are single, divorced, separated, or widowed (Prigerson, Maciejewski, Rosenheck, 1999;

Hahn, 1993). Marital status also may proxy for a more stable living environment or more family support, which suggests that married individuals may be less likely to use mental health care. On the other hand, married clients may have more family responsibilities or family conflicts which may be associated with increased mental health disorders that could result in mental health care use. Thus, marital conflict may increase the risk for mental health problems while marital harmony may be a protective factor against use of mental health care (Prigerson, Maciejewski, Rosenheck, 1999).

Previous studies of mental health care use have typically found that being married is associated with better mental health for both men and women (Simon, 2002; Waite and Gallagher, 2000). Given the poorer mental health among non-married individuals, we might expect greater mental health care use by non-married persons. For example, Lin et al. (1996) using data from a household survey in Ontario, Canada, found greater service use among separated, divorced or widowed individuals compared to married or single individuals. On the other hand, Sturm et al. (1995) found no difference in the likelihood of any mental heath visit by marital status, but they did find that being married was negatively associated with number of mental health visits among individuals who had any use. Finally, individuals with mental health problems may be less likely to get married in the first place. Combining all these aspects, I expect that mental health care use will be positively associated with not being married.

<u>Household Size</u>

Although I expect that household size will affect the propensity to use mental health care services, I do not know the direction of this effect a priori. Studies suggest that individuals living with others have less mental health care use than persons living alone

(Badawi, Kramer, and Eaton, 1996), and that larger households may provide social attachment and emotional support (Hughes and Waite, 2002; Rogers et al., 2000). These findings suggest that mental health needs may be less among individuals in larger households. On the other hand, larger households may provide greater emotional stress and financial strain for family members (Rogers et al., 2000; Gove, Hughes, and Galle, 1979). Furthermore, depending on the structure of the household (e.g., age of children; single-parent family versus two-parent family) and the economic demands which it faces, it may be difficult for a family member in need of mental health care to actually use such services.

For children and adolescents, the presence of the father in the household may be a protective factor against mental health problems (Zimmerman, 2005), but depending on the father's beliefs and stigmas associated with mental health, his presence may also inhibit use of mental health care services when needed. In addition, children of single-parent families are at greater risk for mental health problems (Cairney et al., 2004; Weitoft et al., 2003; Lipman, et al., 2002). Badawi, Kramer, and Eaton (1996) found that individuals in female-headed households and persons living alone had higher use of mental health care services.

Worker Characteristics

Job demands and job stress can be associated with higher levels of psychological impairment and with higher rates of mental health care utilization (Dooley, Prause, and Ham-Rowbotton, 2000; Atkinson, Liem, and Liem, 1986; Dooley, Catalano, and Rook, 1988; Turner, Kessler, and House, 1991). Theoretical frameworks of job characteristics and work stress (e.g., the Job Characteristics Model [Oldham and Hackman, 1981; Hackman and Oldham, 1980]; the Demand-Control-Support Model [Karasek and Theorell, 1990]; Warr's Vitamin Model [Warr, 1987]) suggest that jobs characterized by greater demands, low control, and low social support increase the likelihood for worker's anxiety and emotional exhaustion. Furthermore, some studies suggest that family members of workers who experience job stress and associated psychological impairment may also suffer from anxiety and psychological problems. My data have limited variables which measure job characteristics, but I include dichotomous variables that represent the industry in which the worker is employed. Although I have no clear expectations a priori as to the direction of the effect that these variables may have on mental health care utilization, it seems reasonable to expect that workers in different industries experience different work environments and therefore different levels of demands, control, and social support. Furthermore, different industry environments may foster different stigmas or support towards mental health care. In addition to industry, I also include variables to control for the work status of the primary beneficiary—salaried, hourly, or other status. Salaried work status may proxy for more white-collar job positions whereas hourly work status may proxy for more blue-collar job positions. These characteristics may also indirectly proxy for differences in earnings or hours worked. Individuals with more leisure time or lower hourly wages have a lower time price and may be more willing to invest time into mental health production, at least in the short-run (Ruhm, 2005). For example, an individual suffering from depression may choose to see a counselor for several therapy sessions for help with this disorder. However, all else equal, an individual with less leisure time or facing greater time costs may choose to use antidepressant drugs for their depression rather than take time away from market activities for therapy sessions.

Region of Residence

Variability in mental health care utilization exists across different states and regions (Sturm, Ringel, and Andreyeva, 2003; Sturm, Andreyeva, and Ringel, 2002; DHHS, 1999). Variation in service utilization may be due to differences in need—either in the types of mental disorders experienced by individuals or the percentage of individuals with mental health disorders. Geographic differences also may reflect differences in population characteristics (e.g., socioeconomic disparities), state/regional characteristics (Sturm, Ringel, and Andreyeva, 2003), and social beliefs and stigmas related to mental health disorders and mental health care services. For these reasons, I expect that the geographic area in which the individual lives may affect utilization of mental health care services, but the direction of this effect is uncertain a priori. To control for these geographic differences in my models, I include 4 dichotomous variables that represent the 4 U.S. Census regions (Northeast, South, West, and Midwest [omitted reference category]).

Substance Abuse Treatment Utilization

Addiction can enter an individual's utility-maximization problem in multiple ways. Numerous studies have shown that excessive alcohol use and illicit drug use have adverse effects on health (both physical and mental health). In addition, substance use may lead to inefficiency in production of market and non-market goods either directly or through an effect on human capital accumulation. Because of its negative consequences on health, one might expect that substance use should increase the demand for health and, consequently, the demand for health care services. However, many people with addictive disorders do not seek substance abuse treatment. This observation raises the same question for substance users that often is raised for individuals with mental disorders—can individuals engaged in addictive activities behave in an economically rational way? If not, then implications from a utility-maximization model regarding demand's response to price may no longer be valid.

Addiction can be entered into a utility-maximizing if we recognize that a substance user's problem is to maximize their utility which is now a function of their health stock and current consumption of non-addictive goods *plus* current consumption of an addictive good (for my purposes, the consumption of alcohol or other drugs) and their addiction stock (i.e., habit) that is built up by previous consumption of the addictive good (Fergusen, 2000). An individual gets direct utility from current consumption of alcohol or drugs. They also get utility from their addiction stock which has an effect on their efficiency in producing their addictive kicks (i.e., their enjoyment in consuming the addictive good). However, their addiction has a negative effect on their health stock (both mental and physical) and a negative effect on their production efficiency for health and for non-addictive commodities. In each period, individuals divide their time and income among work activities, time lost due to illness or injury, the production of health, the consumption of alcohol or other drugs (if a substance user), and the consumption of other non-addictive goods. In this framework, it is reasonable to expect that substance users engage in utility-maximizing behavior subject to budget and time constraints and that we can expect their demand for health and other goods (both addictive and non-addictive) to rationally respond to changes in prices.

Hypotheses/Expectations for Substance Use Treatment Models

My empirical models for substance abuse treatment utilization are identical to my mental health care utilization models except that the cost-sharing variables now pertain to substance abuse treatment services. Below I explain the inclusion of these variables and the other non-economic variables in my substance use models and my expectations regarding the relationship between each of these variables and substance abuse treatment utilization. In most cases, these variables play the same role for substance use as I described with mental health. This highlights the fact that substance use and mental health are often related, and the factors associated with mental health disorders may also be related to substance use behavior.

Main Explanatory Variables

<u>Cost-sharing for Substance Abuse Treatment Services</u>

The level of cost-sharing that the individual faces for SA treatment services is the main variable of interest in my empirical models of SA treatment utilization. Again, I represent this cost-sharing with 3 variables that measure applicable coinsurance rates. The 3 coinsurance measures are all measured as the percentage of costs for the service that must be paid by the individual. For my outpatient substance use treatment services models, the included coinsurance rates are:

1. Coinsurance rate for outpatient substance use treatment provided by in-network providers;
2. Coinsurance rate for outpatient substance use treatment provided by out-of-network providers; and
3. Coinsurance rate for inpatient substance use treatment provided by in-network providers.

The first two measures represent the level of cost-sharing faced by the individual for the outpatient substance abuse treatment service. The third cost-sharing measure represents the level of cost-sharing for the alternative inpatient SA treatment service that the individual could choose to use. As the level of cost-sharing of inpatient care faced by individuals increases relative to outpatient care, individuals may substitute outpatient care for inpatient care, and vice versa.

For my inpatient substance use treatment services models, the included coinsurance rates are:

1. Coinsurance rate for inpatient substance use treatment provided by in-network providers;
2. Coinsurance rate for inpatient substance use treatment provided by out-of-network providers; and
3. Coinsurance rate for outpatient substance use treatment provided by in-network providers.

These coinsurance rates are defined as above except that the mode of care to which they apply is reversed—inpatient instead of outpatient for the first 2 rates and outpatient instead of inpatient for the last rate.

In addition, I again include a variable indicating whether precertification by the EAP for service use is required, and this variable is included in both the outpatient and inpatient models. For the same reasons that I described above for mental health care, I expect that required EAP precertification will have a negative association with utilization of substance use treatment services. These hypothesized reasons include increased time costs associated with going through the EAP, fear of stigma, and receipt of necessary services from the EAP.

Other Explanatory Variables

Age

As with mental health, Grossman-type health demand models suggest that age has a positive effect on an individual's choice to seek substance abuse treatment because the rate of depreciation of the health stock is a positive function of age (Muurinen, 1982). Futhermore, Suranovic, Goldfarb, and Leonard (1999) suggest that older individuals are more motivated to quit using substances, which may suggest that older individuals may be more likely to seek treatment. Using data from the 1999 National Household Survey on Drug Abuse, Wu and Ringwalt (2004) found that younger adults (typically 18-25 years of age) were more likely to be dependent on alcohol but less likely to perceive a need for treatment or to use treatment services compared to older adults. And, Hajema et al. (1999) had similar findings in their study of male problem drinkers in the Netherlands. Therefore, I hypothesize that the likelihood of using any substance abuse treatment services will be positively associated with age. Furthermore, given the greater motivation to quit among older adults and some studies that have found greater treatment retention among older adults despite lower dependency levels (Satre et al., 2004), I hypothesize that among service users, the number of days of substance abuse treatment also will be positively associated with age.

For adolescents and young children, the story is similar. Given that the age of first use for most substances is usually after age 12 with the majority initiating alcohol use and drug use between the ages of 15 and 20 (SAMHSA, 2003 NSDUH), and furthermore given that the age when normative substance use patterns usually reach their peak is around 20 years (Labouvie, Bates, and Pandina, 1997), I hypothesize that the likelihood of seeking substance abuse treatment will be greater in my older age cohorts (12-17 years and greater than 17 years) than in the younger age cohorts.

Gender

Women are less likely to seek treatment for substance abuse problems than men (Holbeck and Segal, 2005; Wu and Ringwalt, 2004; Dawson, 1996; Schober and Annis, 1996; Walitzer and Connors, 1997). Some studies suggest that women are less likely to seek treatment for substance use because of greater stigma towards women with addiction problems (Holbeck and Segal, 2005; Finkelstein, 1994; Schober and Annis, 1996; Thom, 1986). Women may also be more concerned about losing their partners or children upon treatment entry (Wu and Ringwalt, 2004). Research suggests that alcoholic women are more likely than alcoholic men to be left by their partners (Holbeck and Segal, 2005). Furthermore, women with substance use problems are less likely than men to receive support from family or friends to enter substance abuse treatment or to remain in treatment (Holbeck and Segal, 2005). Previous research on gender differences among adolescents is less clear. Although earlier studies suggest that boys are more likely to enter substance use treatment, more recent studies find no gender differences (Wu, Hoven, and Fuller, 2003; Wu et al., 2002). Despite some inconsistencies in previous research studies, I hypothesize that being female is negatively associated with any substance abuse treatment use and with days of use among treatment users.

Marital Status

Similar to mental health, marital status may affect substance use behavior and use of substance use treatment services. Marital status may proxy a more stable living environment or more family support, which suggests that married individuals may be less likely to need substance use treatment. On the other hand, married clients may have more family responsibilities or family conflicts which may be associated with increased mental health disorders that could result in substance use. These same family responsibilities may provide a barrier to seeking treatment services. Westermeyer and Boedicker (2000) found that both family responsibilities and a substance-abusing spouse reduced the likelihood of substance abuse treatment for women. Although previous studies suggest that married alcoholic men are more likely to receive pressure/support to enter treatment from their spouses, alcoholic women are more likely to view their spouse as the problem and as an obstacle to treatment (Smith, 1992). These findings suggest that being married may have a negative effect on substance use and/or substance use treatment utilization, therefore I hypothesize that any use of SA treatment and days of use will be negatively associated with being married.

Household Size

Larger households may provide social attachment and emotional support (Hughes and Waite, 2002; Rogers et al., 2000) that may be a protective factor against substance use and abuse. On the other hand, larger households may provide greater emotional stress and financial strain for family members (Rogers et al., 2000; Gove, Hughes, and Galle, 1979) that may lead to substance use and need of treatment services. Although, family members may provide pressure to enter treatment, the structure of the household and the economic demands of the family may make it difficult for a family member in need of substance use treatment to actually use such services. For example, a mother with young children may not be able to use treatment services if she does not have access to daycare for the time of the treatment sessions. Therefore, as with mental health, I expect household size will affect the propensity to use substance use treatment services, but I do not know the direction of this effect a priori.

Worker Characteristics

Similar to mental health, job demands and job stress may be associated with higher rates of substance use (Moisan et al., 1999; Lindquist; Beilin; and Knuiman, 1997; Ames and Janes, 1992; Atkinson, Liem, and Liem, 1986; Dooley, Catalano, and Rook, 1988; Turner, Kessler, and House, 1991). For example, workers suffering from employment-related stress may use alcohol as a coping mechanism (Ruhm, 2005; Lindquist; Beilin; and Knuiman, 1997). Most major theories of addiction propose that stress plays an important role in increasing substance use and relapse (Sinha, 2001). Certain work cultures and environments may also promote substance use through informal social controls that support values, attitudes, and expectations about substance use (Ames and Janes, 1992; Mensch and Kandel, 1988; Guinn, 1983). Work-related stress and work environments may differ by industry or by employee status. Therefore, I expect that workers in different industries (e.g., sales versus manufacturing) or different employee types (e.g., salaried versus hourly) may have different levels of substance use and substance use treatment needs. Taken together, these notions suggest that the job characteristics of a worker may affect the use of substances and the potential need for treatment services for the worker and, possibly for members of the worker's family. However, certain job characteristics or work environments also may hinder use of treatment services even when needed. For example, some workers may fear reprisals from their employers or fear stigma from fellow workers if their substance use problems become known. Therefore, although I hypothesize that job characteristics may affect need for treatment services and access to services, I have no expectations a priori regarding the direction of this effect.

I include the same variables for job characteristics in the models for the spouses sample and dependents sample. In this case, these variables represent the job characteristics of the primary beneficiary to whom the spouse and/or dependent are related. Spouses and children of worker's in high stress or high demand jobs may also suffer from psychological distress that may lead to higher rates of substance use. In addition, family members of substance-using individuals may also be more likely to use substances themselves.

Region of Residence

Similar to mental health care utilization, studies have found that substance abuse treatment utilization rates vary substantially across states and different regions (Dayhoff, Pope, and Huber, 1994; McAuliffe and Dunn, 2004). Variation may be due to differences in drug-of-choice mix by individuals within the state/region or to the treatment concerns targeted by specific state administrations (McAuliffe and Dunn, 2004). In addition, geographic differences may reflect differences in population characteristics, regional characteristics, social beliefs and stigmas. Therefore, I expect that the geographic area in which the individual lives may affect utilization of SA treatment services. To control for these geographic differences in my models, I include 4 dichotomous variables that represent the 4 U.S. Census regions (Northeast, South, West, and Midwest [omitted reference category]).

Primary Hypotheses to be Tested in Models Regarding Utilization

Hypothesis 1: The coefficients for the behavioral health care services' primary coinsurance rates are expected to be negative and significant indicating that as the cost-sharing faced by the individual increases the likelihood of any use of that service decreases.

Hypothesis 2: The coefficient for the coinsurance rates of an alternative service is expected to be positive and significant indicating that individuals' likelihood of using a behavioral health care service increases as the level of cost-sharing of the service decreases relative to other service alternatives.

Hypothesis 3: The coefficient for the EAP precertification requirement is expected to be negative and significant indicating that requiring EAP precertification for behavioral health care services decreases the use of these services.

Hypothesis 4: Conditional on use, individuals who face higher out-of-pocket expenditures (as measured by the coinsurance rates) will have fewer behavioral health visits than individuals who face lower out-of-pocket expenditures.

Hypothesis 5: Conditional on use, the required EAP precertification will have a negative and significant effect on the amount of services used.

Job Choice and Health Plan Choice: The First Step towards Utilization

Consideration of the individual's job choice and health plan choice decisions is important in my analysis because of the potential for adverse selection. To estimate the true effect of health insurance on service use, I must be able to distinguish the effect of the job or health plan selection from the effects of the health insurance. Ignoring these effects will lead to misleading results with the effect of insurance being overstated (Waters, 1999; Manning, Wells, and Benjamin, 1987). Adverse selection can occur at either the level of the job choice, the level of the health plan choice, or both. Much of the literature on adverse selection refers to the health plan choice where the most commonly discussed situations in the adverse selection literature are those in which employees within a given company may switch easily among plans (Harris and Sturm, 2002). Under this scenario, individuals who expect to use mental health or substance use treatment (MH/SA) services may be more likely to choose the health plan that provides more generous coverage for MH/SA services among a menu of health plans offered by an employer. In reality, nearly all plan switching reflects changes in employment (the job choice) or in employer offerings (Cunningham and Kohn, 2000) rather than in individual-driven switching among current plans. Furthermore, even when an employer offers multiple medical care plans, increasing numbers of employers are carving out MH/SA services and offering these services as a uniform benefit that covers all employees regardless of their main medical plan (Frank, Huskamp, and McGuire, 1996). Both of these situations are found in my data where I observe most switching between health plans to be due to employment attrition or to changes in the plans offered by the company and where for most firms the MH/SA benefits offered within a firm are uniform across its workers regardless of plan type. In this situation, individuals seeking generous MH/SA coverage will choose a job in which they expect the employer to provide better benefits, making the actual selection at the level of the job choice decision rather than afterwards.

For MH/SA-related adverse selection to occur at the job choice level, the individual needs to have information on MH/SA health plan offerings before taking employment. Gathering this information may not be easy. MH/SA benefits are less likely to be listed on benefit summary sheets that may be available to prospective employees, and job candidates are likely to be reluctant to make inquiries about MH/SA benefits for fear of harming their employment prospects (Harris and Sturm, 2002). However, firm characteristics may provide signals to help the individual decipher what his MH/SA plan offerings might be.

Previous research findings suggest that firm size, unionization, and the proportion of younger workers in the company may provide signals to prospective employees as to the generosity of health benefits (Long and Marquis, 1993; Buchmueller, DiNardo, and Valletta, 2001; Freeman and Medoff, 1984). Small firms may face higher premiums and, therefore, may offer limited benefits or pass these additional costs along to their workers. Firms with predominantly younger workers may indicate high turnover rates or lower-wage workers for whom firms might offer less generous benefits. Finally, unions are in a stronger position than an individual to negotiate better health benefits so firms with higher proportions of unionized workers may signal more generous health benefits than firms with lower unionization.

Therefore, to help separate the effect of the MH/SA health insurance characteristics and the job choice/health plan choice, I incorporate a 2-stage instrumental variable model that is discussed in detail in Chapter 3. In my study selection bias most likely occurs at the level of job choice because most of the employers represented in my data provide uniform MH/SA coverage across all employees (discussed in detail in Chapter 4). Therefore, I chose to handle this selection bias by modeling the health insurance characteristics as a function of employer characteristics that may be associated with the type of health plan benefits offered by the employer. For this first stage modeling of the health insurance characteristics, I include the primary beneficiary's firm size, the proportion of workers at the firm that are less than 30 years of age, and the proportion of workers at the firm that are unionized. These variables should not affect an individual's utilization decisions regarding mental health care or substance use treatment, but as noted above they may be associated with the type of benefits offered by firms thus affecting the individual's choice of employer, and consequently the MH/SA coinsurance rates and EAP requirements that they face when using MH/SA services.

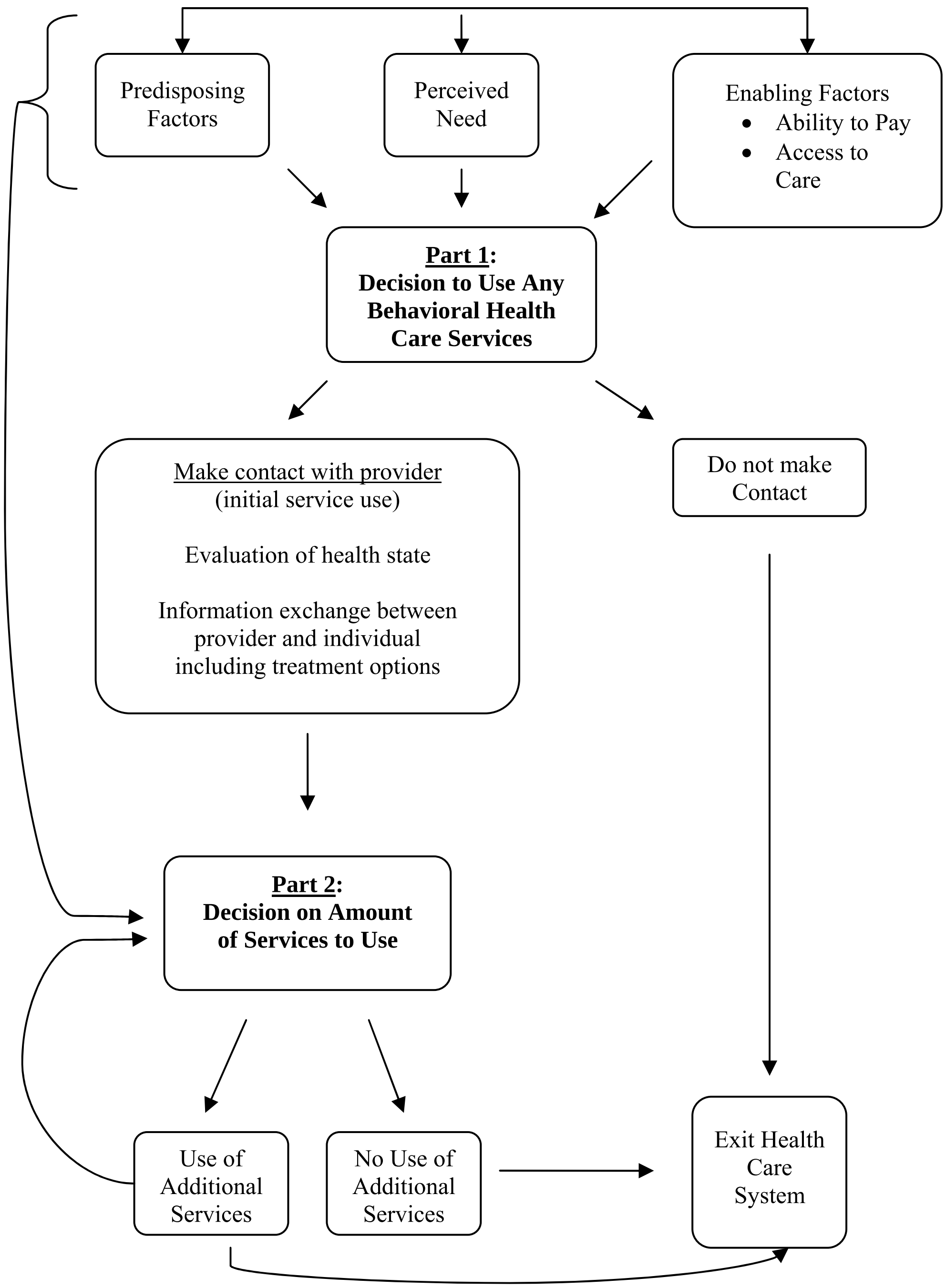
Within this first-stage estimation, I hypothesize the following associations between the firm characteristics and MH/SA coinsurance rates:

- individuals employed in firms with a greater proportion of unionized workers will have more generous MH/SA benefits as measured by lower coinsurance rates for MH/SA services;
- individuals employed in firms with a greater proportion of young workers will have less generous MH/SA benefits as measured by lower coinsurance rates for MH/SA services; and
- individuals employed in larger firms will have more generous MH/SA benefits as measured by lower coinsurance rates for MH/SA services compared to individuals in smaller firms.

Although I expect each of these characteristics to also affect whether EAP precertification is required, I do not know the direction of these effects a priori. For example, EAP precertification may be less likely to be required in smaller firms because smaller firms may not have an EAP. A greater proportion of unionized workers may be associated with required EAP precertification if the union believes in the effectiveness of the EAP; however, if the union believes that attendance at the EAP will harm its members' employment (e.g., fear of stigma), then they may negotiate contract provisions that do not allow EAP requirements (e.g., Delaney, Grube, and Ames,1998).

Figure 1:

Conceptual Model of Decision to Use Health Care Services



CHAPTER 3: METHODS

In this chapter I describe the empirical methods used to estimate the utilization of mental health care and substance abuse treatment services. The conceptual model outlined in Chapter 2 describes a two-step process by which an individual (1) decides to make contact with a health care provider for mental health care or substance abuse treatment and (2) then determines the amount of additional mental health care or substance abuse treatment services to use. The focus of this study is to estimate the separate effects of specific health insurance characteristics on each of these steps, and, therefore, I estimate this relationship using a two-part model. The first part of the model examines the effect of health insurance characteristics on any use of mental health care or substance abuse treatment services in a given year. The second part of the model examines the effect of these same characteristics on the intensity of use for those individuals with any use measured as the number of days of mental health care use or days of substance abuse treatment services. Furthermore, because I observe most individuals across two years, I employ panel estimation techniques as described below.

The unit of analysis is the individual. An individual is categorized into one of 3 groups depending on their relationship with the employer-offered health plan. These 3 groups are primary beneficiaries (employees), their spouses, and other dependents (e.g., children). My econometric models include both individual-specific characteristics (e.g., age, gender) and characteristics that are specific to the primary beneficiary (e.g., industry in which primary beneficiary is employed). I estimate separate models for utilization of mental health care use and substance abuse treatment. I also estimate different models for outpatient and inpatient care because health plans may have different coinsurance rates by type of care and provider.

Because variables representing the characteristics of the primary beneficiary have a slightly different interpretation for the 3 individual types, I estimate my models separately for each group. Furthermore, the null hypothesis that the coefficients are the same in models for the primary beneficiaries and spouses could not be accepted based on results from likelihood ratio tests (LR = 124.018 for outpatient mental health models and LR = 36.96 for outpatient substance use models).

Variables

Dependent Variables

My dependent variables are use of mental health care and substance abuse treatment. Both mental health care and substance abuse treatment are defined separately for inpatient and outpatient care. I first consider dichotomous measures of any outpatient mental health care or outpatient substance abuse treatment in the year. For outpatient mental health care, the dependent variable representing any service use is equal to 1 if the individual used any outpatient mental health care services in time t (defined as one calendar year) and zero otherwise. Similarly, the dependent variable representing any use of outpatient substance abuse treatment is equal to 1 if the individual used any outpatient substance abuse treatment in time t and zero otherwise. Next, for those individuals who used mental health care (or substance abuse treatment), I examine total days of service use in time t. Dependent variables for inpatient mental health care and inpatient substance abuse treatment are defined in the same way.

Main Explanatory Variables

The main explanatory variables of interest are the health insurance characteristics specific to MH/SA services—specifically, the coinsurance rates for MH/SA services and whether the plan required EAP authorization prior to MH/SA service use. Coinsurance rates are defined as the percentage of the service expenses paid by the individual. Higher coinsurance rates indicate less generous plans and result in higher out-of-pocket expenses for the individual if services are used. For my study I am focusing on two types of MH/SA coinsurance rates—(1) the rate applied to services used within the plan's network of providers (referred to as the in-network coinsurance rate); and (2) the rate applied to services used outside the plan's network of providers (referred to as the out-of-network coinsurance rate). For plans that do not distinguish between in-network and out-of-network services, these rates are the same. For plans that do not allow service use outside of the network, the out-of-network coinsurance rate is set to 100 percent indicating that the individual is responsible for all of these expenses. Each of these coinsurance rates differs by the service type (mental health or substance abuse) and the service setting (outpatient versus inpatient) resulting in 8 distinct price measures. These rates and the models in which they are used are summarized in Table 1. For example, as shown in the table, I include the mental health coinsurance rates for (1) outpatient in-network services, (2) outpatient out-of-network services, and (3) inpatient in-network services in the model of outpatient mental health care utilization.

Table 1. **Coinsurance Rates for MH/SA Coverage**

	Regression models in which included:			
	Outpatient Mental Health Care	**Inpatient Mental Health Care**	**Outpatient Substance Use Care**	**Inpatient Substance Use Care**
Mental Health				
Coinsurance Rates				
Outpatient in-network	X	X		
Outpatient out-of-network	X			
Inpatient in-network	X	X		
Inpatient out-of-network		X		
Substance Abuse				
Coinsurance Rates				
Outpatient in-network			X	X
Outpatient out-of-network			X	
Inpatient in-network			X	X
Inpatient out-of-network				X

As presented in Chapter 2, the first two coinsurance rates represent the cost-sharing incurred by the individual if using outpatient mental health services. The third coinsurance rate (inpatient in-network) represents the cost-sharing the individual would incur for using inpatient mental health services and this variable is included to capture any cross-price effect that may be affecting outpatient utilization. In the model of inpatient mental health care utilization, I include the parallel inpatient mental health coinsurance rates for (1) inpatient in-network services, (2) inpatient out-of-network services, and (3) outpatient in-network services. Finally, in the models of substance abuse service utilization I include the same coinsurance rates except that they apply to substance abuse services.

Following economic theory, I expect the coefficient on the outpatient coinsurance rates to be negative for outpatient service use; that is, as the coinsurance rate increases the individual is less likely to use outpatient services because their out-of-pocket expense (or "price" faced) is higher. Inpatient care may be a substitute (although not perfect) for outpatient care. Therefore, I expect the coefficient on inpatient coinsurance to be positive because as the price of alternative inpatient care increases for the individual (i.e., the inpatient coinsurance rate increases) they may be more likely to use outpatient care.

In addition to the coinsurance rates, I also include a dichotomous variable representing whether the individual is required to go through their firm's employee assistance program (EAP) to get precertification prior to using mental health or substance abuse services. Four of the 12 employer-plan groups have such requirements.

These health insurance characteristics are hypothesized to be endogenous because individuals self-select into their health plans and this selection process is affected by unobservable characteristics which also affect the propensity to use services. These unobservables are represented in the error term and lead to unwanted correlation between the error term and the health insurance characteristics. The endogeneity of health care is well-established in numerous studies of health care demand; however the extent of selection bias for MH/SA coverage is less clear. In a study of alcohol benefits offered by 57 firms and administered by a large managed behavioral health care organization, Harris and Sturm (2002) compared alcohol treatment use rates and costs of new and old enrollees between more generous and less generous plans. They found no evidence of adverse selection into more generous plans. Contrary to the selection hypothesis, they found that treatment costs of new members compared to old members were lower in firms with more generous treatment benefits than in firms with more limited benefits. If self-selection bias is present, I need to employ a model that is able to handle this endogeneity to accurately estimate MH/SA demand. I describe this model in more detail below.

Other Explanatory Variables

In addition to the health insurance characteristics, I control for the usual demographic variables such as age, gender, marital status, household size, and region of the U.S. in which the individual lives. I also include variables for the industry in which the primary beneficiary is employed, the employee type of the primary beneficiary (salary versus hourly), whether the individual used any medical care services (physical health), and the total number of months per year that an individual is enrolled in the health plan. These variables may affect use of mental health care or substance abuse treatment.

Age is included in my models as spline variables. For the primary beneficiary and spouse models there are 3 categories for ages 16 to 30, 31 to 45, and 46 to 64. In all the models, I exclude adults aged 65 and older because these individuals are most likely to have additional coverage other than the employer-based plans (e.g., Medicare). For dependents, the age categories are 0 (newborn) to 5, 6 to 11, 12 to 17, and greater than 17 years. Gender enters my models as a dichotomous variable equal to 1 if the individual is male. Household size is a continuous variable equal to the number of individuals covered on the health plan. Although not all individuals in a household may be covered on a plan, the number of individuals on the plan is a good proxy for household size in the absence of its direct measure. Marital status enters my model as a dichotomous variable equal to 1 if the individual is not married. To avoid perfect or near perfect collinearity, I only include marital status in the models for primary beneficiaries. Not surprisingly, none of the dependents are married and almost all spouses (approximately 96 percent) are married. The region of the U.S. in which an individual lives is represented by 4 dichotomous variables that signify the primary U.S. Census regions—northeast, south, midwest and west. Midwest, the most common category in my data, is omitted from the model as the reference category.

The industry in which the primary beneficiary is employed is included in my model as 3 dichotomous variables representing manufacturing, service, and transportation (the largest and omitted reference category). Employee type of the primary beneficiary (salary versus hourly), enters my model as a set of dichotomous variables—salaried equals 1 if the primary beneficiary is a salaried employee (omitted reference category) and zero otherwise. Hourly equals 1 if the primary beneficiary is an hourly employee and zero otherwise. Finally, I created a dichotomous variable equal to 1 if the primary beneficiary is an "other" employee status. Other employee status includes union or non-union without salary or hourly indicated and individuals for whom this status was unknown. As a proxy for the individual's physical health I include a dichotomous variable equal to 1 if the individual used any medical care services (physical health) in time t. Finally, not all individuals are enrolled for the entire period t. Individuals with more months of enrollment have a greater opportunity to be observed using services and therefore I include a continuous variable representing months enrolled in period t.

Ideally, I would like to include variables representing whether the individual has need for mental health care or substance abuse treatment (either self-perceived need or diagnosed need) and the severity of their mental health or substance abuse disorders for those with need. Need and severity measures for these conditions are perhaps the most noticeable omissions from my models. Obviously, only those individuals with perceived need would access mental health or substance abuse care. Furthermore, it is not unreasonable to expect that more severe individuals will use more of these services once treatment is sought. Another desirable explanatory variable to include in my models is some measure of individuals' perception of stigma associated with using MH/SA services. As discussed in Chapter 2, stigma may have a large effect on use of MH/SA services. Stigma can be viewed as part of the full social cost of using MH/SA services. Individuals with greater fear of stigmatization for using MH/SA services may view these services as more costly.

Unfortunately, claims data are limited and do not provide data on need or condition severity a priori. They also do not have any measures of perceived stigma. If available, I would include these variables in both parts of my two-part model with the expectation that individuals with need of MH/SA services will be more likely to use these services, and individuals with greater severity will use more services. Furthermore, individuals with greater fear of stigmatization will be less likely to seek treatment services even when in need, and may have lower levels of use once treatment is sought.

Empirical Specification

The objective of my analysis is to determine the effect of MH/SA health insurance characteristics on the propensity to use MH/SA treatment services and their effect on the level of use among service users, holding all else equal. In my sample, use of outpatient mental health services ranged from 5.1 percent of dependents to 7.2 percent of primary beneficiaries in a given calendar year and use of outpatient substance abuse services was about 0.3 percent per year in each of the samples; therefore I have a large number of zeros for the service use outcomes. To model this pattern of zeros, I use a two-part model (Jones, 2000; Pohlmeier and Ulrich, 1995) that divides the analysis into 2 parts—whether to use any services and then, conditional on use, how many days of service to use. First, separately for each sample I examine how MH/SA health insurance characteristics affect the propensity to use (1) mental health care and (2) substance abuse treatment.

Because my dependent variables for these models are dichotomous, a logit specification is more appropriate than standard ordinary least squares regression. However, the basic logit specification does not take into account the panel nature of my data, but rather assumes that observations for individual *i* for any period *t* are independent. It is more likely that these data contain individual-specific effects that are serially correlated. Therefore, some type of error components model must be combined with the logit specification. A random effects specification is a good choice because it allows heterogeneity across both individuals and time. Random effects will correct for correlation and provide correct standard errors. But, the standard random effects estimation will yield consistent and efficient estimates only if the fixed error component (u_i) is uncorrelated with the explanatory variables (i.e., absence of endogeneity).

Another common panel data technique is the fixed effects approach which yields consistent parameter estimates even in the presence of correlation between the explanatory variables and the fixed effect error component. However, fixed effects estimation does not yield parameter estimates for time-invariant variables because these variables are differenced out in the fixed effects approach. Since many of my explanatory variables, including all my MH/SA health insurance characteristics, are time-invariant across the 2 years observed, fixed effects is not appropriate. Therefore, I use a random effects logit regression of the form

$$\text{Prob}\ (\text{Use}_{it}) = \text{Prob}(y_{it} = 1 \mid I_{it}, X_{it}, u_i) = \Lambda(I_{it}\alpha, X_{it}\beta, \upsilon_{it}) \qquad (3.1)$$

where $\upsilon_{it} = u_i + \varepsilon_{it}$ and Λ represents the logistic distribution.

In Equation 3.1, y_{it} represents the initial demand for health care and enters the model as a dichotomous variable equal to 1 if individual *i* uses any mental health care (or substance abuse treatment services) in time period *t* and zero otherwise; I_{it} is a vector of coinsurance rates for MH/SA services that are potentially endogenous (discussed in more detail below); X_{it} is a vector of exogenous sociodemographic characteristics that may affect use of services; α and β are vectors of parameters to be estimated, υ_{it} represents the error term which can be divided into 2 components—u_i representing the individual-specific component of the error and ε_{it} representing the random error component.

In the second part of my analysis, I examine the effect of MH/SA health insurance characteristics on days of mental health care (or substance abuse treatment). My empirical specification is identical to the logistic models except that the dependent variable is now a count variable representing the number of outpatient days (or inpatient days) received for metal health care or substance abuse treatment services. I use a random effects negative binomial model to estimate the second part—number of days of outpatient (or inpatient) use in period *t*—as a function of the explanatory variables. A negative binomial model relaxes the constraint that the mean and variance of the count variable are equal (a strong assumption in the Poisson model) and it allows for overdispersion (i.e., $E(y_{it}|X_{it}) < V(y_{it}|X_{it})$). Overdispersion may be caused by unobserved heterogeneity in the data or interdependence between occurrences of successive events. If overdispersion is present, failure to account for it in the model will lead to underestimates of the standard errors. The negative binomial regression equation is of the form:

$$\text{Days of Use}_{it} = \lambda_{it} = \exp(I_{it}\alpha + X_{it}\beta + \upsilon_{it}) \tag{3.2}$$

where $\upsilon_{it} = u_i + \varepsilon_{it}$ captures unobserved heterogeneity and is assumed to be uncorrelated with the explanatory variables.

Endogeneity of Health Plans for Utilization

Determining the effect of health insurance characteristics on the use of mental health and substance abuse treatment services is difficult because the choice of health insurance characteristics may be endogenous regressors in the estimation of health care utilization. Endogeneity may enter the model in two ways. First, individuals employed in a given job who expect to use MH/SA services may choose health plans that provide more generous coverage for MH/SA services. This adverse selection is an issue for health insurance in general, but it may be especially serious for mental health and substance abuse (Frank and McGuire, 2000). However, the extent of this selection bias is uncertain. Results of recent studies that have examined this issue (e.g., Deb et al., 1996; Sturm, Meredith, and Wells, 1994; Perneger et al., 1995) suggest that users of substance abuse and mental health care are associated with higher levels of health care spending and that they systematically select health plans that offer more generous coverage for behavioral health treatment (Frank and McGuire, 2000). However, as noted earlier, Harris and Sturm (2002) found no evidence of adverse selection in their study of alcohol treatment benefits.

Second, the presence of endogeneity may exist if individuals with expected MH/SA service needs choose jobs that offer more generous MH/SA health coverage. In the U.S., individuals typically choose their job and health plan as a joint product (Pauly, 2001). The effect of this joint selection is reflected in previous studies that have found that expected health insurance coverage may affect an individual's job choice and their propensity to remain at a job (referred to as job-lock; e.g., Gruber and Madrian, 1994; Madrian, 1994; Buchmueller and Valletta, 1996). Stroupe, Kinney, and Kniesner (2001) examined the effect of health insurance on job duration for chronically ill individuals or individuals with a chronically ill family member. They found that job-lock among individuals facing a chronic illness was substantial. Job-lock reduced the propensity to quit for men facing a chronic illness by about 41 percent; for women, this propensity was reduced by about 39 percent. Their findings suggest that the link between health insurance and job choice may be stronger among individuals with chronic mental health or substance abuse conditions.

In this study, the potential for selection bias for MH/SA health insurance characteristics is more likely occurring through job choice rather than through direct choice of health plans; that is, individuals are selecting jobs in which they expect more generous MH/SA coverage to be offered. Although almost all the firms represented in my data offer multiple medical care plans to their employees, most only offer a single plan for MH/SA services, either through a carve-out or a single plan managed by the same administrators as the general medical care plans.

Empirically, endogeneity may enter my models as a correlation between the explanatory variable I_{it} and υ_{it} (the error component in the main utilization model (Equation 3.1)). As noted above, the standard random effects' specification assumes that there is no correlation between the explanatory variables and the error term. However, in the presence of endogeneity random effects' assumptions are violated and techniques must be employed to handle the endogeneity. Otherwise, with correlation between I_{it} and υ_{it}, then $E(\upsilon \mid I)$ is not zero and estimates of α, the coefficient on I_{it} in the main equation will be biased.

To estimate the true effect of health insurance on service use, I need to disentangle the effect of the job selection from the effects of the health insurance characteristics. Much of the previous work examining the effect of health insurance on service use ignores the endogeneity issue, however, ignoring the endogeneity of insurance will likely lead to misleading results with the effect of insurance being overstated (Waters, 1999; Manning, Wells, and Benjamin, 1987). A common approach employed to deal with endogeneity is to use an instrumental variable (IV) technique which allows estimation of asymptotically unbiased parameter estimates and reduce measurement error. Therefore, I use a two-stage instrumental variable approach combined with the random effects model to correct for the endogeneity of MH/SA health insurance characteristics. In addition, I also estimate a simple two-part random effects model which assumes all right hand side variables as exogenous. This allows me to compare my results and ascertain the effect that not accounting for the endogeneity of MH/SA health insurance characteristics has on my results. In the results chapter, I focus my discussion on the results from the simple random effects model due to my lack of confidence in the chosen instruments for the IV estimation which is discussed below.

As a first step in the IV estimation, the MH/SA health insurance characteristics are specified as a linear function of some or all of the exogenous variables in the main utilization model above (3.1) as well as one or more identifying variables (Z_i). This regression is of the form:

$$\mathrm{I}_{it} = \gamma X_{it} + \delta Z_i + \eta_{it} \qquad (3.3)$$

For instruments to be valid, Z_i needs to include variables that (1) affect the choice of MH/SA health insurance characteristics and (2) that have no direct effect on MH/SA health care service use. Since I have 4 potentially endogenous variables, I need at least 4 instruments for the system to be exactly identified and greater than 4 for the system to be overidentified. The Marketscan data are limited, and I was only able to identify 5 potential variables to use as instruments in estimating the MH/SA health insurance characteristics. These instruments represent 3 characteristics of the primary beneficiary's firm—proportion of unionized workers at firm, proportion of workers less than 30 years of age, and 3 dichotomous variables representing firm size [<20,000 workers, 20,000 to 50,000 workers, and 50,001 to 100,000 workers, with firm size >100,000 workers as the omitted reference category]. These firm characteristics may affect the types of plans offered to employees and, therefore, their selection of MH/SA health insurance coverage.

Studies have found that generosity of mental health benefits vary by firm size (Burndorf, 2002) with larger firms offering more, generous benefits. Long and Marquis (1993) found that firms with younger employees were less likely to offer health insurance and this may mean that, of those that do offer insurance, health plan offerings are less generous in firms with a greater proportion of younger employees. Finally, studies have found that greater unionization in firms tends to increase health plan coverage and reduce employee cost-sharing (e.g., Buchmueller, DiNardo, and Valletta, 1999; Long and Marquis, 1993).

Estimating the first part of the two-part model with IV estimation requires an iterative process. First, I estimated regression models for each of the 3 coinsurance rates and for the probability that an EAP precertification is required. Because these health characteristics do not vary for individuals between years, each of these first-stage equations is estimated as pooled OLS or logit using robust standard errors and accounting for clustering on individuals. In reality, individuals' coinsurance rates are variables that take on one of several discrete values with the majority of individuals falling into categories of 0, 10, 20, 50, or 100, depending on the coinsurance rate. However, I chose to treat these variables as continuous variables which imposes a slightly different functional form on these data, but allows me to avoid collinearity issues within the second-stage utilization model that arise when sets of dichotomous variables for the coinsurance rates are used. Next, I inserted the predicted values of the relevant coinsurance rates and EAP precertification for each individual into the random effects logit equation (3.1) and the negative binomial equation (3.2).

By using this mechanical approach, the estimated standard errors of the coefficients in the second stage models are not correct. Using the predicted values for the health insurance variables introduces noise into the second-stage utilization model from the first-stage estimation. To be correct, standard errors should be adjusted for using the predicted values of health insurance characteristics rather than the actual values (Bollen, Guilkey, and Mroz, 1995). One method to calculate correct standard errors is to use boostrapping, but this technique can be complex and very computer time intensive, especially for panel data models. Because of the size of my samples and the complexity of my models, it is not unreasonable to expect this computation to take hundreds of hours of computer time. Evidence from Guilkey, Mroz, and Taylor (1992) suggests that for large samples asymptotically correct standard errors are no more effective than the conditional standard errors. Therefore, I do not estimate the asymptotically correct standard errors for the IV two-part model. To determine the degree of bias introduced by using the mechanical approach to IV estimation, I estimate correct standard errors using linear probability models (LPMs) and canned Stata programming (e.g., ivreg/ivreg2 command) and compare these with standard errors using the mechanical approach with LPMs. These comparisons suggest that the degree of bias is extremely small giving me confidence that my results are robust even with the uncorrected standard errors. As shown in Table 2, the average difference between the correct standard errors and the uncorrected standard errors for the primary beneficiary sample is less than 0.001. Comparisons for the spouse and dependent samples had similar findings.

Table 2. Comparisons of Linear Probability Model for Outpatient MH Care among Primary Beneficaries

Model	Correct Standard Errors from computer IV estimation	Uncorrected Standard Errors from mechanical IV estimation
In-network Coinsurance	0.0001477	0.001605
Out-of-network Coinsurance	0.0000977	0.0000988
Inpatient Coinsurance	0.0002427	0.00025
EAP required	0.0044083	0.0039129

Specification Tests

I applied several specification tests to my models and the results of these tests for the regressions on outpatient mental health care and outpatient substance abuse treatment are presented for each sample in Table 3 through Table 8. First, since I have only two time periods represented in my data, an obvious question is whether panel techniques are more appropriate than pooled estimation. Estimation with pooled data is appropriate if u_i equals zero (i.e., does not exist) and all the variation in service use is due to between-group variation. As shown in the tables, results from the Breusch-Pagan (1980) test which tests the presence of the fixed error component (i.e., whether u_i is equal to zero) yield large and significant χ^2 values and thereby support use of a panel data model to explicitly account for the unobserved heterogeneity.

Next, I tested whether the coinsurance rates and EAP requirement are endogenous as suspected. To do this, I use an augmented version of the Durbin-Wu-Hausman test as suggested by Davidson and MacKinnon (1993) and Rivers and Vuong (1988). This test is conducted by running the second-stage utilization models including both the residuals from the first-stage estimation of coinsurance rates and the EAP requirement and the actual values of coinsurance rates and EAP requirement. If the coinsurance rates and the EAP requirement are exogenous, then the coefficients for residuals should not be significant (Wooldridge, 2002; Rivers and Vuong, 1988). As shown in the tables, results from these tests are mixed. Health insurance characteristics are found to be endogenous in the mental health care utilization equations for all samples, but these characteristics are found to be exogenous in the substance abuse treatment utilization equations for primary beneficiaries and spouses. In theory, health insurance characteristics should be consistently endogenous or exogenous across all types of health care utilization. Furthermore, the results from the tests on the substance abuse treatment utilization may be affected by the low prevalence of utilization in the samples.

Since my system is over-identified (5 instruments for 4 endogenous variables), I am able to perform tests of the identifying restrictions. First, I test the strength of my instruments in predicting the values of the MH/SA health insurance characterstics by conducting joint F-tests (χ^2 for the logit estimation of EAP requirement) of the instruments in the first-stage regressions. As shown in the tables, across the board, the instruments are found to be highly significant. Furthermore, the first-stage regressions have high R^2 statistics indicating that the model does well in predicting values. The R^2 values from the first stage regressions ranged from 0.592 to 0.981. The marginal R^2 from including the instruments in the first stage regression are also quite large ranging 0.19 to 0.56.

Next, I test for the validity of the exclusion restrictions with 2 tests for overidentification of instruments using LPM-version of my models—Sargan's NR^2 test and

Basmann's test for weak instruments (Basmann, 1960). These test results also are inconsistent. For outpatient mental health care utilization, both tests indicate valid exclusion of the instruments for the primary beneficiaries and dependents, but not for spouses. For outpatient substance abuse treatment utilization, both tests indicate valid exclusion of the instruments for the primary beneficiaries and spouses, but not for dependents. Taken together, these tests suggest that I have identified good instruments for most (if not all) of my models.

A final point to consider is whether I have chosen instruments that are truly exogenous. For example, an individual that expects large firms to offer better MH/SA coverage may self-select into large firms so that they can obtain this coverage. Under this scenario, the size of the firm in which the individual is employed is not exogenous. Rather, the individual self-selected into this firm size and their selection is based on unobserved characteristics that may also affect their health plan choice and MH/SA service use. This argument could be made for each of my firm characteristics. Therefore, as is sometimes the case with instruments chosen for IV estimation, even though the instruments pass the empirical specification tests they may not be ideal for use in my first stage estimation. Correcting for selection at the level of the job or firm choice is beyond the scope of my estimation abilities given my dataset. I do not observe individuals' job searches or the choice set from which they made the job selection, and I do not have sociodemographic variables that would help explain this job choice but that are not related to the health insurance choice or to MH/SA service use. Therefore, as noted earlier, in the next chapter I focus my discussion on the results from the simple random effects model due to the suspected endogeneity of the chosen instruments for the IV estimation, although the IV estimation results are presented for comparison.

Table 3. **Specification Tests for Outpatient Mental Health Care for Primary Beneficiary Sample**

Test	Distribution	DF	Test Statistic	p-value	Implication
Breusch-Pagen, OLS versus error component	X^2	1	3232.27	<0.001	Cannot accept u_i equals zero. Error components are significant. Panel technique preferred
Augmented Durbin-Wu-Hausman test (Davidson and MacKinnon), endogeneity of health insurance characteristics	X^2	4	90.78	<0.001	Health Insurance Characteristics are endogenous
Tests of Instrument Strength:					
First Stage Outpatient In-Network Coinsurance Rate	F	5	16110.23	<0.001	Strong Instruments
First Stage Outpatient Out-of-Network Coinsurance Rate	F	5	74409.40	<0.001	Strong Instruments
First Stage Inpatient In-Network Coinsurance Rate	F	5	1.9e+05	<0.001	Strong Instruments
First-stage EAP Precertification Requirement	X^2	4	59055.26	<0.001	Strong Instruments
Test for overidentifying restrictions:					
Sargan NR^2 Test	X^2	1	0.382	0.537	Instruments validly excluded from main equation
Basmann Test	X^2	1	0.382	0.537	

Table 4. Specification Tests for Outpatient Mental Health Care for Spouse Sample

Test	Distribution	DF	Test Statistic	p-value	Implication
Breusch-Pagen, OLS versus error component	X^2	1	1601.93	<0.001	Cannot accept u_i equals zero. Error components are significant. Panel technique preferred
Augmented Durbin-Wu-Hausman test (Davidson and MacKinnon), endogeneity of health insurance characteristics	X^2	4	76.13	<0.001	Health Insurance Characteristics are endogenous
Tests of Instrument Strength:					
First Stage Outpatient In-Network Coinsurance Rate	F	5	11315.40	<0.001	Strong Instruments
First Stage Outpatient Out-of-Network Coinsurance Rate	F	5	40259.57	<0.001	Strong Instruments
First Stage Inpatient In-Network Coinsurance Rate	F	5	1.2e+05	<0.001	Strong Instruments
First-stage EAP Precertification Requirement	X^2	4	6.2e+05	<0.001	Strong Instruments
Test for overidentifying restrictions:					
Sargan NR^2 Test	X^2	1	5.729	0.017	Instruments are not validly excluded from main equation
Basmann Test	X^2	1	5.727	0.017	

Table 5. Specification Tests for Outpatient Mental Health Care for Dependent Sample

Test	Distribution	DF	Test Statistic	p-value	Implication
Breusch-Pagen, OLS versus error component	X^2	1	1791.14	<0.001	Cannot accept u_i equals zero. Error components are significant. Panel technique preferred
Augmented Durbin-Wu-Hausman test (Davidson and MacKinnon), endogeneity of health insurance characteristics	X^2	4	50.40	<0.001	Health Insurance Characteristics are endogenous
Tests of Instrument Strength:					
First Stage Outpatient In-Network Coinsurance Rate	*F*	5	6024.13	<0.001	Strong Instruments
First Stage Outpatient Out-of-Network Coinsurance Rate	*F*	5	79566.07	<0.001	Strong Instruments
First Stage Inpatient In-Network Coinsurance Rate	*F*	5	1.5e+05	<0.001	Strong Instruments
First-stage EAP Precertification Requirement	X^2	4	8.5e+05	<0.001	Strong Instruments
Test for overidentifying restrictions:					
Sargan NR^2 Test	X^2	1	0.222	0.638	Instruments validly excluded from main equation
Basmann Test	X^2	1	0.222	0.638	

Table 6. Specification Tests for Outpatient Substance Use Care for Primary Beneficiary Sample

Test	Distribution	DF	Test Statistic	p-value	Implication
Breusch-Pagen, OLS versus error component	X^2	1	60.39	<0.001	Cannot accept u_i equals zero. Error components are significant. Panel technique preferred
Augmented Durbin-Wu-Hausman test (Davidson and MacKinnon), endogeneity of health insurance characteristics	X^2	4	18.97	<0.001	Health Insurance Characteristics are endogenous
Tests of Instrument Strength:					
First Stage Outpatient In-Network Coinsurance Rate	F	5	9369.71	<0.001	Strong Instruments
First Stage Outpatient Out-of-Network Coinsurance Rate	F	5	62633.52	<0.001	Strong Instruments
First Stage Inpatient In-Network Coinsurance Rate	F	5	7.7e+05	<0.001	Strong Instruments
First-stage EAP Precertification Requirement	X^2	4	59055.26	<0.001	Strong Instruments
Test for overidentifying restrictions:					
Sargan NR^2 Test	X^2	1	3.316	0.069	Instruments validly excluded from main equation at 5% level
Basmann Test	X^2	1	3.315	0.069	

Table 7. Specification Tests for Outpatient Substance Use Care for Spouse Sample

Test	Distribution	DF	Test Statistic	p-value	Implication
Breusch-Pagen, OLS versus error component	X^2	1	23.77	<0.001	Cannot accept u_i equals zero. Error components are significant. Panel technique preferred
Augmented Durbin-Wu-Hausman test (Davidson and MacKinnon), endogeneity of health insurance characteristics	X^2	4	9.09	0.059	Health Insurance Characteristics are exogenous at 5% level
Tests of Instrument Strength:					
First Stage Outpatient In-Network Coinsurance Rate	F	5	5557.31	<0.001	Strong Instruments
First Stage Outpatient Out-of-Network Coinsurance Rate	F	5	41080.69	<0.001	Strong Instruments
First Stage Inpatient In-Network Coinsurance Rate	F	5	5.3e+05	<0.001	Strong Instruments
First-stage EAP Precertification Requirement	X^2	4	6.2e+05	<0.001	Strong Instruments
Test for overidentifying restrictions:					
Sargan NR^2 Test	X^2	1	0.228	0.633	Instruments validly excluded from main equation
Basmann Test	X^2	1	0.228	0.633	

Table 8. Specification Tests for Outpatient Substance Use Care for Dependent Sample

Test	Distribution	DF	Test Statistic	p-value	Implication
Breusch-Pagen, OLS versus error component	X^2	1	46.14	<0.001	Cannot accept u_i equals zero. Error components are significant. Panel technique preferred
Augmented Durbin-Wu-Hausman test (Davidson and MacKinnon), endogeneity of health insurance characteristics	X^2	4	12.32	0.015	Health Insurance Characteristics are endogenous
Tests of Instrument Strength:					
First Stage Outpatient In-Network Coinsurance Rate	F	5	4778.77	<0.001	Strong Instruments
First Stage Outpatient Out-of-Network Coinsurance Rate	F	5	37408.62	<0.001	Strong Instruments
First Stage Inpatient In-Network Coinsurance Rate	F	5	8.4e+05	<0.001	Strong Instruments
First-stage EAP Precertification Requirement	X^2	4	8.5e+05	<0.001	Strong Instruments
Test for overidentifying restrictions:					
Sargan NR^2 Test	X^2	1	8.430	0.004	Instruments are not validly excluded from main equation
Basmann Test	X^2	1	8.428	0.004	

CHAPTER 4: DATA

The primary data used in this study are private insurance enrollment and claims data for 1997-1998 from MEDSTAT's Marketscan® claims database. These files contain the basic enrollment data and service-level claims for inpatient and outpatient treatment of employees and retirees from participating large corporations and their dependents across the U.S. Collectively, the data include individuals enrolled in 72 different health insurance plans. These data are particularly good to study the effect of health insurance on utilization because they include detailed information on individuals' health plan designs. Furthermore, these data include limited information on all enrollees regardless of service use and therefore allow me to study the individual's decision to access care as well as the decisions regarding the frequency of service use.

Sample Selection

The enrollment data for 1997 and 1998 include approximately 2.1 million individuals (see Table 9). I exclude those individuals with less than one month enrollment in this period (*n*=126,865) and those for whom no plan information was collected by MEDSTAT. This left a usable sample of 1,637,535 individuals. Because the number of enrollees is considerable and computations performed on such a large quantity of data require extensive amounts of computer memory and time, I conducted my analyses on a subsample of the data. I used Stata's commands for sampling (StataCorp, 2004) to obtain a 10 percent simple random sample of individuals resulting in a dataset with 163,754 individuals. Sampling was done on the level of the individual so that once an individual was chosen all of his/her enrollment and claims data were extracted for both years of analysis.

After taking the initial random sample, I conducted additional quality checks on the smaller dataset that were not possible with the initial data given its size, and I found some discrepancies in the data from one firm. After discussing these discrepancies with MEDSTAT programmers familiar with these data, it was determined that these data did not meet the quality standards established by MEDSTAT and should not have been included in the original data. Therefore, I excluded this firm's observations from my analysis (n = 20,685 individuals). Based on the limited data that I had for these individuals, I examined whether their exclusion from my analyses would introduce bias in my results. This examination included both statistical test comparisons on mean values of selected variables and conducting limited regression analyses with and without these observations. Based on this examination, I concluded that the exclusion of these individuals would not bias my results. My final analytic dataset includes 143,069 individuals employed in 12 firms and enrolled in 52 different medical plans.

Using these data, I constructed a panel dataset with yearly individual observations for two years—the data time period is from January 1, 1997 through December 31, 1998. Over this two-year study period, some individuals are observed to move in and out of health plan enrollment. For example, an individual may be observed to be enrolled in a participating health plan for only 6 months of the two-year period. This does not necessarily mean that the individual does not have health insurance during the unobserved time. Instead, it indicates that the individual is not enrolled in any of the health plans that provided data for this period to MEDSTAT.

Table 9. Selection of Individuals for Analytic Sample

	N
Total Enrollment Data (individuals with plan end after Jan 01, 1997)	2,057,521
Less individuals with no plan data provided	293,121
Less Individuals with less than one month enrollment	126,865
Initial Sample	1,637,535
10% Sample (simple random sample)	163,754
Less suspect data observations from one firm	20,685
Final Analytic Sample	**143,069**
Number of Employer Groups Represented	12
Number of health plans represented	52

Description of Health Plans

The 52 health plans represented in the analytic dataset denote the health care coverage for employees (and their spouses and other dependents) working in companies across the United States. Most of these companies are national corporations with employees located in numerous states, and therefore a health plan may have enrollees located across the U.S. Furthermore, a company may offer multiple plans and it is probable that several plans may be available to an individual within a company. An examination of health plans and discussions with other researchers and MEDSTAT programmers revealed that the plans represented in my analytic dataset and the individuals they cover can be assembled into 12 employer groups. Health plans within a single employer group represent the plans offered to employees working for the same corporation although not necessarily for the same immediate employer, at the same facility, or in the same location.

The primary variables of interest for my study are MH/SA coinsurance rates and whether precertification by an employee assistance program (EAP) is required prior to use of MH/SA services. This information was obtained by MEDSTAT from the health plan informational booklets that are distributed to employees and supplemental information provided by the employer. These characteristics may differ for in-network and out-of-network services and therefore separate variables exist for in-network and out-of-network coinsurance rates. Table 10 presents the MH/SA health plan characteristics for the 52 health plans organized by the 12 employer groups. As shown, plans within the same employer group had little or no difference in insurance coverage for MH/SA services. Across employer groups, outpatient in-network coinsurance rates ranged from 0 to 50 percent; that is, plans covered 50 to 100 percent of expenses. Outpatient out-of-network coinsurance rates ranged from 50 percent to 100 percent (no coverage). Similar ranges are found for inpatient coinsurance rates. Some employers did not provide information on out-of-network coinsurance rates—meaning that these coinsurance rates were not mentioned in the plan booklet and no additional information was provided by the employer to MEDSTAT. For my analysis, I took a conservative view and assumed that no mention of an out-of-network rate means that the plan does not cover out-of-network services which results in a coinsurance rate of 100 percent. This assumption was made for 6 of the 12 employer groups. Discussions with MEDSTAT personnel and other researchers familiar with the MEDSTAT data support my conservative assumption of the coverage for out-of-network services; however, I analyze the effect of this assumption in my sensitivity analyses. Specifically, I re-ran my analyses under a less conservative view and assumed that no mention of an out-of-network rate means that the plan covers out-of-network services at the same level of cost-sharing as in-network services. The results of this analysis are reported in Chapter 5.

Seventy-three percent of the health plans carved-out MH/SA services from general medical care (see Table 10). This means that a separate network of providers and separate claims administrators provide MH/SA services. Only 16 of the 52 plans (31 percent) required EAP precertification prior to use of MH/SA services. For some employers, no information was provided on their EAP in the plan booklet (listed as "No Mention" in the table). Based on conversations with MEDSTAT personnel, I determined that lack of data most likely means that an EAP, if available, played no role in the health plan coverage and its requirements. Therefore, for those plans with no mention of an EAP requirement in their plan descriptions, I assumed that no EAP requirement existed. Finally, Table 10 presents the calendar dates in which plans were offered by the employer groups and these data reveal that plan offerings varied within employer groups across the two years of data resulting in an unbalanced panel.

Twenty-six health plans are represented in both years of my data, 10 plans are represented in 1997 only, and 16 plans are represented in 1998 only (see Table 11). Looking at it from the employer group perspective, individuals from 7 employer groups are represented in both years, individuals from 2 employer groups are represented in 1997 only, and individuals from 3 employer groups are represented in 1998 only. Thus, individuals may not be included in both years of the analysis either because they no longer work for a represented employer or because the employer did not provide data to MEDSTAT for that year.

Table 11. Plans Offered

	N
Number of health plans represented	52
Number of employer groups	12
Plans Offered:	
In both 1997 and 1998	26
In 1997 only	10
In 1998 only	16
Employer Groups Represented:	
In both 1997 and 1998*	7
In 1997 only*	2
In 1998 only	3
Number of plans with plan year from:	
January through December	44
June through May	4
July through June	4

*One employer group had health plan offerings in both 1997 and 1998, however they did not provide utilization data for 1998 and therefore they are only included in 1997 only.

Analytic Variables

Dependent Variables

For my different analyses, I created several dependent variables. The dependent variables for the main analyses include four dichotomous variables equal to 1 if the individual was observed to use any of the following service types during period *t*: (1) outpatient MH care services; (2) inpatient MH care services; (3) outpatient SA treatment services; and (4) inpatient SA treatment services. Similarly, I created separate count variables measuring the number of days in period *t* in which the individual received services for: (1) outpatient MH care; (2) inpatient MH care; (3) outpatient SA treatment; and (4) inpatient SA treatment. I chose days of service for my count variable instead of encounters because encounters are not consistently defined in health services literature and they may be inconsistent in representing the number of services, costs, or intensity. Days may also be inconsistent, but they are easier to define and use of days can be found in previous health services literature.

Identification of Service Encounter Type

To create the dependent variables, I first identified the claims encounters as mental health care, substance abuse treatment, or general medical care (SAMHSA, 2003). The variables used to identify encounters and their definitions from the Marketscan database are presented in Table A-1 in Appendix A located at the end of the report. These variables include diagnosis codes (see Table A-2 in appendix A), procedure codes (Table A-3), service and provider types (Table A-4), and major diagnostic codes and diagnosis-related groups (Table A-5).

Identification of the service encounter as either mental health or substance abuse was based on the primary reason for the encounter. Using this method applies a more narrow identification criterion for a service encounter because it focuses on primary diagnoses and procedures rather than secondary ones. However, this approach is advantageous because it is similar to the approaches applied in previous studies allowing for better comparison. Plus, it allows me to assign copayment (including coinsurance) and deductible dollar amounts to the service encounters.

The specific steps used in the identification process for *outpatient* service encounters are as follows. First, I evaluated the primary diagnosis code (if available) for a given outpatient service encounter. If the service encounter had a primary diagnosis code that was for a mental health condition then that outpatient service encounter was identified as a mental health encounter. Similarly, if the primary diagnosis was for substance abuse condition then the outpatient service encounter was identified as a substance abuse treatment encounter. If the primary diagnosis code was missing for the outpatient service encounter, then I evaluated the secondary diagnosis code (if present) and followed the same steps as described above for the primary diagnosis code. If no diagnosis codes were reported for the outpatient service encounter, I evaluated the procedure codes. If the primary procedure codes were missing, I used the secondary procedure codes. If no procedure codes were reported for the outpatient service encounter, I used the service type, followed by the type of provider, and finally the major diagnostic code if all previous variables were missing.

The steps used in the identification process for *inpatient* service encounters are similar to those used for outpatient service encounters with the follow exceptions. Service types and provider types were not provided for inpatient service encounters, and therefore could not be used for identification. If no diagnosis codes or procedure codes were reported for the inpatient service encounter, I used the major diagnostic code followed by the diagnosis-related groups. For both outpatient and inpatient service encounters, most encounters were identified using the diagnosis codes and procedure codes. Few service encounters required identification using the other identification variables.

Once all service encounters were identified, I summed encounters in a given day to create individual-level variables for days of mental health care, days of substance abuse treatment, and days of general medical care. I then summed these days across the entire year to create the total days of mental health care, total days of substance abuse treatment, and total days of general medical care in period *t* by individual i. Finally, separate dichotomous variables were created equal to 1 if an individual had any use of these services and zero otherwise.

Explanatory Variables

MH/SA Coinsurance Rates

The main explanatory variables of interest for my study are MH/SA coinsurance rates and EAP precertification requirements. Coinsurance rates are the percentage of the service encounter costs that an individual pays after the deductible has been met. Plans typically differentiated between in-network and out-of-network coinsurance rates and between inpatient and outpatient services, therefore I created 8 variables to represent coinsurance rates for MH/SA services which include:

Outpatient Coinsurance Rates

1. Coinsurance rate for In-Network MH Care
2. Coinsurance rate for Out-of-Network MH Care
3. Coinsurance rate for In-Network SA Treatment
4. Coinsurance rate for Out-of-Network SA Treatment.

Inpatient Coinsurance Rates

1. Coinsurance rate for In-Network MH Care
2. Coinsurance rate for Out-of-Network MH Care
3. Coinsurance rate for In-Network SA Treatment
4. Coinsurance rate for Out-of-Network SA Treatment.

Outpatient coinsurance rates for MH/SA treatment services range between 0 and 75 percent for in-network services and between 50 and 100 percent for out-of-network services. Inpatient coinsurance rates range between 0 and 50 percent for in-network services and between 20 and 100 percent for out-of-network services. All plans cover at least part of in-network services, but some plans do not cover any of the costs for out-of-network service use. Some plans allow use of services outside of the network but at penalty (i.e., higher coinsurance rates). In other plans, no out-of-network service use is allowed which means that the individual must use a provider in the network or pay the full cost of the service. In other words, the coinsurance rate for out-of-network services in these plans is 100 percent.

Health plan coverage is extremely complex and, in addition to coinsurance, may include other cost control mechanisms such as limits on the annual number of MH/SA visits in the plan year or the total annual amount paid by the plan. Once an individual reaches any of these limits their coinsurance rate effectively become 100 percent. Furthermore, many plans had sliding scale coinsurance rates that increase as service use increases. For example, in one plan, the outpatient MH coinsurance rate is 20 percent for the first 10 outpatient mental health visits and then rises to 50 percent for additional visits over 10 visits. Furthermore, over half of the plans have some type of annual limit on visits or dollars paid which effectively increases the coinsurance rate to 100 percent for visits over this annual limit.

To allow for this variation due to plan limits, I created counter variables that calculated the cumulative number of MH and SA days used and the cumulative net payments made by the plan for the year. Using these variables, I was able to assign an enrollee with a revised coinsurance rate if they had reached one of the limits imposed by the plan. To create the variables of cumulative MH/SA service days or payment amounts, I had to make an assumption about how the plans counted visits and dollars towards their annual limits. MEDSTAT's Marketscan® provided additional detailed documentation on plan descriptions in their Research Databases User's Guide and Database Dictionary (MEDSTAT, 2000). For plans in which it was clearly indicated how annual limits were applied, I used the limits as indicated in adjusting the coinsurance rates. However, for some of the plans, the descriptions of annual limits for MH/SA visits and/or dollars did not clearly indicate whether MH/SA treatment visits or dollars were summed together and jointly applied towards a combined MH/SA annual limit or if visits and payments for mental health were counted separately from substance abuse treatment. Therefore, I created two versions of the cumulative count variables—one set of variables in which MH/SA treatment visits and dollar amounts were summed jointly and applied towards combined annual MH/SA limits and another set of variables in which visits and dollar amounts were counted separately for MH and SA treatment and applied towards separate annual limits. The difference in these two different methods for calculating cumulative days and dollar amounts was small and had a negligible effect on the adjustments to the coinsurance rates. Therefore, I use the former method in my analyses in which number of visits and dollars paid are applied to a combined MH/SA limit. This is the more stringent limit and it seems reasonable to assume that insurance plans would apply the most stringent limits on service use, especially for MH/SA use.

I followed the same method to create the variables for the outpatient out-of-network coinsurance rates and inpatient coinsurance rates for MH/SA. For plans that did not allow out-of-network service use, the coinsurance rate was set to 100 percent.

EAP Precertification Required

Some health plans required that the individual receive precertification for a MH/SA service from an EAP. Therefore, I created a dichotomous variable equal to1 if EAP pre-certification is required for use of MH/SA services and zero otherwise.

Other Explanatory Variables

In addition to the health insurance variables, I also include sociodemographic variables that may affect use of health care services. These variables include individual-specific variables such as age, gender (equals 1 if male), household size, region of residence (i.e., northeast, south, west, and Midwest), total months of observed enrollment in period *t*, and any use of medical services. In addition, I include variables specific to the primary beneficiary which describe the industry (set of dichotomous variables for manufacturing, service, and transportation) and employee type (set of dichotomous variables for salary, hourly, and other). These variables are included in all regression models because they may help control for employment differences in lieu of income and specific job data which are unavailable.

Descriptive Statistics for Samples Used in Analyses

Primary Beneficiaries

Tables 12 through 14 show the means of the dependent and explanatory variables as well as other selected characteristics for each of the samples—primary beneficiaries, spouses, and other dependents. Primary beneficiaries are predominantly middle-aged (42.7 years) and male (57.9 percent). A lesser percent of MH care users are male (41.7 percent) while SA treatment users are more likely to be male (68.8 percent). Tables presenting means specific to users of MH care and SA treatment are located in Appendix B at the end of the report. The majority of primary beneficiaries are married (54.5 percent) and most primary beneficiaries live in the Midwest (38.2 percent) and south (29 percent) and work in transportation industries (47.6 percent) or service industries (31.4 percent) as salaried employees (41.7 percent). A greater percentage of MH care users are employed in service industries (41.5 percent) and a greater percentage of SA treatment users are hourly (39.7 percent).

As shown in Table 13, coinsurance rates did not differ much between MH care and SA treatment services with an average outpatient in-network MH coinsurance rate of 9.7 percent and an average outpatient in-network SA coinsurance rate of about 8.3 percent. One average, individuals were significantly penalized for using out-of-network services. The average outpatient out-of-network MH coinsurance rate was 79 percent and the average outpatient out-of-network SA coinsurance rate was 80 percent. Approximately 24 percent of the sample belonged to a plan that required EAP precertication prior to MH/SA service use.

Finally, Table 14 shows the mean MH/SA utilization for primary beneficiaries. Approximately 7 percent of primary beneficiaries used outpatient MH care compared to 69 percent who used general outpatient medical services. Thus, MH care utilization is not a common occurrence in this sample. SA treatment utilization is also not common with only 0.3 percent of the sample using these services. Among these users, utilization of alcohol treatment services is more common than other drug treatment. These prevalence rates are similar to other studies of employed and insured populations. The mean number of days of outpatient MH care among MH users is about 8.9 days. The mean number of days of outpatient SA treatment is 6.5 days.

Not surprisingly, I found that primary beneficiaries are much less likely to use inpatient services. Approximately 0.2 percent and 0.1 percent of the full sample used inpatient MH care and SA treatment, respectively. Considering users only, inpatient care is more common among SA treatment users (16.7 percent) than MH care users (2.7 percent).

Spouses

Similar to primary beneficiaries, spouses are predominantly middle-aged (44.7 years). Most spouses are female (67 percent). However, this pattern flips for SA treatment users who are mostly male (65.1 percent) in the spouse sample. This reveals an interesting pattern between MH care users and SA treatment users with a greater percentage of MH users being female compared to SA treatment users in which a greater percentage are male.

By definition, I expect spouses overwhelmingly to be married and this holds in my data with about 94 percent of the spouse sample being married. The remaining 6 percent are mostly widows. Forty-three percent of spouses live in the Midwest. The northeast (10 percent) and west (12 percent) regions are less common. The majority of spouses have plans associated with primary beneficiaries in the transportation industry (44.3 percent) as salaried employees (47.9 percent).

Spouses' coinsurance rates are very similar to those reported for primary beneficiaries. Approximately 19 percent of the spouse sample belonged to a plan that required EAP precertification prior to service use. Unlike the primary beneficiary sample, this percentage is similar for MH care users and SA treatment users.

Approximately 6 percent of spouses used outpatient mental health, and 0.3 percent of spouses used SA treatment. The mean number of days of outpatient MH care among MH users is 8.1 days. The mean number of days of outpatient SA treatment is 5.7 days. Approximately 0.2 percent and 0.1 percent of the full spouse sample used inpatient MH care and SA treatment, respectively, which are the same prevalence rates observed in the primary beneficiary sample. Again, inpatient care was more common among SA treatment users (16.6 percent) than among MH care users (2.9 percent)

Dependents

Other Dependents are fairly evenly split by gender with 51.6 percent being male. The average age is 12 years and ranges from newborns to past college-aged. However, most (over 95 percent) are 17 years and younger and live in households of about 4 people. Unlike primary beneficiaries and spouses, MH care users as well as SA treatment users are predominantly male in the dependent sample (56.1 percent and 72.1 percent). MH care users and SA treatment users also are slightly older than the full sample with mean ages of 14.9 years for MH care users and 18.7 years for SA treatment users. The majority of dependents live in the Midwest (42.9 percent) with a salaried primary beneficiary (50.7 percent) who works in transportation (46.2 percent).

Dependents' mean coinsurance rates are very similar to both primary beneficiaries and spouses. Approximately 22 percent of dependents belong to a plan that requires EAP precertification prior to MH/SA service use.

Approximately 5 percent and 0.3 percent of dependents used outpatient MH care and outpatient SA treatment, respectively. The mean number of outpatient MH care days among MH users is 7.1 days and the mean number of outpatient SA treatment days among SA users is 5.1 days. Approximately 5.1 percent of MH care users used inpatient MH care and 14.5 percent of SA treatment users used inpatient SA treatment.

Table 10. Health Plan Benefits Specific to MH/SA Use

	Dates Plan Offered				MH Coinsurance Rates				SA Coinsurance Rates			
					In-network		Out-of-network		In-network		Out-of-network	
	From	To	Is MH/SA Coverage Carved Out?	EAP Status	OP	IP	OP	IP	OP	IP	OP	IP
Group 1												
1A	Jan-93	Dec-98	Carve-out	Available	20	20	100	100	20	20	100	100
1B	Jan-95	Dec-98	Carve-out	Available	0	10	100	100	0	10	100	100
1C	Jan-95	Dec-98	Carve-out	Available	0	10	100	100	0	10	100	100
1D	Jan-96	Dec-98	Carve-out	Available	0	10	100	100	0	10	100	100
Group 2												
2A	Jan-97	Aug-97	Carve-in	No Mention	50	0	100	20	10	0	100	20
2B	Jan-97	Aug-97	Carve-in	No Mention	50	0	100	20	10	0	100	20
2C	Sep-97	Dec-97	Carve-in	No Mention	50	0	100	20	10	0	100	20
2D	Sep-97	Dec-97	Carve-in	No Mention	50	0	100	20	10	0	100	20
Group 3												
3A	Nov-96	May-97	Carve-out	Required	0	0	50	50	0	0	50	50
3B	Nov-96	May-97	Carve-out	Required	0	0	50	50	0	0	50	50
3C	Jun-97	Dec-98	Carve-out	Required	0	0	50	50	0	0	50	50
3D	Jun-97	Dec-98	Carve-out	Required	0	0	50	50	0	0	50	50

Table 10. Continued

	Dates Plan Offered				MH Coinsurance Rates				SA Coinsurance Rates			
					In-network		Out-of-network		In-network		Out-of-network	
	FROM	TO	Is MH/SA Coverage Carved Out?	EAP Status	OP	IP	OP	IP	OP	IP	OP	IP
Group 4												
4A	Jan-95	Dec-98	Carve-out	Available	20	20	50	50	20	50	100	100
4B	Jan-95	Dec-98	Carve-out	Available	20	20	50	50	20	50	100	100
4C	Jan-95	Dec-98	Carve-out	Available	20	20	50	50	20	50	100	100
4D	Jan-95	Dec-98	Carve-out	Available	20	20	50	50	20	50	100	100
4E	Jan-95	Dec-98	Carve-out	Available	20	20	50	50	20	50	100	100
Group 5												
5A	Jan-98	Dec-98	Carve-out	Required	20	0	100	100	20	0	100	100
Group 6												
6A	Jan-97	Dec-98	Carve-out	Available	20	20	100	100	20	20	100	100
6B	Jan-97	Dec-98	Carve-out	Available	20	20	100	100	20	20	100	100
6C	Jan-97	Dec-98	Carve-out	Available	20	20	100	100	20	20	100	100
6D	Jan-97	Dec-98	Carve-out	Available	20	20	100	100	20	20	100	100
6E	Jan-97	Dec-98	Carve-out	Available	20	20	100	100	20	20	100	100
6F	Jan-98	Dec-98	Carve-out	Required	20	20	100	100	20	20	100	100
6G	Jan-98	Dec-98	Carve-out	Required	20	20	100	100	20	20	100	100

Table 10. Continued

	Dates Plan Offered				MH Coinsurance Rates				SA Coinsurance Rates			
					In-network		Out-of-network		In-network		Out-of-network	
	FROM	TO	Is MH/SA Coverage Carved Out?	EAP Status	OP	IP	OP	IP	OP	IP	OP	IP
6H	Jan-98	Dec-98	Carve-out	Required	20	20	100	100	20	20	100	100
6I	Jan-98	Dec-98	Carve-out	Required	20	20	100	100	20	20	100	100
6J	Jan-98	Dec-98	Carve-out	Required	20	20	100	100	20	20	100	100
Group 7												
7A	Jan-98	Dec-98	Carve-in	No Mention	10	10	100	100	10	10	100	100
7B	Jan-98	Dec-98	Carve-in	No Mention	20	20	100	100	20	20	100	100
7C	Jan-98	Dec-98	Carve-in	No Mention	20	20	100	100	20	20	100	100
Group 8												
8A	Jan-97	Dec-98	Carve-out	Available	0	0	50	100	50	0	100	100
8B	Jan-97	Dec-98	Carve-out	Available	0	0	50	100	50	0	100	100
8C	Jan-97	Dec-98	Carve-out	Available	0	0	50	100	50	0	100	100
Group 9												
9A	Jan-98	Dec-98	Carve-out	No Mention	0	0	50	50	0	0	50	50
9B	Jan-98	Dec-98	Carve-out	No Mention	0	0	50	50	0	0	50	50

Table 10. Continued

	Dates Plan Offered				MH Coinsurance Rates				SA Coinsurance Rates			
					In-network		Out-of-network		In-network		Out-of-network	
	From	To	Is MH/SA Coverage Carved Out?	EAP Status	OP	IP	OP	IP	OP	IP	OP	IP
9C	Jan-98	Dec-98	Carve-out	No Mention	0	0	50	50	0	0	50	50
9D	Jan-98	Dec-98	Carve-out	No Mention	0	0	50	50	0	0	50	50
9E	Jan-98	Dec-98	Carve-out	No Mention	0	0	50	50	0	0	50	50
Group 10												
10A	Jul-90	Dec-98	Carve-in	No Mention	10	0	100	100	10	0	100	100
10B	Jul-90	Dec-98	Carve-in	No Mention	10	0	100	100	10	0	100	100
10C	Jul-90	Dec-98	Carve-in	No Mention	10	0	100	100	10	0	100	100
10D	Jul-90	Dec-98	Carve-in	No Mention	10	0	100	100	10	0	100	100
Group 11												
11A	Jan-96	Dec-98	Carve-in	Available	0	10	50	50	0	10	50	50
11B	Jan-98	Dec-98	Carve-in	Available	0	10	50	50	0	10	50	50
11C	Jan-98	Dec-98	Carve-in	Available	0	10	50	50	0	10	50	50

Table 10. Continued

	Dates Plan Offered				MH Coinsurance Rates				SA Coinsurance Rates			
					In-network		Out-of-network		In-network		Out-of-network	
	FROM	TO	Is MH/SA Coverage Carved Out?	EAP Status	OP	IP	OP	IP	OP	IP	OP	IP
Group 12												
12A	Jan-97	Dec-97	Carve-out	Required	0	10	100	100	0	10	100	100
12B	Jan-97	Dec-98	Carve-out	Required	0	10	100	100	0	10	100	100
12D	Jan-97	Dec-97	Carve-out	Required	0	10	100	100	0	10	100	100
12E	Jan-97	Dec-97	Carve-out	Required	0	10	100	100	0	10	100	100
12F	Jan-97	Dec-98	Carve-out	Required	0	10	100	100	0	10	100	100
12G	Jan-97	Dec-97	Carve-out	Required	0	10	100	100	0	10	100	100

Table 12. Mean Sociodemographic Characteristics

	Mean (standard deviation)		
Variable	**Primary Beneficiaries**	**Spouses**	**Other Dependents**
Number of Observations	*100,398*	*55,906*	*78,794*
Number Unique Individuals	*58,842*	*32,451*	*46,262*
Male (proportion)	0.579	0.326	0.516
	(0.494)	(0.469)	(0.500)
Age (years)	42.673	44.714	12.023
	(11.680)	(10.102)	(7.175)
Not Married (proportion)	0.454	0.055	1.000
	(0.498)	(0.227)	(0.000)
Household Size (# persons)	2.449	3.296	4.293
	(1.457)	(1.227)	(1.251)
Lives in (proportion)			
Northeast	0.112	0.100	0.105
	(0.315)	(0.301)	(0.306)
South	0.289	0.262	0.276
	(0.453)	(0.440)	(0.447)
Midwest	0.381	0.434	0.429
	(0.486)	(0.496)	(0.495)
West	0.120	0.098	0.100
	(0.324)	(0.298)	(0.300)
Region Unknown	0.098	0.104	0.090
	(0.298)	(0.306)	(0.286)
Employment Characteristics of Primary Beneficiary			
Employee Type (proportion)			
Salary	0.417	0.479	0.507
	(0.493)	(0.500)	(0.500)
Hourly	0.361	0.286	0.312
	(0.480)	(0.452)	(0.463)
Other Status	0.222	0.235	0.181
	(0.416)	(0.424)	(0.442)

Table 12. Continued

Variable	Mean (standard deviation)		
	Primary Beneficiaries	Spouses	Other Dependents
Industry of Primary Beneficiary (proportion)			
Manufacturing	0.211 (0.408)	0.217 (0.412)	0.209 (0.407)
Transportation	0.478 (0.500)	0.443 (0.497)	0.462 (0.499)
Service	0.311 (0.463)	0.340 (0.474)	0.329 (0.470)

Table 13. Mean MH/SA Insurance Characteristics

Variable	Mean (standard deviation) Primary Beneficiaries	Spouses	Other Dependents
Number of Observations	*100,398*	*55,906*	*78,794*
Number Unique Individuals	*58,842*	*32,451*	*46,262*
Coinsurance Rates for MH Visit			
Outpatient In-network	9.725	9.258	8.716
	(12.603)	(12.900)	(9.529)
Inpatient In-network	7.454	5.927	7.373
	(8.378)	(7.944)	(8.514)
Outpatient Out-of-Network	78.997	77.046	79.903
	(24.954)	(25.289)	(24.847)
Inpatient Out-of-Network	75.742	73.526	80.024
	(27.324)	(27.666)	(25.078)
Coinsurance Rates for SA Visit			
Outpatient In-network	8.330	7.874	9.105
	(9.688)	(9.861)	(9.926)
Inpatient In-network	7.932	6.430	7.955
	(9.814)	(9.598)	(10.211)
Outpatient Out-of-Network	80.419	78.860	81.743
	(24.699)	(25.089)	(24.418)
Inpatient Out-of-Network	76.539	74.365	80.993
	(27.291)	(27.698)	(24.864)
EAP Precertification Required (proportion)	0.244	0.194	0.223
	(0.429)	(0.395)	(0.416)
Total months enrolled in year	10.657	10.826	10.720
	(2.751)	(2.581)	(2.686)

Table 14. Mean Utilization Characteristics

Variable	Mean (standard deviation) All Primary Beneficiaries	Spouses	Other Dependents
Number of Observations	*100,398*	*55,906*	*78,794*
Number Unique Individuals	*58,842*	*32,451*	*46,262*
Outpatient Services			
Proportion of Users with:			
At least one day of outpatient SA services	0.003	0.003	0.003
	(0.059)	(0.053)	(0.056)
At least one day of outpatient MH services	0.072	0.062	0.051
	(0.259)	(0.241)	(0.221)
At least one day of outpatient medical services	0.692	0.693	0.642
	(0.462)	(0.461)	(0.479)
Total Annual Days of Use (conditional on use)			
Outpatient MH Services	8.890	8.108	7.113
	(11.183)	(10.637)	(9.069)
Outpatient SA Services	6.499	5.684	5.141
	(9.614)	(8.708)	(7.003)
Outpatient Medical Services	7.664	7.652	4.810
	(9.835)	(9.779)	(6.258)
Inpatient Services			
Proportion of Users with:			
At least one day of inpatient SA services	0.001	0.001	0.0004
	(0.025)	(0.022)	(0.022)
At least one day of inpatient MH services	0.002	0.002	0.003
	(0.044)	(0.043)	(0.052)
At least one day of inpatient medical services	0.058	0.070	0.040
	(0.234)	(0.256)	(0.195)

Table 14. Continued

Variable	All Primary Beneficiaries	Spouses	Other Dependents
	Mean (standard deviation)		
Total Annual Days of Use (conditional on use)			
Inpatient MH Services	5.905 (7.902)	4.363 (4.884)	6.019 (8.093)
Inpatient SA Services	2.656 (2.732)	2.321 (1.657)	3.395 (5.679)
Inpatient Medical Services	3.730 (7.897)	3.038 (5.091)	2.909 (5.078)

CHAPTER 5: RESULTS

In this chapter I present the main results of my analyses that examine the effect of health insurance characteristics on the utilization of mental health (MH) care and substance abuse (SA) treatment for primary beneficiaries, their spouses, and other dependents. Overall, my econometric models show that individuals are responsive to at least some of the MH/SA health insurance characteristics for outpatient MH care utilization, but these health insurance characteristics have less effect on SA treatment decisions and no effect on inpatient MH care utilization. Comparing results across the different samples, my models show that the effect of MH/SA health insurance characteristics varies for individuals by their relationship to the health plan (i.e., primary beneficiary versus spouse or other dependent). Primary beneficiaries are found to be more responsive to these characteristics than spouses and other dependents. Furthermore, when significant, the requirement of EAP precertification always has a negative effect on use. Thus, unlike other studies which find that use of an EAP increases MH/SA utilization (e.g., Zarkin, Bray, and Qi, 2000; Deitz, Cook, and Hersch, 2005), I find that *required* EAP involvement decreases MH/SA utilization in the formal health care system.

The chapter is divided by service type. In the first section, I provide detailed results of my analyses for outpatient MH care. The remaining sections of this chapter present the parallel analysis findings for (2) outpatient SA treatment, (3) inpatient MH care, and (4) inpatient SA treatment. At the end of the chapter, I provide a brief summary and comparison of results across the three samples.

Regression results are presented in Tables 21 through 32 (located at the end of this chapter) and include estimated coefficients from the standard random effects (RE) estimation (without instrumented health insurance characteristics) and the instrumental variable random effects (RE-IV) estimation models. The results from the two models are similar suggesting that self-selection bias for MH/SA coverage may not be a major concern for these data. In each table, the first two columns present the parameter estimates from the standard RE estimation of any use (logit model) and the number of days of use (negative binomial model). The second two columns present the parameter estimates for the RE-IV estimation.

For the logit analysis, each parameter estimate measures the change in the log odds ratio for a change of one unit in the explanatory variable (Hosmer and Lemeshow, 1989). The log odds ratio is defined as the ratio of the log odds for 2 groups—one group in which the event occurs and one group in which the event does not occur. For dichotomous variables, a more intuitive interpretation is either the adjusted odds ratio, which is simply derived by exponentiating the parameter coefficient, or the adjusted relative risk ratio. As noted by Kleinman and Norton (working paper), the adjusted odds ratio is often misunderstood in interpretations of the effect of dichotomous explanatory variables and adjusted risk ratios and risk differences provide more intuitive measures of effect. Therefore, in my discussion of results, I present adjusted risk ratios in lieu of odds ratios for key dichotomous explanatory variables including EAP precertification, gender, and marital status. These adjusted risk ratios are shown in separate tables located within the chapter and are calculated using Stata programming developed by Kleinman and Norton.

For the negative binomial estimation, the parameter estimate measures the percent change in the mean of the outcome (days of service use) given a unit change in the explanatory variable.

Outpatient Mental Health Care

Effect of Coinsurance Rates

In each of my analyses the individual's level of cost-sharing for MH/SA care is represented by three coinsurance variables. The main cost-sharing variables for the outpatient MH care services are the outpatient in-network coinsurance rate and the outpatient out-of-network coinsurance rate which measure the percentage of the service cost that the individual must pay for in-network and out-of-network services. A higher coinsurance rate means that the individual incurs a higher cost for using the service. Based on economic theory and all else equal, I expect that individuals with greater outpatient coinsurance rates will have a smaller likelihood of using outpatient MH care services.

As shown in Table 21, the likelihood that a primary beneficiary uses any outpatient MH care significantly decreases as the outpatient in-network coinsurance rate increases; that is, as the individual's expected out-of-pocket expense increases. The coefficient on the outpatient in-network coinsurance rate for primary beneficiaries is –0.009 (p<0.01). This translates into a marginal effect of about –0.0003 which means a 1-percentage point increase in the outpatient in-network coinsurance rate is associated with a 0.03 percentage point decrease in the probability of using outpatient MH care among primary beneficiaries. This a very small effect and, given that a 1-percentage point change in the coinsurance rate is highly unlikely, it may be more intuitive to examine a 10-percentage point change on the likelihood of MH care utilization, especially since coinsurance rates typically occur in 10-percent

Table 15. Incremental Effects of Changes in Coinsurance Rates for Outpatient Mental Health Care

Sample	Incremental Effect for Any Use (standard deviations)	Incremental Effect for Level of Use (standard deviations)	Total Incremental Effect[b] (standard deviations)
Outpatient In-network Rate (change from 10% to 20%)			
Primary Beneficiaries	–0.003***	0.024	–0.004
	(0.002)	(4.98e-08)	(0.003)
Spouses	-----[a]	-----[a]	-----[a]
Other Dependents	-----[a]	-----[a]	-----[a]
Outpatient Out-of-network Rate (change from 50% to 100%)			
Primary Beneficiaries	0.013***	0.130	0.031
	(0.010)	(5.08e-08)	(0.020)
Spouses	0.003	0.319***	0.018
	(0.002)	(4.24e-08)	(0.008)
Primary Beneficiaries	–0.003***	0.024	–0.004
	(0.002)	(4.98e-08)	(0.003)
Spouses	-----[a]	-----[a]	-----[a]
Other Dependents	-----[a]	-----[a]	-----[a]
Inpatient Rate (change from 10% to 20%)			
Primary Beneficiaries	–0.006***	–0.205***	–0.022
	(0.005)	(4.04e-08)	(0.014)
Spouses	-----[a]	–0.119	–0.117
Other Dependents	–0.003***	–0.222***	0.002
	(0.003)	(2.74e-08)	(0.001)

***Indicates associated estimated coefficient is statistically significant at the 1% level in regression equation.
[a]Coefficients are not statistically different from zero in either equation.
[b]Statistical significance was not evaluated for total effects.

intervals such as 10%, 20%, and 50%. Because 10% and 20% coinsurance rates for in-network services are two of the most common rates in my data, I focus on changes between these two rates for my examination of the in-network coinsurance rates. All else equal, what is the incremental effect of changing from 10% coinsurance to 20% coinsurance? In other words, what is the difference in the Prob(Y_i =1 | rate = 20) and Prob(Y_i =1 | rate = 10)? This difference can be calculated by taking the difference in the predicted probability under the 20% coinsurance scenario and the predicted probability under the 10% coinsurance scenario. For primary beneficiaries, this incremental effect is –0.003 (see Table 15); that is, increasing the outpatient in-network coinsurance rate from 10% to 20% is associated with a 0.3 percentage point (approximately 8 percent) decrease in the probability of outpatient MH care use, which is still a very small effect even for a 10-percentage point change.

The incremental effect of changing from 10% coinsurance to 20% coinsurance on the days of outpatient MH care for primary beneficiaries is not statistically significant from zero. Thus, it appears that for primary beneficiaries the outpatient in-network coinsurance rate is more likely to affect the initial decision to seek care rather than the extent of care once treatment is sought. Unlike primary beneficiaries, the outpatient in-network coinsurance rate does not have any significant effect on either the likelihood of outpatient MH care or on the number of days of MH care for either spouses or other dependents

The outpatient out-of-network coinsurance rate does not have a significant effect on the probability of any outpatient MH care utilization for either spouses or other dependents (see Tables 22 through 23). For primary beneficiaries the probability of using outpatient MH care *increases* as the outpatient out-of-network coinsurance rate increases. This finding is contrary to my expectations that higher out-of-pocket expense will be associated with lower likelihood of use. However, the marginal effect (ME) of the outpatient out-of-network coinsurance rate is extremely small (ME ≈ 0.0003) indicating that a 1-percentage point increase in the outpatient out-of-network coinsurance rate is associated with a 0.03 percentage point increase in likelihood of use. Thinking in terms of more realistic rate changes, a change in the outpatient out-of-network coinsurance rate from 50% to 100% (no coverage) is associated with an 0.013 percentage point increase in the probability of using MH care among primary beneficiaries (a 53 percent increase).

The outpatient out-of-network coinsurance rate does not have a significant effect on days of outpatient MH care for primary beneficiaries. However, the outpatient out-of-network coinsurance rate does have a significant effect on days of outpatient MH care for spouses. The estimated coefficient is 0.006 (p<0.01) which implies that a change in the outpatient out-of-network coinsurance rate from 50% to 100% is associated with an increase of 0.319 days of outpatient MH care (a 35 percent increase) among spouses.

The unexpected positive association between the level of cost-sharing for out-of-network services and outpatient MH demand may be capturing a cross-price effect between in-network and out-of-network outpatient services rather than an own-price effect. This finding suggests that these two types of services may be substitutes. As the individual's level of cost-sharing for out-of-network outpatient MH services increases relative to the in-network service, individuals may substitute out-of-network care for in-network care. Unfortunately, my data do not contain information on whether the service was received by in-network or out-of-network providers so I am unable to the formally test this hypothesis.

As discussed earlier, I included inpatient coinsurance rates in the outpatient models to capture the cross-price effect of inpatient MH care which I hypothesized might be a substitute for outpatient care. If they are substitutes, then I would expect that as the level of cost-sharing for inpatient care increases relative to outpatient care, an individual will choose to use outpatient care in lieu of inpatient care. If this hypothesis is true, then I would expect a positive coefficient for the inpatient coinsurance rate. However, I find that the inpatient coinsurance rate is negatively associated with outpatient MH care utilization.

The estimated coefficient for primary beneficiaries is –0.025 ($p<0.01$) for the probability of any outpatient MH care utilization. This translates into a marginal effect of –0.0008 which implies that a 1-percentage point increase in the inpatient coinsurance rate is associated with a 0.08 percentage point decrease in the probability of any MH care utilization. Again, examining a more intuitive 10-percentage point change on the likelihood of MH care utilization, I find that the incremental effect of changing the inpatient coinsurance rate from 10% to 20% is –0.006 which means that increasing the inpatient coinsurance rate is associated with a 22 percent decrease (0.6 percentage points) in the probability of any outpatient MH care. I also found a negative and significant association between the inpatient coinsurance rate and days of outpatient MH care among primary beneficiaries. The incremental effect of changing from 10% coinsurance to 20% coinsurance on the days of outpatient MH care use for primary beneficiaries is –0.205 which means that increasing the outpatient out-of-network coinsurance rate from 10% to 20% is associated with a decrease of 0.205 days of use (a 20 percent decline).

I found nearly the same effect for the inpatient coinsurance rate on outpatient MH care utilization among other dependents. The estimated inpatient coinsurance rate coefficient for other dependents is –0.017 ($p<0.01$) for the probability of any outpatient MH care. This translates into an incremental effect of changing the inpatient coinsurance rate from 10% to 20% coinsurance of –0.003. Thus, increasing the inpatient coinsurance rate from 10% to 20% is associated with a 15 percent decrease (0.3 percentage points) in the probability of any outpatient MH care among other dependents. The incremental effect of changing from 10% coinsurance to 20% coinsurance on the days of outpatient MH care for dependents is –0.230 which means that increasing the inpatient coinsurance rate is associated with a decrease of 0.230 days of outpatient MH care (a 23 percent decline).

Finally, I did not find a significant association between the probability of any outpatient MH care and the inpatient coinsurance rate for spouses. However, I did find a negative and significant association between the inpatient coinsurance rate and days of outpatient MH care. The estimated incremental effect associated with changing from 10% to 20% for inpatient coinsurance is –0.200. Thus, increasing the inpatient coinsurance rate from 10% to 20% is associated with a decrease of 0.2 days of outpatient MH care (a 20 percent decline) among spouses.

<u>Effect of EAP Precertification Requirement</u>

The effect of requiring EAP precertification prior to using services significantly decreases the probability that individuals will use any outpatient MH care services. Furthermore, for spouses only, EAP precertification also has a negative effect on the number of days of outpatient MH care. The interpretation of this EAP effect is not straightforward. On the one hand, EAP precertification, rather than facilitating treatment, may create an obstacle to treatment and discourage utilization. On the other hand, EAP precertification may decrease utilization through the formal health care system by providing employees' and their dependents with some MH services. Individuals with milder conditions may receive an adequate dose of services through the EAP and, therefore, not need additional services.

The estimated parameter coefficients on EAP precertification range from –0.254 (Spouses) to –0.393 (Primary Beneficiaries) and all are statistically significant at the 1 percent level. For ease of interpretation, I present the adjusted risk ratios (ARRs) and adjusted risk differences (ARDs) calculated from these parameter coefficients (see Table 16). The estimated ARR indicates that primary beneficiaries without an EAP requirement are 1.4 times more likely to use outpatient mental health care services (1/ARR = 1.4) than primary beneficiaries with an EAP requirement. Using both the ARR and ARD results, I mathematically derived probabilities for these 2 groups. The probability of outpatient MH care use for those with an EAP requirement is approximately 5.6 percent and the probability of use for those without an EAP requirement is approximately 7.7 percent (yielding ARD= Risk Exposed – Risk Unexposed = –2.14 percentage points). A 2-percentage point difference in MH care utilization between these two groups may not seem large, but it indicates that having an EAP requirement is associated with a 28 percent decrease in the probability of outpatient MH care use among primary beneficiaries.

For spouses, the effect of an EAP requirement is also significant and sizeable, although not quite as sizeable as the effect found for primary beneficiaries. Given that spouses should not face workplace stigma for using the EAP (unless they are afraid that their spouse who is the primary policyholder will be stigmatized), this finding may suggest the "help factor" of EAPs for spouses. Those spouses who are required to contact the EAP for preauthorization of services may receive limited treatment services from the EAP, thereby lowering their need of services through the formal treatment system. Spouses without an EAP requirement are 1.3 times more likely to use outpatient MH care services than spouses with an EAP requirement (1/ARR = 1.3). The probability of use for those spouses not facing an EAP requirement is approximately 5 percent and the probability of use for those with an EAP requirement is approximately 6.5 percent, which means that, all else equal, an EAP requirement is associated with a 21 percent decrease in probability of outpatient MH care use among spouses.

In addition, spouses are the only sample for which the EAP requirement affects the number of days of outpatient MH care use. The negative binomial coefficient for having an EAP requirement is –0.199 (see Table 22) which when converted into an incidence rate ratio (IRR) of 0.820 (IRR = exp(β)) implies that having an EAP requirement decreases the expected number of days of outpatient MH care by a factor of 0.820. An even better way to interpret the effects of the EAP requirement is in terms of the percent change in the IRR which is –18.03 percent (Percent Change in IRR = $(\text{IRR} - 1) \times 100$). Thus, an EAP precertification requirement decreases the expected number of days of outpatient MH care for spouses by about 18 percent.

The size of the effect of an EAP requirement for other dependents lies between primary beneficiaries and spouses. Dependent's ARR is 0.678 indicating that the probability of MH care use for other dependents with an EAP requirement is 0.678 times the likelihood of use for those without an EAP requirement. An EAP requirement decreases the probability of use among other dependents by 32 percent; from about 5.5 percent for dependents without an EAP requirement to 3.7 percent for dependents with an EAP requirement.

Table 16. Selected Adjusted Risk Ratios (ARR) for Outpatient MH Use

	ARR (standard error)	Risk if Exposed (%; RE)[a]	Risk if not Exposed (%; RU)[b]	Adjusted Risk Difference (% points; RE-RU)	Percent Change base = RU)
Primary Beneficiaries					
EAP Required	0.722 (0.023)	5.55	7.69	–2.14	-27.83%
Used Outpatient Medical Services	3.032 (0.038)	8.75	2.89	5.87	203.21%
Male	0.704 (0.013)	5.98	8.50	–2.52	–29.62%
Not Married	1.321 (0.027)	8.45	6.39	2.05	32.10%
Lives in South	0.921 (0.029)	6.77	7.35	–0.58	-7.95%
Lives in West	1.250 (0.047)	8.79	7.03	1.76	24.99%
Spouses					
EAP Required	0.792 (0.037)	5.12	6.46	–1.34	–20.79%
Used Outpatient Medical Services	3.776 (0.067)	7.82	2.07	5.75	277.58%
Male	0.722 (0.026)	4.90	6.79	–1.89	–27.78%
Lives in South	0.835 (0.036)	5.41	6.48	–1.07	–16.49%
Hourly	0.845 (0.035)	5.47	6.47	–1.00	–15.51%
Dependents					
EAP Required	0.789 (0.036)	4.21	5.34	–1.13	–21.12%
Used Outpatient Medical Services	2.931 (0.050)	6.79	2.32	4.47	193.07%
Male	1.264 (0.026)	5.74	4.54	1.20	26.41%
Manufacturing	0.768 (0.057)	4.18	5.44	–1.26	–23.23%
Lives in West	1.272 (0.071)	6.40	5.03	1.37	27.18%
Hourly	0.714 (0.029)	3.97	5.56	–1.59	–28.62%

[a]RE equals the calculated probability of use (i.e., risk) for individuals belonging (i.e., exposed) to the indicated characteristic group.
[b]RU equals the calculated probability of use (i.e., risk) for individual not belonging (i.e., not exposed) to the indicated characteristic group.

Effect of Other Variables

Not surprisingly, other confounders were found to be significant predictors of outpatient MH care utilization. In all three samples, the strongest predictor of any outpatient MH care utilization is whether the individual used outpatient or inpatient medical services. Users of medical care are more likely to use outpatient MH care than non-users of medical care. These associations are consistent with previous research studies that have shown that individuals with MH disorders are high users of medical care compared to the general population.

Based on the ARRs, both primary beneficiaries and other dependents who use outpatient medical services are about 3 times more likely to use outpatient MH care than primary beneficiaries and other dependents who do not use outpatient medical services. The effect is slightly greater among spouses in which those who use outpatient medical services are 4 times more likely to use outpatient MH care services. The effect of inpatient medical services is slightly less but still significant with the likelihood of outpatient MH care ranging from 1.2 times for primary beneficiaries to 1.7 times for other dependents who use inpatient medical services compared to those individuals without use of inpatient medical services.

Use of medical services did not have a significant effect on number of days of outpatient MH care use for primary beneficiaries or spouses. However, use of both outpatient and inpatient medical services among other dependents is positively associated with the number of days of outpatient MH care. The negative binomial coefficient for using outpatient medical services is 0.111 ($p<0.01$) yielding an incidence rate ratio of 1.117 which indicates that using outpatient medical services is associated with a 12 percent increase in the expected number of days of outpatient MH care. Similarly, use of inpatient medical services among other dependents is associated with a 20 percent increase in the expected number of days of outpatient MH care based on an incidence rate ratio of 1.205.

Being male significantly decreased the probability of any outpatient mental health care use among primary beneficiaries and spouses. In both samples, men are 0.7 times as likely to use outpatient mental health care services than women (based on ARRs). Being male also is negatively associated with days of outpatient MH care use among primary beneficiaries ($p<0.01$), but not among spouses. In the estimation for primary beneficiaries, the negative binomial coefficient for being male is –0.066 which when converted into an IRR of 0.936 implies that being male is associated with a 6 percent decrease in the expected number of days of outpatient MH care.

Being male has mixed effects for other dependents. Being male significantly increases the probability of any outpatient MH care use among other dependents with boys being 1.3 times more likely to use outpatient MH care compared to girls. This finding is not surprising given that among youths mental health care is more often sought for behavioral problems such as aggression which is more commonly identified among boys. MH care is less often sought for depression which is more common among girls. However, being male is associated with a 12 percent decrease in the expected number of days of outpatient MH care (based on percent change in the IRR).

In each of the samples, the use of outpatient MH care varies significantly by age with younger individuals significantly more likely to use outpatient MH care services and to have more days of use. Finally, family structure plays a role for primary beneficiaries and other dependents. For primary beneficiaries, larger households are associated with increased likelihood of any outpatient mental health care use, but fewer days of use. Furthermore, being single increases the likelihood of any use, with single individuals 1.3 times more likely to use outpatient MH care. On the other hand, for other dependents, larger households are associated with *decreased* likelihood of any outpatient MH care use, and had no effect on the number of days of use.

Outpatient Substance Use Treatment

Effect of Coinsurance Rates

Similar to my analysis of outpatient MH care, the main insurance variables for outpatient SA treatment are the outpatient in-network coinsurance rate, the outpatient out-of-network coinsurance rate, and the inpatient coinsurance rate that are specific to SA treatment services. These variables are interpreted in the same way—that is, the rate represents the percentage of the service cost that the individual must pay.

The outpatient coinsurance rates have no significant effect on the likelihood of using outpatient SA treatment services for any of the three samples (see Tables 24 through 26). Furthermore, the inpatient coinsurance rate has no effect on days of outpatient SA treatment across the three samples. But, among primary beneficiaries the outpatient coinsurance rates have a significant effect on the number of days of outpatient SA treatment. In addition, the inpatient coinsurance rate has a significant and negative association with the probability of any outpatient SA treatment among primary beneficiaries.

The incremental effect of changing the outpatient in-network coinsurance rate from 10% to 20% on days of SA treatment for primary beneficiaries is –0.644 which means that increasing the outpatient in-network coinsurance rate from 10% to 20% is associated with a decrease of 0.644 days of use (a 27 percent decrease). However, the incremental effect of changing the outpatient out-of-network coinsurance from 50% to 100% (no coverage) on

Table 17. Incremental Effects of Changes in Coinsurance Rates for Outpatient Substance Abuse Treatment

Sample	Incremental Effect for Any Use (standard deviations)	Incremental Effect for Level of Use (standard deviations)	Total Incremental Effect[b] (standard deviations)
Outpatient In-network Rate (change from 10% to 20%)			
Primary Beneficiaries	–0.3.44e-06 (0.002)	–0.644*** (3.80e-08)	–0.002 (0.002)
Spouses	-----[a]	-----[a]	-----[a]
Other Dependents	-----[a]	-----[a]	-----[a]
Outpatient Out-of-network Rate (change from 50% to 100%)			
Primary Beneficiaries	–0.3.79e-05 (2.97e-05)	1.903*** (8.06e-08)	0.007 (0.005)
Spouses	-----[a]	-----[a]	-----[a]
Other Dependents	-----[a]	-----[a]	-----[a]
Inpatient Rate (change from 10% to 20%)			
Primary Beneficiaries	–0.5.30e-04*** (4.34e-04)	–0.217 (4.52e-08)	–0.002 (0.001)
Spouses	-----[a]	-----[a]	-----[a]
Other Dependents	-----[a]	-----[a]	-----[a]
Outpatient In-network Rate (change from 10% to 20%)			
Primary Beneficiaries	–0.3.44e-06 (0.002)	–0.644*** (3.80e-08)	–0.002 (0.002)

***Indicates associated estimated coefficient is statistically significant at the 1% level in regression equation.
[a]Coefficients are not statistically different from zero in either equation.
[b]Statistical significance was not evaluated for total effects.

days of outpatient SA treatment for primary beneficiaries is an *increase* of 1.9 days of SA treatment (a 68 percent increase). Again, this positive effect on treatment days suggests substitution may be occurring between in-network and out-of-network services for outpatient SA treatment.

Taken together, these findings show that for primary beneficiaries the effect of cost-sharing is greater for outpatient SA treatment days demanded compared to outpatient MH care. On the other hand, unlike outpatient MH care, cost-sharing has no significant effect on the probability of outpatient SA treatment utilization for primary beneficiaries.

Effect of EAP Precertification Requirement

Similar to outpatient MH care, an EAP requirement is associated with a lower likelihood of use for outpatient SA treatment services among primary beneficiaries, but has no significant effect on the number of days of use. The estimated parameter coefficient is –0.506 (p<0.01) which translates into an adjusted risk ratio (ARR) of 0.602 (see Table 18).

Primary beneficiaries with an EAP precertification requirement are 0.6 times as likely to use outpatient SA treatment as primary beneficiaries without an EAP requirement. In other words, having an EAP requirement is associated with a 40 percent decrease in the probability of outpatient SA treatment among primary beneficiaries. Unlike primary beneficiaries, the EAP requirement does not have any significant effect on SA treatment demand for either spouses or other dependents.

Effect of Other Variables

The effect of variables on outpatient SA treatment demand varies considerably between the participation equation (logit model) and the intensity of use equation. Use of medical services, gender, age, and employee status (hourly) are found to have a significant association with the likelihood of using outpatient SA treatment in all three samples, but none of these variables is found to have a significant effect on the number of days of use. On the other hand, industry type among primary beneficiaries and living in the Northeast among other dependents are found to have a statistically significant effect on the number of days of use, but no effect on the likelihood of use.

Adjusted risk ratios indicate that individuals in all samples who use outpatient medical services are about 2 to 3 times more likely to use outpatient SA treatment as individuals without outpatient medical service use (see Table 18). In addition, the likelihood of any outpatient SA treatment is about 2.5 times greater among individuals who use inpatient medical services. The likelihood of using outpatient SA treatment is significantly greater among primary beneficiaries aged 16 to 30 years and is lower for both primary beneficiaries and spouses aged 46 to 64 years. The likelihood of outpatient SA treatment is significantly greater among other dependents aged 12 to 17 years and this likelihood significantly decreases after 17 years of age.

As expected, being male is significantly associated with greater use of outpatient SA treatment in all samples. The gender effect is largest in the spouse sample where men are 5 times more likely to use outpatient SA treatment services compared to women. Men are 2.1 and 2.4 times more likely to use outpatient SA treatment services among primary beneficiaries and other dependents, respectively.

Although industry type is not associated with the likelihood of service use, being employed in the transportation and service industry are found to be positively associated with the number of days of outpatient SA treatment for primary beneficiaries (p<0.01) when compared to primary beneficiaries employed in the manufacturing industry. Being employed in the transportation industry substantially increases the expected number of days of outpatient SA treatment by about 139 percent. Being employed in the service industry is

Table 18. Selected Adjusted Risk Ratios (ARR) for Outpatient SA Treatment

	ARR (std error)	Risk if Exposed (%; RE)[a]	Risk if not Exposed (%; RU)[b]	Adjusted Risk Difference (% points; RE-RU)	Percent Change (base = RU)
Primary Beneficiaries					
EAP Required	0.602 (0.081)	0.24	0.39	–0.16	–39.78%
Used Outpatient Medical Services	1.632 (0.103)	0.40	0.24	0.15	63.23%
Used Inpatient Medical Services	2.354 (0.368)	0.77	0.32	0.44	135.44%
Male	2.102 (0.142)	0.47	0.22	0.25	110.18%
Not Married	1.731 (0.163)	0.47	0.27	0.20	73.09%
Hourly	2.181 (0.280)	0.60	0.28	0.32	118.41%
Spouses					
Used Outpatient Medical Services	1.958 (0.183)	0.34	0.18	0.17	95.05%
Used Inpatient Medical Services	2.609 (0.558)	0.67	0.26	0.41	160.85%
Male	5.005 (0.560)	0.66	0.13	0.53	400.52%
Hourly	2.252 (0.481)	0.52	0.23	0.29	125.25%
Other Dependents					
Used Outpatient Medical Services	3.116 (0.225)	0.43	0.14	0.29	211.58%
Used Inpatient Medical Services	2.440 (0.578)	0.74	0.30	0.43	143.98%
Male	2.589 (0.194)	0.46	0.18	0.28	158.89%

[a]RE equals the calculated probability of use (i.e., risk) for individuals belonging (i.e., exposed) to the indicated characteristic group.
[b]RU equals the calculated probability of use (i.e., risk) for individual not belonging (i.e., not exposed) to the indicated characteristic group.

associated with an increase in the expected number of days of almost 70 percent. Similarly, region of residence is not associated with the likelihood of service use, but living in the Northeast compared to the Midwest substantially increases the expected number of days of outpatient SA treatment by about 96 percent for other dependents.

Inpatient Mental Health Care

Effect of Health Insurance Characteristics

As shown in Tables 27 through 29, none of the health insurance characteristics had any significant effect on inpatient MH care demand for any of the samples. Unlike outpatient MH care, it appears that individuals do not respond to expected levels of cost-sharing or preauthorization requirements in making decisions about inpatient MH care utilization.

Effect of Other Variables

Although most of the variables included in the estimation of inpatient MH utilization are not found to be significant, there are some notable exceptions. Primary beneficiaries who use outpatient or inpatient medical services are about 2 and 6 times more likely to use inpatient MH care than their non-using counterparts (see Table 19). Similarly, spouses who use either outpatient or inpatient medical services are 4 times more likely to use inpatient MH care than their non-using counterparts. Primary beneficiaries who work hourly are 2 times more likely to use inpatient MH care than salaried employees, and primary beneficiaries aged 46 to 64 are significantly less likely to use inpatient MH services (see Table 28). Finally, although region of residence has no effect on the likelihood of using inpatient MH care services, region does have a significant effect on the expected number of days of inpatient MH care for primary beneficiaries. Living in the south and west is

Table 19. Selected Adjusted Risk Ratios (ARR) for Inpatient MH Care

	ARR (std error)	Risk if Exposed (%; RE)[a]	Risk if not Exposed (%; RU)[b]	Adjusted Risk Difference (% points; RE-RU)	Percent Change (base = RU)
Primary Beneficiaries					
Used OP Medical Services	2.419 (0.189)	0.23	0.09	0.14	141.87%
Used IP Medical Services	6.374 (0.836)	0.92	0.14	0.78	537.42%
Hourly	1.948 (0.329)	0.31	0.16	0.15	94.79%
Spouses					
Used OP Medical Services	3.991 (0.424)	0.23	0.06	0.17	299.13%
Used IP Medical Services	4.413 (0.831)	0.62	0.14	0.48	341.32%
Dependents					
Used OP Medical Services	3.557 (0.274)	0.36	0.10	0.26	255.68%
Used IP Medical Services	7.362 (1.181)	1.63	0.22	1.41	636.17%

[a]RE equals the calculated probability of use (i.e., risk) for individuals belonging (i.e., exposed) to the indicated characteristic group.
[b]RU equals the calculated probability of use (i.e., risk) for individual not belonging (i.e., not exposed) to the indicated characteristic group.

associated with a decrease in the expected number of days of inpatient MH care of about 38 percent and 44 percent compared to primary beneficiaries living in the Midwest.

Inpatient Substance Abuse Treatment

Effect of Health Insurance Characteristics

As shown in Table 30, the likelihood that a primary beneficiary uses any inpatient SA treatment significantly decreases as the inpatient in-network coinsurance rate increases. The primary beneficiaries' incremental effect associated with changing the inpatient in-network coinsurance rate from 10% to 20% for inpatient SA treatment is –0.0005. This effect indicates that changing the inpatient in-network coinsurance rate is associated with a 0.05 percentage point decrease in the probability of any inpatient SA treatment utilization (a 73 percent decrease). The estimated coefficient for inpatient out-of-network coinsurance rate was positive and also significant. The incremental effect of increasing the inpatient out-of-network coinsurance rate from 50% to 100% is 0.002, indicating that going from half-coverage to no coverage of out-of-network inpatient SA treatment services is associated with an increase in the probability of use of 0.2 percentage points. Again, an examination of the statistical significance of the estimated coefficients clearly shows that the inpatient coinsurance rates affect the primary beneficiary's initial decision to use inpatient SA treatment services. Once that decision is made, the inpatient coinsurance rates have little or no effect on the intensity of service use.

Neither the outpatient coinsurance rate nor the EAP requirement is found to have a significant effect on the utilization of inpatient SA services for primary beneficiaries. In addition, as shown in Tables 31 and 32, none of the health insurance characteristics had any significant effect on inpatient SA treatment for spouses or other dependents.

Effect of Other Variables

Adjusted risk ratios indicate that primary beneficiaries who use inpatient medical services are 5.5 times more likely to use inpatient SA treatment as primary beneficiaries without inpatient medical service use (see Table 20). The effect of inpatient medical service use is even greater among spouses and other dependents with individuals who use inpatient medical services being over 9 times more likely to use inpatient SA treatment than individuals who do not use inpatient medical services. In addition, the likelihood of any SA treatment is 5.5 times greater among other dependents with *outpatient* medical service use.

Similar to outpatient SA treatment, being male is significantly associated with use of inpatient SA treatment. Men are 2.4 to 5.6 times more likely to use inpatient SA treatment than women across the three samples. The gender effect is greatest among other dependents.

The likelihood of any inpatient SA treatment is less among spouses aged 46 to 64 years, while other dependents aged 12 to 17 years have a greater likelihood of inpatient SA treatment. Although age has no effect on likelihood of use among primary beneficiaries, the number of treatment days is negatively associated with being aged 46 to 64 years.

For spouses, being from a larger household decreases the likelihood of any inpatient SA treatment. This finding is not surprising because greater family responsibilities may be associated with a larger household making it more difficult for a spouse to enter inpatient treatment. Household size was not a significant factor for primary beneficiaries, but being single increases the likelihood of any inpatient SA treatment. Based on ARRs, non-married primary beneficiaries are about 2 times more likely to use inpatient SA treatment as married primary beneficiaries.

Industry type is associated with the likelihood of inpatient SA treatment for primary beneficiaries only. Individuals employed in the service industry are 0.18 times as likely to use inpatient SA treatment as individuals employed in the manufacturing industry. Furthermore, being employed in the service industry is associated with an 83 percent decrease in days of inpatient SA treatment compared to individuals in the manufacturing industry (p<0.05).

Table 20. Selected Adjusted Risk Ratios (ARR) for Inpatient SA Treatment

	ARR (std error)	Risk if Exposed (%; RE)[c]	Risk if not Exposed (%; RU)[d]	Adjusted Risk Difference (% points; RE-RU)	Percent Change (base = RU)
Primary Beneficiaries					
Used Inpatient Medical Services	5.493 (1.513)	0.26	0.05	0.22	449.28%
Male	3.574 (0.544)	0.09	0.03	0.07	257.44%
Not Married	1.949 (0.439)	0.09	0.05	0.04	94.87%
Service	0.181 (0.759)	0.02	0.11	–0.09	–81.86%
Hourly	2.356 (0.664)	0.11	0.05	0.06	135.60%
Spouses					
Used Inpatient Medical Services	9.522 (3.453)	0.32	0.03	0.29	852.22%
Male	2.448 (0.756)	0.008	0.003	0.01	144.83%
Dependents					
Used Outpatient Medical Services	5.473 (0.981)	0.07	0.01	0.06	447.34%
Used Inpatient Medical Services	9.723 (3.190)	0.36	0.04	0.32	872.31%
Male	5.553 (1.009)	0.09	0.02	0.07	455.33%

[a]RE equals the calculated probability of use (i.e., risk) for individuals belonging (i.e., exposed) to the indicated characteristic group.
[b]RU equals the calculated probability of use (i.e., risk) for individual not belonging (i.e., not exposed) to the indicated characteristic group.

Sensitivity and Other Special Analyses

In this section, I briefly present the results of my sensitivity analysis pertaining to my assumptions about out-of-network coinsurance rates as well as the results of my specialized analysis pertaining to gender differences.

<u>Sensitivity Analysis for Out-of-Network Coinsurance Rates</u>

In Chapter 4, I stated that some employers did not provide clear information on out-of-network coinsurance rates, and that for my analysis I took a conservative view and assumed that no mention of an out-of-network rate means that the plan does not cover out-of-network services which results in a coinsurance rate of 100 percent (Scenario 1). This assumption was made for 6 of the 12 employer groups. To test this assumption, I re-ran my analyses under a less conservative view and assumed that no mention of an out-of-network rate means that the plan covers out-of-network services at the same level of cost-sharing as in-network services (Scenario 2). The results from this analysis revealed that my assumption had little effect on the overall findings. In most cases, regressions under Scenario 2 yielded results that were similar showing little response to cost-sharing. For example, in the outpatient MH care analysis, the incremental effect of changing the outpatient out-of-network from 50% to 100% on the probability of any MH care goes from 0.013 (a 53% decrease) under Scenario 1 to 0.007 (a 20% decrease) under Scenario 2 for primary beneficiaries. The incremental effect of a similar change on the outpatient out-of-network coinsurance rate on days of MH care goes from a statistically insignificant 0.130 to a statistically significant 0.392 ($p<0.01$). Similarly, the incremental effect of changing the out-of-network coinsurance rate on the probability of any outpatient MH care for spouses is the same under Scenarios 1 and 2. And, the incremental effect of changing the outpatient out-of-network rate on days of use among spouses goes from 0.319 under Scenario 1 to 0.446 under Scenario 2 with both being statistically significant at the 1% level. Although the out-of-network coinsurance rate is insignificant for days of MH care under Scenario 1 among dependents, in my sensitivity analysis this variable is statistically significant at the 5 percent level under Scenario 2, but the estimated incremental effect is still extremely small; 0.184 under Scenario 2 compared to 0.161 under Scenario 1.

In the outpatient SA treatment analysis, all coinsurance variables remained insignificant under Scenario 2 for spouses and other dependents. For primary beneficiaries, the incremental effect of changing the outpatient out-of-network from 50% to 100% on the probability of any SA treatment goes from –0.00004 under Scenario 1 (not statistically significant) to 0.011 ($p<0.01$). The incremental effect on days of SA treatment is similar under both scenarios. I found similar results for inpatient MH and SA treatment. Thus, it appears that overall my results are robust to changes in the assumptions regarding the out-of-network coinsurance rates.

Gender Analysis

As part of my examination of the price effect, I examined whether men and women respond differently to the coinsurance rates and the EAP requirement. To do this analysis, I added 4 interactive terms to each of the regression equations that interacted each of the health insurance characteristics to the dichotomous variable for gender. The results of this analysis revealed no statistically significant differences in the effect of the health insurance characteristics by gender.

Table 21. Estimation of outpatient MH care utilization (Primary beneficiaries)

	Model 1: Basic RE Coefficients (standard errors)		**Model 2: IV RE Coefficients (standard errors)**	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*100398*	*7246*	*100398*	*7246*
n unique individuals	*58842*	*5488*	*58842*	*5488*
Health Insurance Characteristics				
Outpatient Coinsurance (in-network)	-0.009***	0.002	-0.014***	0.006***
	(0.002)	(0.002)	(0.003)	(0.002)
Outpatient Coinsurance (out-of-network)	0.009***	0.003	0.005**	-0.006***
	(0.002)	(0.001)	(0.002)	(0.002)
Inpatient Coinsurance (in-network)	-0.025***	-0.021***	-0.007	-0.003
	(0.004)	(0.003)	(0.005)	(0.004)
EAP Precertification Required	-0.393***	-0.034	-0.666***	-0.142**
	(0.048)	(0.036)	(0.083)	(0.066)
Total Months Enrolled in Year	0.048***	0.040***	0.047***	0.040***
	(0.007)	(0.006)	(0.007)	(0.006)
Physical Health Behavior				
Used outpatient medical services	1.313***	0.016	1.304***	0.018
	(0.048)	(0.037)	(0.048)	(0.037)
Used inpatient medical services	0.249***	-0.043	0.266***	-0.034
	(0.056)	(0.037)	(0.056)	(0.037)
Demographics				
Male	-0.492***	-0.066**	-0.495***	-0.075***
	(0.036)	(0.027)	(0.036)	(0.027)
Age				
16 to 30 years	0.114***	0.025**	0.118***	0.028**
	(0.014)	(0.011)	(0.014)	(0.011)
31 to 45 years	0.025***	0.004	0.023***	0.004
	(0.004)	(0.003)	(0.004)	(0.003)

*** significant at the 1 percent level
** significant at the 5 percent level

Table 21. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	Days of Use	Probability of Any Use	Days of Use
46 to 64 years	-0.071***	-0.023***	-0.066***	-0.022***
	(0.004)	(0.003)	(0.004)	(0.003)
Household Size	0.035**	-0.023**	0.049***	-0.019
	(0.015)	(0.011)	(0.016)	(0.011)
Not Married	0.360***	0.041	0.418***	0.062
	(0.045)	(0.033)	(0.045)	(0.033)
Region of Residence (Midwest omitted)				
Northeast	0.059	0.343***	0.121	0.400***
	(0.064)	(0.047)	(0.065)	(0.048)
South	-0.129**	0.034	-0.128**	0.027
	(0.052)	(0.041)	(0.054)	(0.042)
West	0.271	0.298***	0.257***	0.276***
	(0.061)	(0.046)	(0.063)	(0.048)
Unknown Region	0.072	0.201***	0.041	0.216***
	(0.069)	(0.047)	(0.074)	(0.051)
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	0.150	-0.003	0.085	0.125
	(0.085)	(0.066)	(0.102)	(0.078)
Service	0.066	-0.210***	0.323***	0.170**
	(0.089)	(0.070)	(0.103)	(0.081)
Employee Type of Primary Beneficiary (Salary omitted)				
Hourly	-0.080	-0.233***	-0.048	-0.226***
	(0.050)	(0.039)	(0.051)	(0.040)
Other Status	0.189**	0.028	0.176	-0.181**
	(0.082)	(0.065)	(0.098)	(0.076)
Intercept	-8.846***	-0.012	-8.806***	0.266
	(0.403)	(0.332)	(0.406)	(0.334)
Joint Significance				
All Insurance Variables *X-sq(4)*	128.78	48.90	176.82	54.67
p-value	<0.001	<0.001	<0.001	<0.001

*** significant at the 1 percent level
** significant at the 5 percent level

Table 22. Estimation of outpatient MH care utilization (Spouses)

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*55906*	*3472*	*55906*	*3472*
n unique individuals	*32451*	*2667*	*32451*	*2667*
Health Insurance Characteristics				
Outpatient Coinsurance (in-network)	-0.004	-0.004	-0.011***	-0.007**
	(0.003)	(0.003)	(0.004)	(0.003)
Outpatient Coinsurance (out-of-network)	0.003	0.006***	-0.003	0.001
	(0.002)	(0.002)	(0.003)	(0.002)
Inpatient Coinsurance (in-network)	0.0003	-0.021***	0.015**	-0.008
	(0.006)	(0.005)	(0.006)	(0.005)
EAP Precertification Required	-0.254***	-0.199***	-0.355***	-0.281***
	(0.067)	(0.053)	(0.096)	(0.078)
Total Months Enrolled in Year	0.053***	0.038***	0.052***	0.038***
	(0.011)	(0.009)	(0.011)	(0.009)
Physical Health Behavior				
Used outpatient medical services	1.525***	0.061	1.513***	0.058
	(0.069)	(0.058)	(0.069)	(0.058)
Used inpatient medical services	0.360***	-0.009	0.360***	-0.017
	(0.071)	(0.048)	(0.071)	(0.048)
Demographics				
Male	-0.432***	-0.061	-0.429***	-0.062
	(0.057)	(0.048)	(0.058)	(0.049)
Age				
16 to 30 years	0.059**	0.024	0.061**	0.023
	(0.025)	(0.021)	(0.025)	(0.021)
31 to 45 years	0.029***	-0.0004	0.027***	-0.0004
	(0.006)	(0.005)	(0.006)	(0.005)

*** significant at the 1 percent level
** significant at the 5 percent level

Table 22. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	Days of Use	Probability of Any Use	Days of Use
46 to 64 years	-0.063***	-0.022***	-0.059***	-0.019***
	(0.006)	(0.005)	(0.006)	(0.005)
Household Size	-0.009	-0.011	-0.001	-0.009
	(0.021)	(0.017)	(0.021)	(0.017)
Region of Residence (Midwest omitted)				
Northeast	-0.053	0.317***	-0.028	0.329***
	(0.091)	(0.070)	(0.091)	(0.071)
South	-0.237***	0.053	-0.264***	0.012
	(0.071)	(0.060)	(0.072)	(0.061)
West	0.102	0.271***	0.048	0.223***
	(0.088)	(0.072)	(0.089)	(0.072)
Unknown Region	-0.047	0.188***	-0.129	0.144**
	(0.091)	(0.068)	(0.095)	(0.072)
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	0.0003	-0.120	-0.154	-0.189
	(0.125)	(0.109)	(0.143)	(0.121)
Service	0.105	-0.305***	0.380***	-0.059
	(0.124)	(0.102)	(0.131)	(0.107)
Employee Type of Primary Beneficiary (Salary omitted):				
Hourly	-0.220***	-0.209***	-0.206***	-0.200***
	(0.068)	(0.056)	(0.069)	(0.057)
Other Status	-0.052	0.140	0.010	0.137
	(0.116)	(0.101)	(0.130)	(0.109)
Intercept	-7.193***	-0.096	-6.884***	0.188
	(0.731)	(0.604)	(0.735)	(0.607)
Joint Significance				
All Insurance Variables *X-sq(4)*	15.29	40.89	39.59	43.21
p-value	0.004	<0.001	<0.001	<0.001

*** significant at the 1 percent level
** significant at the 5 percent level

Table 23. Estimation of outpatient MH care utilization (Dependents)

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*78794*	*4055*	*78794*	*4055*
n unique individuals	*46262*	*3101*	*46262*	*3101*
Health Insurance Characteristics				
Outpatient Coinsurance (in-network)	0.001	0.004	-0.015**	0.006
	(0.004)	(0.003)	(0.006)	(0.005)
Outpatient Coinsurance (out-of-network)	0.004	0.003	0.004	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)
Inpatient Coinsurance (in-network)	-0.017***	-0.022***	-0.005	-0.011**
	(0.006)	(0.005)	(0.006)	(0.005)
EAP Precertification Required	-0.260***	-0.050	-0.495***	-0.112
	(0.063)	(0.050)	(0.109)	(0.088)
Total Months Enrolled in Year	0.063***	0.031***	0.062***	0.031***
	(0.010)	(0.009)	(0.010)	(0.009)
Physical Health Behavior				
Used outpatient medical services	1.245***	0.111***	1.238***	0.109***
	(0.051)	(0.041)	(0.051)	(0.041)
Used inpatient medical services	0.641***	0.186***	0.655***	0.194***
	(0.105)	(0.065)	(0.105)	(0.065)
Demographics				
Male	0.301***	-0.118***	0.307***	-0.117***
	(0.042)	(0.033)	(0.042)	(0.033)
Age				
0-5 years	0.535***	0.225***	0.537***	0.225***
	(0.052)	(0.053)	(0.052)	(0.053)
6-11 years	0.278***	0.028	0.278***	0.028
	(0.017)	(0.015)	(0.017)	(0.015)
12-17 years	-0.044***	0.001	-0.044***	0.001
	(0.011)	(0.009)	(0.011)	(0.009)

*** significant at the 1 percent level
** significant at the 5 percent level

Table 23. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
Greater than 17 years	-0.009	-0.003	-0.006	-0.003
	(0.008)	(0.006)	(0.008)	(0.006)
Household Size	-0.128***	-0.025	-0.124***	-0.024
	(0.018)	(0.014)	(0.018)	(0.014)
Region of Residence (Midwest omitted)				
Northeast	0.104	0.184***	0.084	0.211***
	(0.086)	(0.066)	(0.088)	(0.067)
South	-0.017	-0.025	-0.044	-0.027
	(0.069)	(0.056)	(0.073)	(0.059)
West	0.303***	0.082	0.254***	0.065
	(0.084)	(0.065)	(0.089)	(0.069)
Unknown Region	0.001	0.160**	-0.120	0.176**
	(0.089)	(0.063)	(0.101)	(0.072)
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	-0.323***	0.073	-0.528***	0.121
	(0.119)	(0.097)	(0.144)	(0.116)
Service	-0.139	-0.400***	-0.092	-0.152
	(0.121)	(0.102)	(0.133)	(0.108)
Employee Type of Primary Beneficiary (Salary omitted)				
Hourly	-0.429***	-0.136***	-0.395***	-0.139***
	(0.065)	(0.051)	(0.066)	(0.052)
Other Status	0.241**	-0.007	0.324**	-0.112
	(0.117)	(0.098)	(0.129)	(0.105)
Intercept	-8.850***	-0.486	-8.734***	-0.260
	(0.296)	(0.285)	(0.302)	(0.286)
Joint Significance				
All Insurance Variables *X-sq(4)*	30.62	28.47	59.31	20.77
p-value	<0.001	<0.001	<0.001	<0.001

*** significant at the 1 percent level
** significant at the 5 percent level

Table 24. Estimation of outpatient SA treatment utilization (Primary Beneficiaries)

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*100398*	*351*	*100398*	*351*
n unique individuals	*58842*	*307*	*58842*	*307*
Health Insurance Characteristics				
Outpatient Coinsurance (in-network)	-0.0001	-0.064***	-0.066	-0.054
	(0.012)	(0.014)	(0.035)	(0.039)
Outpatient Coinsurance (out-of-network)	-0.0003	0.038***	0.017	0.018
	(0.007)	(0.008)	(0.012)	(0.015)
Inpatient Coinsurance (in-network)	-0.027**	-0.022	-0.021	-0.012
	(0.011)	(0.015)	(0.013)	(0.019)
EAP Precertification Required	-0.506***	-0.044	-0.623**	0.726**
	(0.159)	(0.176)	(0.280)	(0.327)
Total Months Enrolled in Year	-0.009	0.022	-0.015	0.017
	(0.023)	(0.023)	(0.023)	(0.023)
Physical Health Behavior				
Used outpatient medical services	0.494***	0.020	0.491***	0.015
	(0.140)	(0.134)	(0.141)	(0.132)
Used inpatient medical services	0.869***	-0.145	0.869***	-0.170
	(0.170)	(0.175)	(0.171)	(0.179)
Demographics				
Male	0.751***	0.077	0.757***	0.013
	(0.124)	(0.132)	(0.124)	(0.129)
Age				
16 to 30 years	0.245***	0.065	0.246***	0.071
	(0.055)	(0.054)	(0.055)	(0.054)
31 to 45 years	0.012	-0.005	0.010	-0.005
	(0.013)	(0.015)	(0.013)	(0.014)
46 to 64 years	-0.088***	-0.024	-0.079***	-0.024
	(0.015)	(0.017)	(0.016)	(0.017)

*** significant at the 1 percent level
** significant at the 5 percent level

Table 24. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
Not Married	0.552***	-0.092	0.586***	-0.173
	(0.144)	(0.155)	(0.148)	(0.158)
Household Size	0.007	-0.060	0.026	-0.067
	(0.048)	(0.056)	(0.049)	(0.055)
Region of Residence (Midwest omitted)				
Northeast	-0.335	-0.060	-0.645**	-0.230
	(0.224)	(0.239)	(0.288)	(0.327)
South	-0.042	-0.184	-0.218	-0.369
	(0.154)	(0.168)	(0.192)	(0.205)
West	-0.002	-0.145	-0.233	-0.357
	(0.190)	(0.204)	(0.233)	(0.235)
Unknown Region	-0.437	0.204	-0.915***	-0.145
	(0.251)	(0.256)	(0.340)	(0.372)
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	0.197	0.872***	0.361	0.559
	(0.252)	(0.311)	(0.281)	(0.307)
Service	0.234	-1.165***	-0.480	-0.772
	(0.329)	(0.356)	(0.584)	(0.718)
Employee Type of Primary Beneficiary (Salary omitted)				
Hourly	0.788***	-0.073	0.765***	-0.178
	(0.169)	(0.186)	(0.188)	(0.195)
Other Status	0.415	-0.486	-0.085	-0.515
	(0.251)	(0.309)	(0.337)	(0.354)
Intercept	-14.304***	-2.656	-14.731***	-1.600
	(1.639)	(1.629)	(1.669)	(1.681)
Joint Significance				
All Insurance Variables *X-sq(4)*	24.77	25.09	37.40	6.12
p-value	<0.001	<0.001	<0.001	0.1903

*** significant at the 1 percent level
** significant at the 5 percent level

Table 25. Estimation of outpatient SA treatment utilization (Spouses)

	Model 1: Basic RE Coefficients (standard errors)		**Model 2: IV RE Coefficients (standard errors)**	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*55906*	*158*	*55906*	*158*
n unique individuals	*32451*	*140*	*32451*	*140*
Health Insurance Characteristics				
Outpatient Coinsurance (in-network)	0.008	-0.003	0.036	0.033
	(0.019)	(0.024)	(0.037)	(0.043)
Outpatient Coinsurance (out-of-network)	-0.003	0.0005	-0.017	-0.017
	(0.011)	(0.014)	(0.016)	(0.021)
Inpatient Coinsurance (in-network)	0.005	-0.0004	0.007	0.012
	(0.015)	(0.020)	(0.016)	(0.020)
EAP Precertification Required	-0.475	-0.317	-0.376	-0.420
	(0.265)	(0.251)	(0.370)	(0.401)
Total Months Enrolled in Year	0.048	0.062	0.051	0.068
	(0.039)	(0.039)	(0.039)	(0.039)
Physical Health Behavior				
Used outpatient medical services	0.679***	-0.218	0.690***	-0.206
	(0.206)	(0.206)	(0.206)	(0.204)
Used inpatient medical services	0.975***	-0.058	0.979***	0.012
	(0.237)	(0.275)	(0.237)	(0.275)
Demographics				
Male	1.624***	-0.101	1.655***	-0.054
	(0.188)	(0.201)	(0.189)	(0.205)
Age				
16 to 30 years	0.064	0.131	0.067	0.128
	(0.092)	(0.086)	(0.092)	(0.084)
31 to 45 years	0.011	-0.00002	0.010	-0.002
	(0.020)	(0.023)	(0.020)	(0.023)
46 to 64 years	-0.105***	-0.032	-0.108***	-0.031
	(0.024)	(0.029)	(0.025)	(0.030)
Household Size	-0.058	-0.010	-0.055	-0.003
	(0.074)	(0.078)	(0.074)	(0.079)

*** significant at the 1 percent level
** significant at the 5 percent level

Table 25. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
Region of Residence (Midwest omitted)				
Northeast	0.181	0.350	0.314	0.560
	(0.330)	(0.339)	(0.360)	(0.404)
South	-0.213	-0.273	-0.187	-0.229
	(0.258)	(0.306)	(0.269)	(0.317)
West	-0.372	-0.309	-0.329	-0.207
	(0.359)	(0.403)	(0.375)	(0.413)
Unknown Region	-0.324	0.704	-0.307	0.827
	(0.422)	(0.423)	(0.444)	(0.453)
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	0.046	0.353	-0.113	0.277
	(0.394)	(0.421)	(0.425)	(0.505)
Service	0.418	0.183	0.849	0.824
	(0.499)	(0.615)	(0.654)	(0.802)
Employee Type of Primary Beneficiary (Salary omitted)				
Hourly	0.824***	0.326	0.859***	0.373
	(0.266)	(0.306)	(0.270)	(0.311)
Other Status	0.315	0.140	0.464	0.199
	(0.381)	(0.440)	(0.449)	(0.552)
Intercept	-9.820***	-3.380	-9.299***	-2.717
	(2.700)	(2.597)	(2.736)	(2.583)
Joint Significance				
All Insurance Variables *X-sq(4)*	3.72	1.73	2.53	2.29
p-value	0.445	0.786	0.639	0.682

*** significant at the 1 percent level
** significant at the 5 percent level

Table 26. Estimation of outpatient SA treatment utilization (Dependents)

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*78794*	*248*	*78794*	*248*
n unique individuals	*46262*	*213*	*46262*	*213*
Health Insurance Characteristics				
Outpatient Coinsurance (in-network)	-0.023	0.040	-0.129**	0.134**
	(0.018)	(0.024)	(0.064)	(0.059)
Outpatient Coinsurance (out-of-network)	0.011	-0.012	0.048**	-0.039**
	(0.010)	(0.009)	(0.021)	(0.018)
Inpatient Coinsurance (in-network)	-0.026	-0.010	-0.059**	0.0003
	(0.017)	(0.022)	(0.024)	(0.017)
EAP Precertification Required	-0.224	-0.214	0.390	-0.591
	(0.240)	(0.244)	(0.437)	(0.391)
Total Months Enrolled in Year	0.016	0.032	0.011	0.048
	(0.034)	(0.033)	(0.034)	(0.035)
Physical Health Behavior				
Used outpatient medical services	1.153***	0.066	1.145***	0.044
	(0.175)	(0.160)	(0.175)	(0.157)
Used inpatient medical services	0.917***	0.284	0.887***	0.317
	(0.259)	(0.228)	(0.260)	(0.229)
Demographics				
Male	0.970***	-0.038	0.959***	-0.012
	(0.144)	(0.147)	(0.144)	(0.146)
Age				
0 to 5 years	0.070	-0.032	0.072	-0.106
	(0.321)	(0.274)	(0.321)	(0.278)
6 to 11 years	0.205	0.088	0.210	0.121
	(0.160)	(0.148)	(0.160)	(0.154)
12 to 17 years	0.536***	0.055	0.532***	0.062
	(0.064)	(0.075)	(0.064)	(0.075)

*** significant at the 1 percent level
** significant at the 5 percent level

Table 26. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
Greater than 17 years	-0.053**	0.014	-0.045	0.003
	(0.025)	(0.026)	(0.026)	(0.026)
Household Size	-0.061	-0.004	-0.079	0.012
	(0.057)	(0.047)	(0.057)	(0.047)
Region of Residence (Midwest omitted)				
Northeast	-0.078	0.675**	-0.699	1.327***
	(0.302)	(0.309)	(0.462)	(0.454)
South	-0.058	0.181	-0.308	0.500
	(0.236)	(0.259)	(0.282)	(0.307)
West	0.064	0.128	-0.207	0.466
	(0.301)	(0.317)	(0.356)	(0.364)
Unknown Region	-0.500	0.769***	-1.275**	1.586***
	(0.312)	(0.289)	(0.544)	(0.511)
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	-0.357	0.346	0.204	-0.626
	(0.361)	(0.429)	(0.535)	(0.548)
Service	-0.503	0.040	-2.284**	1.457
	(0.464)	(0.469)	(0.956)	(0.845)
Employee Type of Primary Beneficiary (Salary omitted)				
Hourly	-0.396	0.223	-0.558**	0.365
	(0.212)	(0.203)	(0.236)	(0.211)
Other Status	-0.111	-0.425	-1.164	1.079
	(0.350)	(0.427)	(0.787)	(0.787)
Intercept	-11.320***	0.613	-12.224***	1.003
	(1.368)	(1.283)	(1.418)	(1.319)
Joint Significance				
All Insurance Variables *X-sq(4)*	6.16	3.92	9.29	6.30
p-value	0.188	0.417	0.054	0.178

*** significant at the 1 percent level
** significant at the 5 percent level

Table 27. Estimation of inpatient MH care utilization (Primary Beneficiaries)

	Model 1: Basic RE Coefficients (standard errors)		**Model 2: IV RE Coefficients (standard errors)**	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*100398*	*199*	*100398*	*199*
n unique individuals	*58842*	*198*	*58842*	*198*
Health Insurance Characteristics				
Inpatient Coinsurance (in-network)	-0.035	0.019	-0.027	0.014
	(0.022)	(0.021)	(0.024)	(0.023)
Inpatient Coinsurance (out-of-network)	0.003	-0.001	0.003	-0.001
	(0.007)	(0.007)	(0.007)	(0.007)
Outpatient Coinsurance (in-network)	0.007	0.001	0.004	0.001
	(0.008)	(0.006)	(0.012)	(0.010)
EAP Precertification Required	-0.404	0.075	-0.445	0.249
	(0.225)	(0.217)	(0.369)	(0.345)
Total Months Enrolled in Year	0.027	-0.002	0.026	-0.0001
	(0.035)	(0.035)	(0.035)	(0.035)
Physical Health Behavior				
Used medical services	0.904***	0.301	0.904***	0.297
	(0.247)	(0.246)	(0.247)	(0.246)
Used inpatient medical services	1.939***	0.156	1.945***	0.142
	(0.182)	(0.155)	(0.183)	(0.157)
Demographics				
Male	-0.124	-0.068	-0.126	-0.066
	(0.158)	(0.150)	(0.159)	(0.150)
Age				
16 to 30 years	0.082	0.044	0.083	0.044
	(0.059)	(0.061)	(0.059)	(0.061)
31 to 45 years	0.015	0.002	0.015	0.002
	(0.019)	(0.019)	(0.019)	(0.019)
46 to 64 years	-0.055***	0.019	-0.052***	0.018
	(0.019)	(0.018)	(0.019)	(0.018)

*** significant at the 1 percent level
** significant at the 5 percent level

Table 27. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	Days of Use	Probability of Any Use	Days of Use
Not Married	0.342	0.166	0.351	0.177
	(0.203)	(0.205)	(0.206)	(0.204)
Household Size	-0.097	-0.022	-0.093	-0.016
	(0.076)	(0.075)	(0.077)	(0.075)
Region of Residence (Midwest omitted)				
Northeast	-0.340	-0.514	-0.337	-0.519
	(0.322)	(0.321)	(0.322)	(0.316)
South	0.343	-0.470**	0.315	-0.478**
	(0.221)	(0.208)	(0.231)	(0.219)
West	0.088	-0.581**	0.055	-0.583**
	(0.289)	(0.271)	(0.301)	(0.283)
Unknown Region	-0.108	- 0.929***	-0.093	- 0.939***
	(0.338)	(0.327)	(0.359)	(0.345)
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	-0.397	0.151	-0.469	0.102
	(0.517)	(0.431)	(0.573)	(0.509)
Service	-0.174	-0.249	-0.134	-0.310
	(0.362)	(0.357)	(0.379)	(0.370)
Employee Type of Primary Beneficiary (Salary omitted)				
Hourly	0.687***	0.193	0.667***	0.163
	(0.230)	(0.219)	(0.234)	(0.219)
Other Status	1.030	0.215	1.075	0.258
	(0.585)	(0.540)	(0.618)	(0.593)
Intercept	-11.305***	0.098	-11.379***	0.104
	(1.926)	(1.886)	(1.936)	(1.895)
Joint Significance				
All Insurance Variables *X-sq(4)*	9.00	2.35	6.15	2.89
p-value	0.061	0.671	0.187	0.577

*** significant at the 1 percent level
** significant at the 5 percent level

Table 28. Estimation of inpatient MH care utilization (Spouses)

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*55906*	*102*	*55906*	*102*
n unique individuals	*32451*	*101*	*32451*	*101*
Health Insurance Characteristics				
Inpatient Coinsurance (in-network)	0.010	-0.015	0.033	-0.024
	(0.028)	(0.027)	(0.031)	(0.031)
Inpatient Coinsurance (out-of-network)	-0.004	0.004	-0.013	0.012
	(0.009)	(0.011)	(0.011)	(0.014)
Outpatient Coinsurance	0.001	0.008	-0.024	0.004
	(0.013)	(0.011)	(0.020)	(0.018)
EAP Precertification Required	0.003	-0.410	0.541	-0.602
	(0.301)	(0.253)	(0.410)	(0.381)
Total Months Enrolled in Year	0.077	-0.031	0.074	-0.014
	(0.061)	(0.058)	(0.061)	(0.057)
Physical Health Behavior				
Used outpatient medical services	1.396***	0.636	1.408***	0.645
	(0.386)	(0.426)	(0.386)	(0.427)
Used inpatient medical services	1.543***	-0.061	1.539***	-0.076
	(0.241)	(0.199)	(0.242)	(0.203)
Demographics				
Male	0.197	-0.224	0.244	-0.237
	(0.244)	(0.223)	(0.246)	(0.218)
Age				
16 to 30 years	0.224	0.082	0.222	0.092
	(0.156)	(0.159)	(0.157)	(0.159)
31 to 45 years	0.010	-0.005	0.007	-0.008
	(0.026)	(0.022)	(0.026)	(0.022)
46 to 64 years	-0.041	-0.010	-0.034	-0.008
	(0.027)	(0.022)	(0.027)	(0.022)

*** significant at the 1 percent level
** significant at the 5 percent level

Table 28. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
Household Size	-0.114	-0.135	-0.110	-0.144
	(0.100)	(0.090)	(0.101)	(0.090)
Region of Residence (Midwest omitted)				
Northeast	0.386	-0.430	0.264	-0.292
	(0.372)	(0.377)	(0.381)	(0.389)
South	-0.005	0.389	-0.239	0.419
	(0.311)	(0.302)	(0.330)	(0.341)
West	-0.187	-0.456	-0.452	-0.410
	(0.423)	(0.417)	(0.438)	(0.447)
Unknown Region	-0.639	0.168	-0.932	0.211
	(0.549)	(0.519)	(0.575)	(0.565)
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	0.098	0.267	-0.376	-0.162
	(0.695)	(0.770)	(0.930)	(0.806)
Service	0.444	0.329	0.653	0.132
	(0.458)	(0.408)	(0.507)	(0.487)
Employee Type of Primary Beneficiary (Salary omitted)				
Hourly	0.553	0.773**	0.409	0.857***
	(0.306)	(0.300)	(0.309)	(0.305)
Other Status	0.106	0.391	0.199	1.046
	(0.744)	(1.007)	(0.953)	(1.039)
Intercept	-16.203***	-0.415	-15.374***	-1.431
	(4.723)	(4.862)	(4.759)	(4.928)
Joint Significance				
All Insurance Variables *X-sq(4)*	0.24	3.68	2.93	3.09
p-value	0.993	0.451	0.570	0.543

*** significant at the 1 percent level
** significant at the 5 percent level

Table 29. Estimation of inpatient MH care utilization (Dependents)

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*78794*	*210*	*78794*	*210*
n unique individuals	*46262*	*209*	*46262*	*209*
Health Insurance Characteristics				
Inpatient Coinsurance (in-network)	-0.040	-0.026	-0.049	0.001
	(0.022)	(0.021)	(0.026)	(0.024)
Inpatient Coinsurance (out-of-network)	-0.002	0.007	0.005	0.003
	(0.008)	(0.008)	(0.009)	(0.009)
Outpatient Coinsurance (in-network)	0.012	0.008	0.007	-0.024
	(0.010)	(0.009)	(0.018)	(0.018)
EAP Precertification Required	-0.272	0.306	-0.504	0.543
	(0.243)	(0.236)	(0.419)	(0.407)
Total Months Enrolled in Year	0.036	-0.083**	0.035	-0.084**
	(0.041)	(0.042)	(0.041)	(0.042)
Physical Health Behavior				
Used outpatient medical services	1.287***	0.380	1.281***	0.352
	(0.209)	(0.218)	(0.210)	(0.216)
Used inpatient medical services	2.088***	0.280	2.108***	0.285
	(0.209)	(0.174)	(0.212)	(0.177)
Demographics				
Male	0.160	-0.011	0.164	-0.019
	(0.143)	(0.143)	(0.143)	(0.141)
Age				
0 to 5 years	-----	-----	-----	-----
	-----	-----	-----	-----
6 to 11 years	0.694***	-0.184	0.694***	-0.164
	(0.139)	(0.130)	(0.138)	(0.130)
12 to 17 years	0.065	0.015	0.064	0.010
	(0.040)	(0.041)	(0.040)	(0.041)
Greater than 17 years	-0.009	-0.009	-0.009	0.002
	(0.021)	(0.020)	(0.021)	(0.020)

*** significant at the 1 percent level
** significant at the 5 percent level

Table 29. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
Household Size	-0.035	0.104	-0.036	0.101
	(0.060)	(0.054)	(0.060)	(0.054)
Region of Residence (Midwest omitted)				
Northeast	-0.070	-1.067***	-0.058	-1.081***
	(0.285)	(0.313)	(0.294)	(0.315)
South	0.139	-0.094	0.177	-0.225
	(0.228)	(0.220)	(0.250)	(0.234)
West	0.007	-0.544	0.037	-0.712**
	(0.313)	(0.299)	(0.334)	(0.317)
Unknown Region	-0.446	-0.371	-0.444	-0.573
	(0.299)	(0.298)	(0.345)	(0.337)
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	-0.479	-0.426	-0.874	-0.880
	(0.536)	(0.476)	(0.604)	(0.634)
Service	-0.664	-0.786	-0.907	-0.514
	(0.421)	(0.412)	(0.431)	(0.414)
Employee Type of Primary Beneficiary (Salary omitted)				
Hourly	0.277	0.217	0.328	0.158
	(0.196)	(0.178)	(0.202)	(0.185)
Other Status	-0.051	0.870	0.498	1.068
	(0.634)	(0.584)	(0.672)	(0.716)
Intercept	14.700***	4.096**	15.092***	4.222**
	(1.709)	(1.648)	(1.746)	(1.676)
Joint Significance				
All Insurance Variables *X-sq(4)*	14.12	4.00	15.85	3.03
p-value	0.007	0.4064	0.003	0.552

*** significant at the 1 percent level
** significant at the 5 percent level

Table 30. Estimation of inpatient SA treatment utilization (Primary Beneficiaries)

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*100398*	*61*	*100398*	*61*
n unique individuals	*58842*	*61*	*58842*	*61*
Health Insurance Characteristics				
Inpatient Coinsurance (in-network)	-0.131***	-0.032	-0.133***	-0.022
	(0.041)	(0.036)	(0.042)	(0.032)
Inpatient Coinsurance	0.029**	0.013	0.035**	0.008
(out-of-network)	(0.013)	(0.011)	(0.015)	(0.011)
Outpatient Coinsurance	-0.005	-0.001	-0.031	0.037
(in-network)	(0.020)	(0.016)	(0.039)	(0.027)
EAP Precertification Required	-0.793	-0.732	-0.601	-1.240**
	(0.419)	(0.388)	(0.596)	(0.494)
Total Months Enrolled in Year	-0.088	0.018	-0.091	0.015
	(0.048)	(0.046)	(0.049)	(0.045)
Physical Health Behavior				
Used outpatient medical services	0.479	0.288	0.497	0.298
	(0.347)	(0.324)	(0.348)	(0.321)
Used inpatient medical services	1.709***	0.207	1.698***	0.211
	(0.316)	(0.251)	(0.316)	(0.241)
Demographics				
Male	1.276***	-0.395	1.261***	-0.316
	(0.328)	(0.245)	(0.328)	(0.242)
Age				
16 to 30 years	0.271	0.315	0.276	0.295
	(0.160)	(0.196)	(0.161)	(0.194)
31 to 45 years	0.030	-0.044	0.028	-0.023
	(0.034)	(0.030)	(0.034)	(0.030)
46 to 64 years	-0.059	0.074***	-0.055	0.066***
	(0.031)	(0.026)	(0.031)	(0.025)

*** significant at the 1 percent level
** significant at the 5 percent level

Table 30. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
Not Married	0.669**	0.244	0.626	0.371
	(0.331)	(0.247)	(0.339)	(0.258)
Household Size	0.013	0.049	0.004	0.047
	(0.115)	(0.102)	(0.118)	(0.100)
Region of Residence (Midwest omitted)				
Northeast	-0.304	-0.835	-0.421	-0.707
	(0.518)	(0.494)	(0.551)	(0.518)
South	0.448	-0.699	0.298	-0.660
	(0.382)	(0.385)	(0.410)	(0.394)
West	0.645	-1.245***	0.463	-1.177***
	(0.463)	(0.425)	(0.502)	(0.423)
Unknown Region	-0.348	-0.347	-0.636	-0.096
	(0.519)	(0.435)	(0.613)	(0.478)
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	-1.711	-0.243	-1.823	0.023
	(0.953)	(0.944)	(0.989)	(0.749)
Service	-1.711**	-1.748**	-2.063***	-1.553**
	(0.719)	(0.794)	(0.784)	(0.716)
Employee Type of Primary Beneficiary (Salary omitted)				
Hourly	0.859**	0.245	0.813**	0.292
	(0.378)	(0.312)	(0.393)	(0.307)
Other Status	2.630**	0.720	2.627**	0.612
	(1.061)	(1.061)	(1.069)	(0.766)
Intercept	-17.742***	5.771	-17.823***	5.957
	(4.736)	(289.136)	(4.775)	(290.025)
Joint Significance				
All Insurance Variables *X-sq(4)*	19.76	4.210	20.10	6.98
p-value	<0.001	0.379	<0.001	0.137

*** significant at the 1 percent level
** significant at the 5 percent level

Table 31. Estimation of inpatient SA treatment utilization (Spouses)

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*55906*	*28*	*55906*	*28*
n unique individuals	*32451*	*28*	*32451*	*28*
Health Insurance Characteristics				
Inpatient Coinsurance (in-network)	-0.008	Did	0.019	Did
	(0.041)	not	(0.065)	not
Inpatient Coinsurance	0.019	converge	0.020	converge
(out-of-network)	(0.025)		(0.031)	
Outpatient Coinsurance	-0.026		-0.127	
(in-network)	(0.053)		(0.167)	
EAP Precertification Required	0.587		2.056	
	(0.530)		(1.308)	
Total Months Enrolled in Year	0.092		0.090	
	(0.099)		(0.099)	
Physical Health Behavior				
Used outpatient medical services	-0.200		-0.098	
	(0.478)		(0.486)	
Used inpatient medical services	2.263***		2.254***	
	(0.441)		(0.441)	
Demographics				
Male	0.899**		0.948	
	(0.418)		(0.421)	
Age				
16 to 30 years	0.083		0.065	
	(0.192)		(0.193)	
31 to 45 years	0.026		0.019	
	(0.046)		(0.047)	
46 to 64 years	-0.131**		-0.128**	
	(0.055)		(0.055)	
Household Size	-0.441**		-0.445**	
	(0.197)		(0.200)	

*** significant at the 1 percent level
** significant at the 5 percent level

Table 31. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
Region of Residence (Midwest omitted)				
Northeast	-0.840		-1.678	
	(0.839)		(1.445)	
South	-1.050		-1.621	
	(0.627)		(0.895)	
West	-0.534		-1.149	
	(0.731)		(1.019)	
Unknown Region	0.699		-0.221	
	(0.807)		(1.644)	
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	-1.771		-3.256	
	(2.150)		(3.262)	
Service	-0.449		-1.031	
	(1.080)		(1.321)	
Employee Type of Primary Beneficiary (Salary omitted)				
Hourly	1.465**		1.027	
	(0.588)		(0.707)	
Other Status	2.159		2.265	
	(2.050)		(2.519)	
Intercept	-11.840**		-10.241	
	(5.690)		(6.127)	
Joint Significance				
All Insurance Variables *X-sq(4)*	2.47	-----	4.77	-----
p-value	0.649	-----	0.312	-----

*** significant at the 1 percent level
** significant at the 5 percent level

Table 32. Estimation of inpatient SA treatment utilization (Dependents)

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
N observations	*78794*	*38*	*78794*	*38*
n unique individuals	*46262*	*38*	*46262*	*38*
Health Insurance Characteristics				
Inpatient Coinsurance (in-network)	-0.119	0.135	-0.168**	0.088
	(0.062)	(0.126)	(0.068)	(0.084)
Inpatient Coinsurance (out-of-network)	0.035	-0.076	0.092**	-0.006
	(0.019)	(0.124)	(0.038)	(0.120)
Outpatient Coinsurance (in-network)	0.002	0.100	-0.206	-0.016
	(0.029)	(0.232)	(0.145)	(0.435)
EAP Precertification Required	0.072	-0.253	1.776**	-0.870
	(0.569)	(0.986)	(0.901)	(1.918)
Total Months Enrolled in Year	0.082	0.167	0.099	0.172
	(0.116)	(0.256)	(0.120)	(0.260)
Physical Health Behavior				
Used outpatient medical services	1.707***	-0.256	1.745***	-0.175
	(0.546)	(0.726)	(0.546)	(0.789)
Used inpatient medical services	2.301***	0.435	2.238***	0.416
	(0.387)	(0.564)	(0.389)	(0.591)
Demographics				
Male	1.728***	-1.088	1.715***	-1.097
	(0.426)	(0.573)	(0.425)	(0.569)
Age				
0 to 5 years	-----	-----	-----	-----
	-----	-----	-----	-----
6 to 11 years	-----	-----	-----	-----
	-----	-----	-----	-----
12 to 17 years	0.580***	0.143	0.572***	0.115
	(0.170)	(0.335)	(0.168)	(0.327)

*** significant at the 1 percent level
** significant at the 5 percent level

Table 32. Continued

	Model 1: Basic RE Coefficients (standard errors)		Model 2: IV RE Coefficients (standard errors)	
	Probability of Any Use	**Days of Use**	**Probability of Any Use**	**Days of Use**
Greater than 17 years	0.017	0.135	0.038	0.138
	(0.033)	(0.085)	(0.035)	(0.089)
Household Size	-0.283	0.290	-0.357**	0.322
	(0.156)	(0.236)	(0.161)	(0.254)
Region of Residence (Midwest omitted)				
Northeast	0.541	-1.332	-0.230	-1.455
	(0.727)	(1.297)	(1.108)	(2.862)
South	0.576	-1.363	0.226	-1.391
	(0.636)	(1.085)	(0.768)	(1.544)
West	1.042	-0.732	0.701	-0.802
	(0.745)	(1.024)	(0.904)	(1.321)
Unknown Region	1.028	0.584	-0.320	0.463
	(0.699)	(0.933)	(1.329)	(3.352)
Industry of Primary Beneficiary (Transportation omitted)				
Manufacturing	-1.930	9.261	-5.033	4.031
	(1.465)	(9.388)	(2.735)	(9.050)
Service	-1.275	2.464	-3.887**	0.021
	(1.006)	(4.239)	(1.897)	(5.866)
Employee Type of Primary Beneficiary (Salary omitted)				
Hourly	0.671	0.837	0.241	0.820
	(0.485)	(0.563)	(0.552)	(0.946)
Other Status	2.919	-7.889	4.683**	-2.224
	(1.555)	(10.027)	(2.169)	(6.179)
Intercept	-21.556***	14.442	-22.716***	11.012
	(3.457)	(697.684)	(3.627)	(783.830)
Joint Significance				
All Insurance Variables *X-sq(4)*	4.33	1.99	9.24	2.11
p-value	0.363	0.739	0.055	0.715

*** significant at the 1 percent level
** significant at the 5 percent level

CHAPTER 6: CONCLUSION AND POLICY IMPLICATIONS

Cost has often been cited as a major reason that people in need of MH/SA treatment do not seek treatment services. In the 2003 NSDUH survey, 33 percent of individuals who wanted treatment for drug or alcohol problems reported that they did not receive it because of the cost (SAMHSA, 2004), yet both MH care and SA treatment have usually received less generous insurance coverage compared to general medical care. The primary justification for the inequitable treatment of MH/SA services has been the belief that MH/SA demand is more responsive to price, which suggests that these services are more discretionary than general medical care and will result in greater welfare loss associated with insurance. However, previous research studies regarding the relationship between the costs faced by individuals and MH/SA demand are not conclusive because of limitations in the data used, the types of insurance examined, and the scope of services studied. More evidence is available for MH care than for SA treatment, but even the evidence for MH care has gaps that need to be addressed (e.g., little evidence for inpatient MH care).

In this study, I find that the demand response relative to cost-sharing differs between MH and SA services and by the relationship of the individual to the health plan. Overall, primary beneficiaries (the primary policy holder) are more responsive to the level of cost-sharing for both outpatient MH care and SA treatment (both inpatient and outpatient) than either spouses or other dependents. However, the size of the incremental effects associated with 10 percentage-point changes in the coinsurance rates are quite small across all samples for both MH care and SA treatment. These findings suggest that individuals may be no more responsive to cost-sharing for outpatient MH/SA care than they are for general medical care. Overall, these findings suggest that the association between the level of cost-sharing and MH/SA treatment utilization may be similar to general medical care and that previous arguments against parity for MH care may not be justified.

Another interesting finding is that cost-sharing has different effects on each stage of the decision-process for utilization. For primary beneficiaries, the coinsurance rates appear to have a greater effect on the probability of any use for both outpatient MH care and inpatient SA treatment. And, the coinsurance rates more greatly affect extent of use among primary beneficiaries for outpatient SA treatment.

On the other hand, the coinsurance rates more greatly affect extent of use for outpatient MH care and outpatient SA treatment among spouses. This is an important finding because it suggests that setting a level of cost-sharing to ensure initial access to services may not be sufficient. Policy makers and insurers need to consider the role that cost-sharing plays in both decisions to ensure not only initial access but also appropriate lengths of treatment episodes once access is obtained.

Contrary to my expectations, the association between cost-sharing levels for inpatient services and outpatient service utilization, when significant, implies a complementary relationship between these different service modalities. This result is only found for outpatient MH care and outpatient SA treatment, but it is important because it suggests that policy holders and insurers should not consider these services separately when making coverage decisions. A similar complementary relationship between inpatient and outpatient care has been put forth in the general medical care literature (Cutler and Zeckhauser, 2000).

When changes in health insurance coverage are being considered for one type of service modality, its impact on other types of services should also be considered before any changes are implemented. Failure to do so may result in undesirable consequences for overall MH/SA utilization.

No study has examined the effect that an EAP precertification requirement has on MH/SA service utilization, although a few studies have found that use of an EAP increases overall healthcare utilization (e.g., Zarkin, Bray, and Qi, 2002; Deitz, Cook and Hersch, 2005). I find that requiring EAP precertification prior to using MH/SA services significantly decreases the probability that individuals will use any outpatient MH care services. Furthermore, for spouses only, EAP precertification also has a negative effect on the number of days of outpatient MH care. The policy implications for this finding are not clear. If EAP precertification decreases utilization in the formal health care system by helping employees and their dependents identify their MH/SA problems, providing limited care for milder conditions, and referring individuals to appropriate additional care as needed, this suggests that firms with an EAP may avoid costly care by implementing EAP precertification as part of their health plan. However, if EAP precertification, rather than facilitating treatment, creates an unintentional obstacle to treatment and discourages utilization, then insurers and employers may want to reconsider this method. Individuals who fear stigma or workplace retaliation because of their MH/SA problems may not want to approach the EAP because of its association with the workplace. Furthermore, this additional step may make treatment too costly for some individuals because of the added time and inconvenience of going through the EAP. Regardless of the reason, untreated MH/SA problems most likely will lead to even more costly health care in the future. Given our lack of understanding regarding the role that the EAP plays in MH/SA service utilization—one of facilitator or one of inadvertent obstacle—it is apparent that more research in this area is needed.

Limitations

This study has some limitations that should be noted. First, because my data are claims data I only observe MH/SA utilization that is covered by the individual's health plan. Use of MH/SA services outside of the plan may occur for a variety of reason such as children's use of school counselors, employees' use of the EAP, or individuals deciding to pay out-of-pocket rather than submit claims. Therefore, my conclusions are based solely on the use of services within the health plan. Second, the data used contain only limited information on sociodemographic variables and do not contain data on MH/SA treatment need or the enrollee's race/ethnicity. Both of these variables have been shown to be strong predictors regarding MH/SA service use and ideally I would like to control for them in my estimations. However, their omission is only a problem for my findings on health insurance characteristics if they are correlated with the insurance variables. I have attempted to control for the self-selection bias often associated with health insurance, and I have also argued that my results suggest that self-selection may not be a serious problem with these data because the uncorrected (standard RE) results and bias-corrected (instrumental RE) results are very similar. Therefore, I believe that these omissions do not bias my findings.

Another limitation is that I only control for selected MH/SA health insurance characteristics. Health plan coverage is extremely complex and, in addition to coinsurance and EAP precertification requirements, may include other cost control mechanisms such as copayments, deductibles, and limits on the annual number of MH/SA visits in the plan year. Furthermore, the structure of the plan management (e.g., carveout versus carvein; indemnity plan versus point of service plan) may affect individuals' utilization decisions. I have attempted to address some of these additional features in my creation of the coinsurance variables, but accounting for all the various health insurance characteristics is beyond the scope of this study. Rather, I focused on the most relevant characteristics associated with the individual's out-of-pocket cost and on those characteristics for which the data are the most reliable.

Although MEDSTAT's Marketscan database is one of the best sources of claims data available to researchers, I encountered some limitations specific to these data that should be noted. I handled some of these limitations by making assumptions about the variables in question and then analyzing these assumptions in my sensitivity analysis. With other limitations, no reliable assumptions could be made and this meant that certain variables were not included in my analyses. First, I could not easily distinguish between in-network and out-of-network services in the MEDSTAT data. This limitation is not uncommon to claims data, but it does mean that I was unable to formally test whether substitution is taking place between these services as level of cost-sharing relative to each service type changes.

Second, the data documentation was not always clear as to the meaning of the coding used for some variables. For example, for some employers, no information was provided on their EAP; however, the data documentation was not clear as to how these missing data points should be interpreted. Fortunately, I was able to determine with the assistance of MEDSTAT personnel that lack of data most likely means that an EAP, if available, played no role in the health plan coverage and its requirements. However, I was not able to determine whether EAP services in general were available at the worksite, and therefore I was not able to include variables related to EAP access beyond the precertification requirements. Another example is that data on out-of-network coinsurance rates were missing for some health plans. Again, data documentation did not provide clear information as to the meaning of these missing data elements. Discussions with MEDSTAT programmers indicated that these coinsurance rates were not mentioned in the plan booklet and no additional information was provided by the employer to MEDSTAT. Therefore, I made assumptions as to the value of the out-of-network coinsurance rates for individuals with missing data, and then I evaluated these assumptions in my sensitivity analysis.

Third, the data documentation often was not clear about the application of annual day or dollar limits on MH/SA service use. Although MEDSTAT's documentation provided additional detail on plan descriptions in their Research Databases User's Guide and Database Dictionary (MEDSTAT, 2000), for some plans the descriptions of annual limits for MH/SA visits and/or dollars did not clearly indicate whether MH/SA treatment visits or dollars were summed together and jointly applied towards a combined MH/SA annual limit or if visits and payments for MH care were counted separately from SA treatment. In most cases, data problems were due to the type and depth of information (or lack thereof) provided by participating employers to MEDSTAT. Furthermore, MEDSTAT staff were available to help with data issues. These data limitations are not unique to MEDSTAT data and can be found in other claims datasets. Even with its limitations, the detailed information contained in MEDSTAT's Marketscan® claims and enrollment data make it one of the more attractive insurance datasets to use for health services research and it provides a valuable opportunity to conduct research specific to MH/SA services.

Despite limitations, my results are noteworthy for several reasons. First, because of the detailed information on individuals' MH/SA coverage included in my data I am able to look beyond the simple question of whether having health insurance per se affects MH/SA utilization and focus on the effects of specific MH/SA health insurance characteristics on each stage of the utilization decision process. I am also able to look at health insurance characteristics beyond the standard price variables. My examination of EAP precertification is an important addition to the literature as EAPs continue to become more prevalent in the workplace and to expand their services as employers seek cost-effective ways to address employee problems.

Second, I am able to separately identify use of MH care and SA treatment for both outpatient and inpatient modalities. My results thus provide insights into the separate demand response for these four treatment modalities and allow comparisons among them. These comparisons suggest that policy makers and insurers should not necessarily lump MH care and SA treatment coverage together because demand responsiveness of these services to cost-sharing differ.

Finally, my analysis is performed on over 150,000 adults and over 75,000 children and young adults enrolled in 12 behavioral health plans and located across the U.S. Many of the previous health utilization studies that used claims data have been limited to examining levels of use among users because they do not have data on non-using enrollees. Furthermore, previous behavioral health utilization studies including those that use self-reported data have tended to use data from limited geographic areas or focused on a small number of health plans. Thus, the results of my study are applicable to a larger population. My results suggest that MH care demand is no more responsive to cost-sharing than general medical demand. However, the findings for SA treatment demand are mixed with the effect of cost-sharing differing across the samples. Still, even with these mixed findings, my results suggest that in determining coverage for behavioral health services MH care and SA treatment should be considered separately. Furthermore, because demand response relative to cost-sharing varies across the two decision stages, equal attention must be placed on evaluating the importance of both the initial decision to use and on the extent of utilization.

Research Implications

My analyses for this study suggest several areas for continued research in the field of MH care and SA treatment. First, the positive coefficient on the out-of-network coinsurance rate raises questions as to whether substitution is occurring between in-network and out-of-network services. Although the data used for this study do not easily lend themselves to analysis of this question, this is an area of research that requires further study. Most health plans allow use of out-of-network services, but this access comes at a higher cost to the individual usually in the form of higher coinsurance rates or more stringent annual limits on use. Given that it is more costly, the question arises as to why an individual might choose out-of-network services and to what extent is this choice occurring? As noted earlier, other factors may influence the individual—such as quality or convenience—which may lead them to choose an out-of-network provider, however research is needed to test these hypotheses and to evaluate other factors that may be affecting this decision.

Another area for future research concerns the role of the EAP. My finding that an EAP precertification requirement has a negative association with MH/SA utilization when significant suggests that more research is needed to better understand the role that the EAP plays in MH/SA health care, especially when it is coupled with health plan coverage. The blending of EAP services and health plan coverage is a fairly recent phenomenon that began with the introduction of the managed behavioral health care company and continues to grow today. However, little research has been done to examine the effect that such a pairing may have on overall MH/SA treatment utilization. As noted earlier, willingness to contact an EAP may be affected by fears of job loss or social stigma perceptions. Therefore, requiring employees and their dependents to contact the workplace EAP to obtain authorization for MH/SA services may create unintended obstacles for those individuals in need of services. On the other hand, use of the EAP may decrease utilization in the formal health care system by providing employees' and their dependents with some MH/SA services. Taken together, these findings suggest that more research is needed to understand the different roles that an EAP may take in the provision of MH/SA services for individuals connected to the labor market and the impact that each of these roles may have on MH/SA service utilization.

More research is also needed examining the effect of additional MH/SA health insurance characteristics on MH/SA service use. For this study, I chose to focus on coinsurance rates and the EAP precertification requirement as a first step in a study of the relationship between specific MH/SA health insurance coverage and service utilization. However, this is just a first step. Rather than relying on coinsurance rates as a means to control utilization, health plans are increasingly turning to other mechanisms such as annual limits on the number of visits covered, limits on lengths of treatment episodes, and annual dollar limits on plan payments to control utilization and costs. The impact of these types of mechanisms need further study, especially in the field of SA treatment. It is not uncommon for private insurance to limit the number of MH/SA outpatient visits to between 20 and 30 visits per year and inpatient days to 30 days per year—limits that may be below the threshold limits that are often cited as being appropriate to achieve successful treatment outcomes. For example, the threshold program length is one year for methadone maintenance and 3 months for residential rehabilitation (Simpson and Joe, 2004). An obvious question to ask is: what happens to those individuals whose treatment needs extend beyond the health plan coverage? And, how prevalent is this problem; that is, for how many individuals do we observe such limits creating obstacles for appropriate levels of treatment?

Finally, although my study focuses on individuals less than 65 years of age, I believe that as the baby boomer cohort continues to age into a managed care Medicare system, we need to continue to extend our research to this aging population. Although use of illicit drugs such as heroin and cocaine are less prevalent among older individuals, we do observe abuse of alcohol and prescription drugs. Most of these individuals have limited financial resources and, therefore, Medicare and other supplemental coverage for health care plays an important role in their decisions regarding MH/SA treatment utilization.

Appendix A

Codes Used in Identifying MH/SA Encounters

Table A-1. Variables Used to Categorize Encounters

Variable Type	Description
Diagnosis Codes	Diagnosis codes use the International Classification of Disease, 9th Division, Clinical Modifications (ICD-9-CM) classification system. For each outpatient encounter, there are up to 2 possible diagnosis codes reported. For each inpatient admission, there may be a principal diagnosis code and up to 14 secondary diagnosis codes reported.
Procedure Codes	Procedure codes use three possible coding systems. The most prevalent is the Current Procedural Terminology, 4th Edition (CPT-4). Less prevalent are the ICD-9-CM procedure codes and the Healthcare Common Procedural Coding System (HCPCS). For each outpatient encounter, there may be up to one procedure code reported. For each inpatient encounter, there may be 14 procedure codes reported.
Service Type (outpatient encounters only)	Service type refers to the type of outpatient claim. For each outpatient encounter, there may be up to one service type reported. The service type codes are mapped from benefit plan carriers' specific coding to MEDSTAT common values. This variable is not available for inpatient admissions.
Provider Type (outpatient encounters only)	Provider type refers to the type of provider providing the service. Provider types include facilities, physicians, and other provider types. For each outpatient encounter, there may be up to one provider type reported. The provider type codes are mapped from benefit plan carriers' specific coding to MEDSTAT common values. This variable is not available for inpatient admissions.
Major Diagnostic Code	For both inpatient admissions and outpatient encounters, a major diagnostic code (MDC) may be reported. The MDC represents the body-system or disease related groupings of clinical conditions, based on diagnosis codes. These codes were assigned by MEDSTAT using DRG grouper 14.0.
Diagnosis-related group (inpatient admissions only)	The diagnosis-related groups (DRGs) represent clinically and statistically distinct categories for inpatient care. DRG codes were developed for HCFA as a proxy for resources to treat a patient. These codes were assigned by MEDSTAT using DRG grouper 14.0. This variable is not available for outpatient encounters.

Table A-2. Diagnosis Codes for Mental Health Care and Substance abuse Services

Description	ICD-9-CM Codes
Mental Health Disorders	
Serious Mental Illnesses (SMI)	
Schizophrenic disorders	295.0–295.95
Major depressive Disorders	296.2–296.36
Other affective psychoses	
Manic disorders	296.0–296.16
Bipolar affective disorders	296.4–296.7
Other and unspecified manic-depressive pyschoses	296.8–296.89
Other and unspecified affective psychoses	296.9–296.99
Other psychoses	
Transient organic psychotic conditions	293–293.9
Other organic psychotic conditions, chronic	294–294.9
Paranoid states or delusional disorders	297–297.9
Other non-organic psychoses	298–298.9
Psychoses with origin specific to childhood	299–299.91
Other Mental Illness (OMI)	
Stress and adjustment disorders	
Acute reaction to stress	308–308.9
Adjustment reaction	309–309.9
Personality disorders	301–301.12, 301.2–301.9
Childhood disorders	
Disturbance of conduct; not elsewhere specified	312–312.9
Disturbance of emotions, specific to childhood and adolescence	313–313.22
Hyperkinetic syndrome of childhood	314–314.9
Other mood disorders and anxiety	
Neurotic disorders	300–300.9
Cyclothymic disorder	301.13
Depressive disorder, not elsewhere specified	311
Other mental disorders	
Sexual deviations and disorders	302–302.9
Physiological malfunction arising from mental factors	306–306.9
Special symptoms or syndromes, not elsewhere specified	307–307.9
Specific non-psychotic mental disorders due to organic brain damage	310–310.9
Psychotic factors associated with diseases specified elsewhere	316
Mental disorders in pregnancy, antepartum, postpartum	648.4–648.44

Table A-2. Continued

Description	ICD-9-CM Codes
Substance Use/Abuse Disorders	
Any Alcohol Diagnosis	
Alcoholic psychoses	291–291.9
Alcohol dependence/nondependent abuse	303–303.93
Alcohol abuse	305.0–305.03
Alcohol screening	V791
Any Drug Diagnosis	
Drug psychoses	292–292.9
Drug dependence/nondependent abuse	304–304.93, 305
Drug abuse	305.1–305.93
Drug dependence in pregnancy, antepartum, and postpartum	6483–6483.4

Table A-3. Procedure Codes for Mental Health and Substance Abuse Services

Description	ICD-9-CM Codes
CPT-4 Codes for Mental Health Services	
Psychiatric diagnostic interview examination	90801
Interactive psychiatric diagnostic interview examination	90802
Psychotherapy in an office or other outpatient facility setting	90804–90809
Interactive psychotherapy in an office of other outpatient facility setting	90810–90815
Psychotherapy in an inpatient or residential facility setting	90816–90822
Interactive psychotherapy in an inpatient or residential facility setting	90823–90829
Individual medical psychotherapy by a physician	90841–90844
Psychoanalysis	90845
Family psychotherapy	90846, 90847
Multiple-family group psychotherapy by a physician	90849
Group psychotherapy	90853
Interactive individual psychotherapy	90855
Interactive group psychotherapy	90857
Medication management	90862
Electroconvulsive therapy	90870, 90871
Narcosynthesis	90865
Psychophysiological therapy	90875, 90876
Hynotherapy	90880
Environmental manipulation	90882
Psychiatric evaluation of records	90885
Family consultation	90887
Report preparation	90889
Psychiatric service/therapy	90899
Psychological testing	96100, G0115
Psychosocial consultation	G0114
Psychosocial counsel	G0116
Intensive outpatient psychiatric services	S9480
Crisis intervention mental health services	S9485
Clinical psychologist services	AH
Clinical social worker services	AJ
ICD-9 Procedure Codes for Mental Health Services	
Psychiatric interviews, consultations, and evaluations	94.0–94.11
Psychiatric somatotherapy	94.2–94.29
Individual psychotherapy	94.3–94.39
Psychotherapy and counseling	94.4–94.44
Referral for psychologic rehabilitation	94.5–94.52, 94.55, 94.59
Other counseling	94.49

Table A-3. Continued

Description	ICD-9-CM Codes
CPT-4 Procedure Codes for Substance Abuse Services	
Methadone	83840
ICD-9 Procedure Codes for Substance Abuse Services	
Alcohol and drug rehabilitation and detoxification	94.6–94.69
Substance abuse counseling	94.45, 94.46
Referral for substance abuse rehabilitation	94.53, 94.54

Table A-4. Provider and Service Codes for Mental Health and Substance abuse Services

Description	CPT-4 Codes
Mental Health Services	
Provider Type	
Mental health facilities	21
Psychiatry	83
Psychologist	171
Service Type	
Psychiatric, not elsewhere coded (NEC)	101
Psychiatric day/night care	104
Psychiatric exam/testing	105
Individual psychiatric therapy	106
Group psychiatric therapy	107
Substance Abuse Treatment Services	
Provider Type	
Chemical dependency treatment center	22
Service Type	
Substance abuse, (NEC)	102
Detoxification	103
Mental Health/Substance Abuse Services (Indistinguishable)	
Provider Type	
Mental health/chemical dependency, (NEC)	20
Mental health/chemical dependency day care	23
Service Type	
Psychiatric/Substance Abuse, (NEC)	100

Table A-5. Major Diagnostic Group and Diagnosis-Related Groups for Mental Health and Substance Abuse Services

Description	ICD-9-CM Codes
Major Diagnostic Group	
Mental Diseases and Disorders	19
Alcohol/Drug Use and Alcohol/Drug Induced Organic Mental Disorders	20
Diagnosis-Related Group	
OR Procedure with Principal Diagnosis of Mental Illness	424

Appendix B

Sample Characteristics for Users of MH/SA Treatment Services

Table B-1. Mean Sociodemographic Characteristics of MH Care Users by Sample

Variable	Mean (proportions unless specified) (standard deviation)		
	Primary Beneficiaries	**Spouses**	**Other Dependents (e.g., children)**
Number of Observations	*7,269*	*3,490*	*4,080*
Number Unique Individuals	*5,507*	*2,683*	*3,121*
Male	0.417	0.244	0.561
	(0.493)	(0.429)	(0.496)
Age (years)	43.283	44.282	14.937
	(10.024)	(9.461)	(5.802)
Not Married	0.466	0.052	1.000
	(0.499)	(0.222)	(0.000)
Household Size	2.559	3.404	4.164
(*number of persons on policy)*	(1.494)	(1.284)	(1.228)
Located in:			
Northeast	0.101	0.095	0.093
	(0.302)	(0.294)	(0.291)
South	0.210	0.219	0.200
	(0.407)	(0.440)	(0.400)
Midwest	0.471	0.472	0.512
	(0.499)	(0.499)	(0.500)
West	0.127	0.113	0.102
	(0.333)	(0.316)	(0.302)
Region Unknown	0.090	0.101	0.093
	(0.287)	(0.301)	(0.290)
Employment Characteristics of Primary Beneficiary Employee Type			
Salary	0.515	0.531	0.616
	(0.500)	(0.499)	(0.486)
Hourly	0.248	0.227	0.200
	(0.432)	(0.419)	(0.400)

Table B-1. Continued

Variable	Mean (proportions unless specified) (standard deviation)		
	Primary Beneficiaries	**Spouses**	**Other Dependents (e.g., children)**
Other Status	0.237	0.242	0.184
	(0.425)	(0.428)	(0.387)
Industry of Primary Beneficiary			
Manufacturing	0.231	0.228	0.190
	(0.421)	(0.420)	(0.392)
Transportation	0.356	0.410	0.391
	(0.479)	(0.492)	(0.488)
Service	0.413	0.362	0.419
	(0.492)	(0.481)	(0.493)

Table B-2. Mean Sociodemographic Characteristics of SA Treatment Users by Sample

Variable	Mean (proportions unless specified) (standard deviation)		
	Primary Beneficiaries	**Spouses**	**Other Dependents (e.g., children)**
Number of Observations	*365*	*169*	*262*
Number Unique Individuals	*318*	*148*	*225*
Male	0.685	0.651	0.721
	(0.465)	(0.478)	(0.449)
Age (years)	42.578	42.432	18.725
	(9.677)	(9.119)	(4.028)
Not Married	0.518	0.041	1.000
	(0.500)	(0.200)	(0.000)
Household Size	2.485	3.408	4.084
(*number of persons on policy)*	(1.442)	(1.293)	(1.395)
Located in:			
Northeast	0.090	0.112	0.076
	(0.287)	(0.317)	(0.266)
South	0.296	0.225	0.168
	(0.457)	(0.419)	(0.375)
Midwest	0.397	0.503	0.603
	(0.490)	(0.501)	(0.490)
West	0.132	0.077	0.073
	(0.338)	(0.267)	(0.260)
Region Unknown	0.085	0.083	0.080
	(0.279)	(0.276)	(0.272)
Employment Characteristics of Primary Beneficiary Employee Type			
Salary	0.337	0.479	0.683
	(0.473)	(0.501)	(0.466)
Hourly	0.397	0.349	0.187
	(0.490)	(0.478)	(0.391)

Table B-2. Continued

Variable	Mean (proportions unless specified) (standard deviation)		
	Primary Beneficiaries	Spouses	Other Dependents (e.g., children)
Other Status	0.266 (0.442)	0.172 (0.378)	0.130 (0.337)
Industry of Primary Beneficiary			
Manufacturing	0.258 (0.438)	0.166 (0.373)	0.122 (0.328)
Transportation	0.452 (0.498)	0.396 (0.491)	0.359 (0.481)
Service	0.290 (0.455)	0.498 (0.498)	0.519 (0.501)

Table B-3. Mean MH/SA Insurance Characteristics of MH Care Users by Sample

Variable	Mean (standard deviation)		
	Primary Beneficiaries	**Spouses**	**Other Dependents**
Number of Observations	*7,269*	*3,490*	*4,080*
Number Unique Individuals	*5,507*	*2,683*	*3,121*
Coinsurance Rates for MH Visit			
Outpatient In-network	8.915	8.539	8.334
	(11.874)	(11.615)	(9.544)
Inpatient In-network	5.656	5.599	5.218
	(7.469)	(7.695)	(7.680)
Outpatient Out-of-Network	80.538	77.007	80.084
	(24.300)	(25.055)	(24.601)
Inpatient Out-of-Network	77.011	74.020	78.794
	(26.970)	(26.958)	(25.637)
Coinsurance Rates for SA Visit			
Outpatient In-network	7.306	7.324	7.764
	(8.257)	(8.817)	(8.062)
Inpatient In-network	5.899	6.218	5.571
	(8.367)	(9.759)	(8.938)
Outpatient Out-of-Network	80.874	78.240	80.778
	(24.445)	(25.135)	(24.561)
Inpatient Out-of-Network	77.416	75.052	79.382
	(26.937)	(26.975)	(25.543)
EAP Precertification Required (proportion)	0.169	0.154	0.135
	(0.375)	(0.361)	(0.342)
Total months enrolled in given year	11.197	11.317	11.377
	(1.988)	(1.830)	(1.768)

Table B-4. Mean MH/SA Insurance Characteristics of SA Treatment Users by Sample

Variable	Mean (standard deviation) Primary Beneficiaries	Spouses	Other Dependents
Number of Observations	*365*	*169*	*262*
Number Unique Individuals	*318*	*148*	*225*
Coinsurance Rates for MH Visit			
Outpatient In-network	8.164	10.000	8.570
	(11.468)	(11.339)	(9.311)
Inpatient In-network	7.233	6.450	3.321
	(8.002)	(8.263)	(6.784)
Outpatient Out-of-Network	76.355	83.730	82.538
	(24.965)	(23.337)	(24.623)
Inpatient Out-of-Network	74.274	80.414	81.183
	(26.682)	(26.443)	(25.381)
Coinsurance Rates for SA Visit			
Outpatient In-network	7.562	8.639	7.580
	(9.824)	(8.305)	(6.522)
Inpatient In-network	7.315	6.805	3.435
	(8.282)	(9.410)	(7.300)
Outpatient Out-of-Network	77.730	84.517	82.729
	(24.627)	(23.061)	(24.563)
Inpatient Out-of-Network	74.411	81.006	81.374
	(26.685)	(26.314)	(25.333)
EAP Precertification Required (proportion)	0.195	0.166	0.103
	(0.396)	(0.373)	(0.305)
Total months enrolled in given year	10.860	11.183	11.294
	(2.464)	(2.040)	(1.942)

Table B-5. Mean MH/SA Utilization Characteristics for MH Care Users by Sample

Variable	Mean (standard deviation) Primary Beneficiaries	Spouses	Other Dependents
	7269	*3490*	*4080*
	5507	*2683*	*3121*
Proportion of Users with:			
At least one day of outpatient SA services	0.018	0.015	0.027
	(0.133)	(0.121)	(0.163)
At least one day of outpatient MH services	0.997	0.995	0.994
	(0.056)	(0.072)	(0.078)
At least one day of outpatient medical services	0.897	0.907	0.835
	(0.303)	(0.291)	(0.371)
At least one day of inpatient SA services	0.004	0.003	0.005
	(0.065)	(0.056)	(0.072)
At least one day of inpatient MH services	0.027	0.029	0.051
	(0.163)	(0.168)	(0.221)
At least one day of inpatient medical services	0.089	0.115	0.045
	(0.285)	(0.319)	(0.207)
By provider type			
At least one day of SA services from MH/SA specialty provider	0.011	0.007	0.014
	(0.104)	(0.086)	(0.116)
At least one day of SA services from non-specialty provider	0.019	0.016	0.029
	(0.137)	(0.127)	(0.167)
At least one day of MH services from MH/SA specialty provider	0.680	0.630	0.646
	(0.467)	(0.483)	(0.478)

Table B-5. Continued

Variable	Mean (standard deviation) Primary Beneficiaries	Spouses	Other Dependents
At least one day of MH services from non-specialty provider	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)
By diagnosis type			
At least one day of MH services for depression	0.265 (0.441)	0.244 (0.429)	0.135 (0.341)
At least one day of services for serious mental illness	0.079 (0.269)	0.087 (0.282)	0.079 (0.270)
At least one day of services for other mental illness	0.803 (0.398)	0.793 (0.405)	0.902 (0.297)
At least one day of services for alcohol treatment	0.012 (0.111)	0.009 (0.097)	0.014 (0.118)
At least one day of services for drug treatment	0.008 (0.090)	0.008 (0.091)	0.018 (0.132)
Total Annual Days of Outpatient Use			
MH Care Services	9.024 (11.422)	8.194 (10.785)	7.379 (9.624)
SA Treatment Services	0.133 (1.621)	0.068 (0.868)	0.185 (1.933)
General Medical Care Services	10.559 (14.399)	11.262 (14.741)	5.617 (8.587)

Table B-6. Mean Utilization Characteristics for SA Treatment Users by Sample

Variable	Mean (standard deviation)		
	Primary Beneficiaries	**Spouses**	**Other Dependents**
	365	*169*	*262*
	318	*148*	*225*
Proportion of Users with:			
At least one day of outpatient SA services	0.962 (0.191)	0.935 (0.247)	0.947 (0.225)
At least one day of outpatient MH services	0.373 (0.484)	0.325 (0.470)	0.435 (0.497)
At least one day of outpatient medical services	0.784 (0.412)	0.781 (0.415)	0.824 (0.381)
At least one day of inpatient SA services	0.167 (0.374)	0.166 (0.373)	0.145 (0.353)
At least one day of inpatient MH services	0.077 (0.266)	0.065 (0.247)	0.134 (0.341)
At least one day of inpatient medical services	0.134 (0.341)	0.154 (0.362)	0.088 (0.284)
By provider type			
At least one day of SA services from MH/SA specialty provider	0.488 (0.500)	0.521 (0.501)	0.492 (0.501)
At least one day of SA services from non-specialty provider	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)

Table B-6. Continued

Variable	Mean (standard deviation)		
	Primary Beneficiaries	Spouses	Other Dependents
At least one day of MH services from MH/SA specialty provider	0.260 (0.439)	0.231 (0.423)	0.378 (0.486)
At least one day of MH services from non-specialty provider	0.381 (0.486)	0.337 (0.474)	0.447 (0.498)
By diagnosis type			
At least one day of MH services for depression	0.134 (0.341)	0.107 (0.309)	0.149 (0.498)
At least one day of services for serious mental illness	0.299 (0.458)	0.284 (0.452)	0.336 (0.473)
At least one day of services for other mental illness	0.058 (0.233)	0.041 (0.200)	0.092 (0.289)
At least one day of services for alcohol treatment	0.658 (0.475)	0.740 (0.440)	0.473 (0.500)
At least one day of services for drug treatment	0.397 (0.490)	0.355 (0.480)	0.531 (0.500)
Total Annual Days of Outpatient Use			
MH Care Services	3.591 (8.164)	3.598 (8.717)	4.950 (9.445)
SA Treatment Services	6.693 (9.658)	5.698 (8.437)	5.359 (7.783)
General Medical Care Services	7.748 (12.278)	9.112 (14.051)	5.023 (7.391)

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