MEDICAL COST OFFSET EFFECT AND ABSENTEEISM IN LONGITUDINAL SAMPLES OF DEPRESSED PULMONARY AND CANCER PATIENTS

By

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To my mother and father

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An intervention that reduces or prevents usual costs to the health care system is called a medical cost offset or the cost offset effect. Past research shows a medical cost offset effect; however, more recent work does not. The purpose of this study was to examine the effects of mental health treatment on health care expenditures and absenteeism in samples of depressed patients with or without comorbid pulmonary conditions or cancer, as well as a general depression group. This study attempted to provide a current assessment of the medical cost offset effect from mental health services. Additionally, this study attempted to provide a more comprehensive examination of mental health treatment effects by including workplace absenteeism as an outcome. The research questions examined in this study were (1) whether total, medical, or drug expenditures were higher for individuals undergoing mental health treatment and whether expenditures reduced over time, (2) whether emergency room, inpatient, outpatient, or office-based provider visits were higher for individuals undergoing mental health treatment and whether utilization decreased over time, and (3) whether work absenteeism rates are lower for individuals undergoing mental health treatment.

Data were obtained from the Medical Expenditure Panel Survey (MEPS), a nationally representative survey of the US non-institutionalized, civilian population. Results demonstrate

that total expenditures were greater for each treatment group and medical expenditures were greater for only the depression general treatment group. Total emergency room visits, inpatient visits, outpatient visits, and office-based provider visits were all greater for the treatment groups than the no treatment group. No treatment group had a significant change in expenditures over time. Mental health treatment only impacted change for inpatient visits for the pulmonary and cancer diagnoses groups. With respect to work absenteeism, mental health treatment was associated with increased absenteeism rates for the general depression group, but the pulmonary and cancer diagnoses groups showed no differece in work absenteeism between mental health treatment and no treatment.

CHAPTER 1
INTRODUCTION

Overview

The health care system in the United States is in a state of fiscal crisis. Total health care expenditures are estimated to be $2.16 trillion in 2006, and are projected to rise to over $4 trillion by 2015 (Borger et al., 2006). There are many reasons for the rise in health care expenditures, one of which is the increase in the number of individuals with chronic diseases. With the aging of the population, chronic diseases have risen dramatically in recent years (World Health Organization [WHO], 2006). By 2040, almost 160 million people will have a chronic condition (The Robert Wood Johnson Foundation, 1996). In 1995, the cost of medical care for Americans with chronic conditions was $470 billion and by 2040, the cost is projected to be as high as $864 billion. In a report by the Agency for Healthcare Research and Quality (AHRQ), the five most expensive types of chronic conditions in 2000 and 2004 were cardiac conditions, trauma-related disorders, cancer, pulmonary conditions, and mental disorders (Soni, 2007). In addition to costing the health care system, chronic conditions result in economic losses in the workplace (Lamb et al., 2006).

Depression is a particularly debilitating condition that, when comorbid with medical conditions, increases health care costs and workplace economic losses (Himmelhoch et al., 2004; Druss, Rosenheck, & Sledge, 2000). A question then becomes whether treating depression can help reduce the financial burden of the condition. The present study examined whether treating depression could result in reductions in health care expenditures and negative work outcomes.

Purpose of the Present Study

The purpose of the present study was to examine the effects of mental health treatment on health care expenditures and absenteeism in a sample of depressed patients with or without

comorbid pulmonary conditions or cancer. This study attempted to provide a current assessment of the medical cost offset effect from mental health services and to provide solutions to limitations apparent in previous studies. Additionally, this study attempted to provide a more comprehensive examination of mental health treatment effects by including workplace absenteeism as an outcome.

CHAPTER 2
LITERATURE REVIEW

Cost of Depression

Estimates of the lifetime prevalence of depression from the National Comorbidity Survey of the US population aged 15-54 is reported to be 15 percent for major depression and 10 percent for subthreshold depression (i.e., 2-4 depression symptoms present) (Kessler et al., 1997). The National Epidemiologic Survey of Alcoholism and Related Conditions (NESARC), which collected data in 2001 and 2002 on the civilian, noninstitutionalized US population aged 18 years and older, reported that the lifetime and 12-month estimates of major depressive disorder were 13 percent and 5 percent, respectively (Hasin et al., 2005). A World Bank study that estimated current and projected patterns of mortality and disability from disease and injury for all regions of the world reported that depression ranked as the fourth highest disabling condition in 1990 and it was projected that depression will rank second by 2020 (Murray & Lopez, 1996).

Depression has an impact on health care expenditures. It is estimated that health care costs tend to be approximately 50 percent higher for those with depression compared to those without depression (Himmelhoch et al., 2004). One study that examined the accounting records of a large health maintenance organization (HMO) revealed that patients diagnosed with depression had higher annual health care costs and higher costs for all categories of care (e.g., primary care, medical specialty, medical inpatient, pharmacy, and laboratory) than patients without depression (Simon, Von Korff, & Barlow, 1995). In a study of 46,000 employed persons, in which factors predicting increases in medical costs were examined, depression accounted for the largest increase in medical costs (Goetzel et al., 1998).

Not only does depression increase medical utilization, it is associated with work impairment. Major depression was found to be only one of seven conditions related to reduced

performance at work (Wang et al., 2004). In an analysis of the economic costs of depression that included direct medical costs, lost wages from suicide, and workplace productivity, it was estimated that depression costs totaled $83.1 billion in 2000. Workplace costs accounted for 62 percent of this total (Greenberg et al., 1998).

Studies demonstrated that depression reduces task focus and productivity (Wang et al., 2004) and employees with depression had greater job performance deficits than employees with a chronic medical condition (Adler et al., 2006). Not only does depression impact performance on the job, depression can result in missed work days, or absenteeism. An analysis of two national surveys revealed that workers who were depressed had between 1.5 and 3.2 more days absent in a month than workers without depression (Kessler et al., 1999). The salary-equivalent disability costs of these absences ranged from $182 to $395 for each depressed employee. Workers with depression have demonstrated more absenteeism than employees with chronic medical conditions (Lerner et al., 2004). However, the combination of depression and chronic medical conditions has an even greater impact on work impairment. It is estimated that employees with depression and comorbid conditions cost 1.7 times more for employers than those with only depression or a medical condition (Druss, Rosenheck, & Sledge, 2000).

The Medical Cost Offset Effect

An intervention that reduces or prevents usual costs to the health care system is termed a medical cost offset effect or cost offset effect. Numerous studies have attempted to ascertain a medical cost-offset effect of mental health care in patients with psychological conditions. One of the first offset studies was conducted by Follette and Cummings (1968). The medical records of 152 randomly selected adults who sought psychological services were examined. Data on their health services utilization were collected one year prior to the beginning of psychological treatment, as well as five years following treatment. Comparing the data to a group matched for

age, sex, socioeconomic status, and medical utilization rates who had not received psychological treatment, it was found that this comparison group had higher health care utilization rates over time, in addition to a reduction in health care utilization for the group receiving psychological treatment.

Following the Follette and Cummings (1968) study, a series of cost-offset studies were conducted. In 1984, Mumford and colleagues (1984) published a study that described two analyses of the medical cost offset effect. One analysis was conducted on Blue Cross Blue Shield Federal Employee Plan claims from 1974 to 1978, and the other analysis was conducted on 58 published studies. Both the Blue Cross Blue Shield analysis and the literature review showed that the medical cost offset effect was more pronounced for older persons and the largest cost offsets were from a reduction in inpatient days. Of the 58 studies reviewed in the second analysis, 85 percent of the studies found a cost-offset effect.

In another meta-analysis of 91 studies from 1967 to 1997, 90 percent of the studies reported a reduction in medical utilization following mental health interventions (Chiles, Lambert, & Hatch, 1999). Twenty-eight articles reported dollar savings and 31 percent of these studies reported savings even after taking into account the cost of mental health treatment. Overall, a savings of about 20 to 30 percent was reported across the articles. The effect was most evident for behavioral medicine and psychoeducational interventions. Hunsley (2003) examined this meta-analysis and reported that it would take 2,694 studies averaging null effects to conclude that results were due to sampling bias.

Despite the evidence supporting the cost offset effect, several studies provide evidence against the effect. The Medical Outcomes Study involved 22,000 outpatients who were screened for several chronic conditions, including depression, and these patients were followed over the

course of four years (Wells et al., 1996). The study examined the health and cost outcomes for depressed individuals who received appropriate mental health treatment, either counseling or medication, according to clinical practice guidelines. The study produced no evidence of reduced inpatient or outpatient services. The researchers observed that effective mental health care that improves patient functioning tends to be more expensive than no mental health treatment or inadequate mental health treatment.

The Fort Bragg Evaluation Project involved data collection of children and their families over seven occasions to evaluate the effectiveness of comprehensive mental health services to children and adolescents (Bickman, 1996). The Fort Bragg Evaluation Project was designed to provide evidence for a continuum model of care and improve the quality of mental health care for children and adolescents in a comprehensive mental health system. The Fort Bragg study offered outpatient therapy, day treatment, in-home counseling, therapeutic foster homes, specialized group homes, 24-hour crisis management services, and acute hospitalization to those in the intervention group. The comparison group consisted of families who were responsible for coordinating their own care and did not have access to Fort Bragg services. The study findings revealed that mental health expenditures were much higher for children who received comprehensive care at Fort Bragg and this rise in cost was not offset by cost savings elsewhere.

Studies published after Chiles et al.'s (1999) meta-analysis have not produced promising results for the medical cost offset effect. In two related studies examining the medical utilization of patients with or without psychological symptoms, it was found that depressed and anxious patients who saw a mental health provider had significantly more medical visits, emergency room visits, and medical outpatient visits than patients with depression or anxiety who had not seen mental health providers (Carbone et al., 2000). There were no significant differences in

medical costs between patients seeing mental health providers and those who had not. However, both studies did not control for illness severity or comorbid medical or psychiatric conditions. The patients in both studies had a relatively young median age and one of the two studies had a small sample size. These factors may have made medical cost-offset effects more difficult to demonstrate.

In a two-year longitudinal study comparing adults who had major depression who had remitted, improved but not remitted, or remained depressed, there were no significant differences in total health services cost among the groups in year one (Simon et al., 2000). However, cost savings for patients with improved outcomes in year two showed a reduction that was marginally significant, suggesting that the medical cost offset effect may become apparent over longer periods. The pattern of cost differences for each group was similar for the categories of cost examined in the study (specialty mental health care, outpatient visits, and prescriptions). The study sample was derived from HMO clinics, which has implications for cost offset effects. Because managed care restrictions reduce length of treatment and introduces a ceiling on the amount of money spent on medical care, it becomes more difficult to demonstrate the medical cost offset effect because there is less money to be saved (Otto, 1999).

Another study of patients receiving treatment under managed care demonstrated that patients who received mental health treatment had the highest proportion of medical services for a mental disorder and a greater proportion of pharmacy claims for all medications (Azocar et al., 2003). There were no significant differences in medical expenditures before, during, or after mental health treatment in this sample.

In summary, past meta-analyses demonstrate that the medical cost offset effect was evident with greatest cost savings from inpatient days. Other studies published after the meta-analyses

reveal no evidence of a medical cost-offset effect in the form of either no difference between treated and untreated groups or higher expenditures for treated groups.

Depression Treatment and Absenteeism

From a financial standpoint, it is in the best interest of both employees and employers for employee absenteeism rates (i.e., number of days of missed work) to be as low as possible. Given the demonstrated negative impact of depression on absenteeism, employers would likely want to know whether absenteeism could be reduced when depressed employees are treated for their depression. In a study examining factors that predict absenteeism in depressed patients, it was found that rates of absenteeism were indeed greater for untreated depressed workers than for treated workers (Souetre, Lozet, & Cimarosti, 1996).

One of the first studies examining whether reduced absenteeism as a result of depression treatment offset the cost of the treatment, interviewed workers with depression over the course of a year and examined provider and insurance records (Zhang et al., 1999). The researchers calculated lost earnings from self-reported missed work days and hourly wage rates. They determined health care costs from charges recorded on billing and insurance records. The study found that the effect of depression treatment on net economic cost was non-significant. That is, the cost of depression treatment was not an additional economic burden to employers or employees. The cost of treatment was fully offset by the savings from reduced absenteeism.

More recent studies have examined the benefits of depression treatment on absenteeism using randomized controlled trials. One such study involved 12 community primary care practices, in which patients were randomized to enhanced or usual care (Rost, Smith, & Dickinson, 2004). The physicians and care managers in the enhanced care condition were trained in guideline-concordant pharmacotherapy or psychotherapy. Enhanced care involved psychoeducation, homework assignments, regular follow-up, adherence, and adjustment of

treatment if symptoms were not improving. Participants in the usual care condition did not receive ongoing intervention from the enhanced care treatment team, but were not prevented from seeking care on their own. Over the course of two years, clinicians in the enhanced care condition provided depression management to patients. Absenteeism rates were evaluated at baseline, 6, 12, 18, and 24 months. Results showed that patients in the enhanced care condition had 22.8 percent lower absenteeism rates (or 10.6 days) than usual care patients over two years. It was estimated that the reduction in absenteeism from the intervention provided an annual economic benefit of $619 per full-time employee.

Another randomized controlled trial involved a national sample of workers (Lo Sasso, Rost, & Beck, 2006). Participants were randomized to enhanced or usual care conditions, similar to the study design by Rost and colleagues (2004). It was demonstrated that when costs of intervention and treatment were taken into account, the economic net benefit to employers was $30 per worker in the first year and the net savings increased to $257 per worker in the second year of the study. This suggests that employers investing in treatment for their depressed workers may experience increased benefits over time.

The effects of mental health treatment for work outcomes are not unanimously positive. A 1.5-year randomized controlled trial examined the effects of a mental health intervention on sick leave duration, and mental and physical health status compared to usual care at three, six, and 18 months (Brouwers et al., 2006). The mental health intervention consisted of five individual 50-minute sessions over 10 weeks and was based on a problem-solving approach to depression treatment. The treatment was administered by a trained social worker using a treatment manual in which three phases were described. The first stage involved acknowledging the problem, the second stage involved making a list of problems and developing problem-solving strategies, and

the final stage focused on implementing the strategies identified in step two. The study found that there were no differences in any of the outcomes between the experimental group and the usual care group. Although participants in the intervention group reported high satisfaction with treatment, the results suggest that the problem-solving approach used in the study was not effective for improving depression outcomes.

Taken together, the aforementioned studies that utilized enhanced (guideline-based) care with medication and/or psychotherapy were shown to reduce absenteeism. The study that did not show a difference used a different approach and it subsequently did not show an effect on absenteeism or depression symptom improvement. Thus, although not reported by these studies, the reduction in absenteeism in the successful studies were likely a result of an improvement in patients' depression. Further studies will need to be done to add to the small body of existing literature.

CHAPTER 3
STUDY SIGNIFICANCE AND RESEARCH QUESTIONS

Significance of this study

There are several limitations in the research literature on the medical cost offset effect. First, when studies compare the costs of treated and untreated patients, there may be a selection bias in which samples are not comparable (Sturm, 2001). That is, patients who received treatment may have different characteristics than patients who did not receive treatment. If there is limited patient information in the data, the selection bias is particularly pronounced. This is particularly problematic with administrative datasets, which are computerized data collected for administrative purposes, such as data from insurance companies. In this study, the use of a large comprehensive dataset allowed for greater control of these potentially confounding variables, such as health status and comorbid medical conditions.

Second, cost offsets have traditionally been referred to as a general phenomenon that applies to all medical populations. Past medical cost offset research has not teased apart which medical populations benefit from psychological interventions with respect to reducing medical cost. When researchers aggregate diverse populations in medical cost offset research, real cost offset effects may be masked. That is, certain vulnerable populations that are high utilizers of medical services may overshadow the medical cost offset effects of other populations (Simon & Katzelnick, 1997). Thus, cost offset research must begin to focus on specific groups of patients because these patients may demonstrate a particular pattern of medical utilization based on common patient needs of the group. This study was a preliminary effort to identify specific cost offset effects in particular populations. In addition to comparing all depressed persons who are treated and untreated, additional populations of interest were pulmonary and cancer patients who have comorbid depression. These populations were chosen because they were among the top

five most expensive conditions in recent years (Soni, 2007). This study utilized a dataset drawn from a nationally representative sample of the US noninstitutionalized, civilian population. This allowed for greater generalizability of the study findings.

Third, rapid changes in healthcare financing and spending patterns necessitate frequent review of cost offset effects reflecting current pricing in pharmacological and medical treatments (Hunsley, 2003). Very few studies of the medical cost offset effect have been published after Chiles et al.'s (1999) meta-analysis. This study updates the literature by using data from 2000 to 2005 (converting cost to 2005 inflation rates), which is more indicative of current economic trends.

This study addressed the aforementioned limitations of the previous medical cost offset research. In addition, it offered insights into absenteeism. Culminating data suggests that treating workers with depression can reduce absenteeism rates. Few studies, however, have examined the effects of depression treatment in workers with comorbid chronic medical conditions. This population is important because the combination of depression with other medical illnesses tend to be more costly to employers than depression alone (Druss, Rosenheck, & Sledge, 2000). Including absenteeism as an outcome variable for the present medical cost offset study allowed for a more complete study of the effects of depression treatment on individuals with depression and a chronic medical condition. To date, few studies examine both medical cost offset and absenteeism in the same study.

Specific Aims and Hypotheses

Aim 1

To examine the relationship between mental health treatment and health care expenditures in samples of depressed patients with or without comorbid pulmonary conditions or cancer and a general depression group.

Hypothesis 1a

Patients receiving mental health treatment (psychotherapy and/or medication) will have lower total health care expenditures, lower medical expenditures, and the same or higher prescription drug expenditures than those who have a pulmonary diagnosis, a cancer diagnosis, and general depression without mental health treatment.

Hypothesis 1b

Patients receiving mental health treatment will have a negative change (decrease in expenditures over time) in total health care expenditures and medical expenditures from time 1 (the end of the first year of the study) to time 2 (the end of the second year of the study) for the pulmonary and cancer diagnoses groups, while the general depression group will have a positive or no change in expenditures. For prescription drug expenditures, it is expected that patients receiving mental health treatment will have a positive change in expenditures from time 1 to time 2 than patients who had not received mental health treatment.

Aim 2

To examine the relationship between mental health treatment and health care utilization in samples of depressed patients with or without comorbid pulmonary conditions or cancer and a general depression group.

Hypothesis 2a

Pulmonary diagnosis and cancer patients receiving mental health treatment will have fewer office-based provider visits, outpatient hospital visits, inpatient nights, and emergency room visits than patients who do not receive mental health treatment, while the general depression group will have a positive (increase) or no change in utilization.

Hypothesis 2b

Patients receiving mental health treatment will have a negative change (decrease) in office-based provider visits, outpatient hospital visits, inpatient nights, and emergency room visits from time 1 to time 2 compared to the pulmonary and cancer diagnosis group, while the general depression group will have a positive (increase) or no change in utilization.

Aim 3

To examine the relationship between mental health treatment and absenteeism in a sample of depressed patients with or without comorbid pulmonary conditions or cancer and a general depression group.

Hypothesis 3

Patients receiving mental health treatment will have fewer total work days missed than those who did not receive mental health treatment for each group (general depression, pulmonary diagnosis group, and the cancer diagnosis group).

CHAPTER 4
CONCEPTUAL MODELS

This study was based on two separate conceptual models. The first model related mental health treatment to health care utilization and health care expenditures and the second model related mental health treatment to absenteeism.

Mental Health Treatment, Health Care Utilization, and Health Care Expenditures

Without mental health treatment, depression is expected to increase health care expenditures through an increased need for medical services. The conceptual framework used in this study posits that mental health treatment for depression would result in reduced need for medical services, health care utilization, and in turn, reduced health care expenditures (Figure 4-1). Proposed mechanisms for how mental health care reduces health care utilization have been identified as the information and decision-support pathway, psychophysiological pathway, behavior change pathway, social support pathway, the undiagnosed psychiatric problem pathway, and the somatization pathway (Friedman et al., 1995). However, examining these pathways is beyond the scope of this study.

This study examined the relationship between mental health treatment and health care expenditures (total, medical, and prescription drug expenditures) in aim one. The relationship between mental health treatment and health care utilization (office-based provider visits, outpatient hospital visits, inpatient nights, and emergency room visits) was examined in aim two of the study.

Mental Health Treatment and Absenteeism

The presence of depression impacts one's mental health status, which in turn increases the number of days missed from work. The conceptual model for mental health treatment and absenteeism proposes that individuals with depression who receive treatment would demonstrate

a reduction in missed days from work. The reduction in missed work days is a result of an improvement in mental health status. However, mental health status also influences seeking mental health treatment (Pincus et al., 2001), creating a bi-directional relationship (Figure 4-2). For example, anhedonia, or a reduction in interest in previously pleasurable activities, may affect one's motivation to return to work as well as the decision to seek mental health treatment. This study examined the relationship between mental health treatment and number of days missed from work (absenteeism) in aim three.

Figure 4-1. Relationship between depression and health care expenditures with mental health treatment.

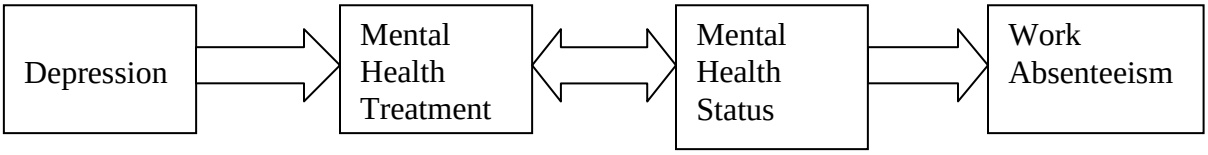

Figure 4-2. Relationship between mental health treatment and work absenteeism.

CHAPTER 5
DATA AND METHODS

Data Source

Data was obtained from a public database, the Medical Expenditure Panel Survey (MEPS), which is a nationally representative survey of the US non-institutionalized, civilian population, sponsored by the Agency for Healthcare Research and Quality (AHRQ). The MEPS began in 1996 and consists of a set of large-scale surveys of households and individuals, and respondents' medical providers and employers. The MEPS is a rich source of information on health services utilization, costs and payments of health services, and health insurance information of respondents.

The MEPS is composed of two main components: the Household Component (HC) and the Insurance Component (IC). The IC is a separate survey that provides data on employer-based health insurance. Due to the aims of this study, only data from the HC will be used. The HC provides data from a sample of families and individuals across the country drawn from a nationally representative subsample of households that were involved with the previous year's National Health Interview Survey. During the household interviews, MEPS collects information from each person in the household on demographic characteristics, health conditions, health status, use of medical care services, charges and payments, access to care, satisfaction with care, health insurance coverage, income, and employment. Data in the HC is supplemented by respondents' medical providers. The MEPS also includes psychological service information, such as whether or not respondents used psychotherapy or psychotropics. Psychological conditions can be identified in MEPS.

The HC interview consists of survey questionnaires covering specific topics that are administered by interviewers. Each section of the survey consists of a series of computer-

assisted personal interview (CAPI) computer screens with questions, interviewing instructions, and skip patterns based on specific topics. The MEPS HC has a panel design in which each panel of households is interviewed five times during a two-year period. During the second year of the original panel, a new sample is drawn to create a new panel. Thus, two separate panels are interviewed in the same year, which makes for an overlapping sampling design and increases the number of individuals interviewed each point in time (see Figure 5-1). The five-panel design of the survey allows researchers to determine how changes in respondents' use of services are related to cost of care and employment. This study combined MEPS data from the years 2000 to 2005 to assess the effect of mental health treatment on health care expenditures, health services utilization, and work absenteeism.

The MEPS oversamples some groups (e.g., minority groups), while undersampling others, and survey participants may either provide a partial response or no response. These factors reduce the national representation of the data. In order to account for these factors in the sample design, a sample weight for each case has been developed in MEPS to incorporate into the estimation processes. These sample weights were included in the analysis process in order to maintain the national representation of the survey.

Variables

This section describes the variables that were used in the regression analyses of this study. Dependent variables, independent variables, and covariates are described. Regression analysis uses variables with numerical values. Many of the variables used in this study are continuous (such as age), but some of the variables are categorical in nature (such as race). Since categorical variables do not have numerical values, they will be dummy coded in order to be used in the regression analyses.

Dependent Variables

Aim 1: Total health care expenditures, medical expenditures, and prescription drug expenditures

Health care expenditures were divided into three variables: total health care expenditures, medical expenditures, and prescription drug expenditures. Expenditures in MEPS are defined as the sum of direct payments for care provided during the year, including out-of-pocket payments and payments by private insurance, Medicaid, Medicare, and other sources. Not included in MEPS total expenditures are payments for over-the-counter drugs and for alternative care services, as well as indirect payments not related to specific medical events. Total expenditures were defined as total payments for all health care services included in MEPS (outpatient department visits, office-based medical provider visits, prescribed medicines, hospital inpatient visits, emergency room visits, home health, dental visits, and other medical expenses) and expenditures for psychological services were included in the total. The variable for total expenditures (totexp) will be obtained from the MEPS HC full year consolidated data file from the years 2000 to 2005.

Medical expenditures were defined as total payments for all health care services associated with medical conditions only. Put another way, any medical expense associated with a psychological condition were excluded from the calculation of the medical expenditure variable. The variable for medical expenditures was constructed by examining the MEPS HC events data files. All payments associated with a psychological condition identified by ICD-9 codes were identified and excluded from the total. The expenditures of every event that were not associated with a psychological condition were summed to create the variable for medical expenditures (medexp).

Prescription drug expenditures were defined as the sum of all amounts paid out-of-pocket and by third party payers for each prescription drug purchased. This variable was obtained from the MEPS HC full year consolidated data files.

When combining all five years of data (2000 to 2005), total expenditures, medical expenditures, and drug expenditures from 2000, 2001, 2002, 2003, and 2004 data were inflated to 2005 dollars using the consumer price index (CPI) for medical care (BLS, 2000-2005).

Aim 2: Health care utilization

Health services utilization was defined using four separate variables: total number of hospital outpatient visits (optotv), total hospital inpatient nights at discharge (ipngtd), total number of all emergency room visits (ertot), and total number of office-based provider visits (obtotv). Each of these variables were obtained from the MEPS HC full year consolidated data file.

Aim 3: Missed days from work

For analyses of absenteeism, the sample used were those employed over the course of data collection and only the working-age population (18-65) were included in the analyses. The variables indicating employment status (EMPST31, EMPST42, EMPST53) were obtained from the MEPS full year consolidated data file.

The variable representing absenteeism were obtained from two variables in the MEPS HC full year consolidated data files. The variables "# days missed work due to illness/injury" and "# days missed work stayed in bed" were combined for each person to create the variable for absenteeism (work).

Independent Variables

Mental health treatment (MHtx)

Mental health treatment was defined in this study as psychotherapy and/or antidepressant medications. Respondents who received psychotherapy were identified from two MEPS HC events files: office-based medical provider visit file and outpatient visit file. In the office-based medical provider visit file, the type of care a patient received was coded under several variables. Respondents will be considered to have undergone psychotherapy if the visit category was "psychotherapy/mental health counseling," if the medical provider type was "psychology," or if psychotherapy was coded "yes." In the MEPS HC prescribed medicines file, the presence of psychotropic medications was determined. If particular anti-depressant drugs are present under the category "medication name" (see Table 5-2), respondents were coded as taking antidepressant medications for depression. Antidepressants included classes of antidepressants, such as selective serotonin reuptake inhibitors and monoamine oxidase inhibitors, and anti-depressant drugs that are prescribed for depression. This variable (MHtx) will be used in all five hypotheses.

Depression Groups (Dep)

The sample of depressed individuals and those with pulmonary conditions or cancer were identified using the MEPS HC medical conditions data files. The medical conditions file codes each self-reported medical condition the individual experiences during the year. In MEPS, medical conditions are coded using the International Classification of Diseases, Ninth Revision (ICD-9). In order to preserve respondent confidentiality, the ICD-9 codes are collapsed from fully-specified codes to 3-digit code categories. Less than 10 percent of codes are collapsed further by combining two or more three-digit codes. The ICD-9 codes are also aggregated into clinically meaningful categories called classification codes (CC) that describe groupings of

similar conditions. This is done with the Clinical Classification Software and the groupings are based on the clinical significance of categories, accurate reporting from respondents, and the frequency of the reported condition.

For this study, depression was identified using ICD-9 code 311. Although ICD-9 code 296 corresponds to depression, it also includes individuals with bipolar disorder. Past research in which ICD-9 codes 296 and 311 were examined, over 90 percent of respondents had a code of 311, which corresponds to unspecified depression (Lee, unpublished Master's thesis). The large number of patients with ICD-9 code 311 suggests that respondents are likely self-reporting depression (as opposed to major depression), which then received a code of 311 instead of 296. Thus, ICD-9 code 311 was used to identify respondents with depression and ICD-9 code 296 will be excluded. The resultant variable Dep and MHtx was combined to identify individuals who have been treated for depression (Deptx), and those who have not been treated for depression (Depntx).

Pulmonary condition (Pulm) & Cancer (Canc)

Using the methodology of past research identifying spending and service use trends for various medical conditions in MEPS, pulmonary conditions were identified from the MEPS HC medical conditions file using CC 127-134 and cancer was identified using CC 11-45 (Soni, 2007) (see Table 5-1). Once all of the conditions were identified, pulmonary and cancer patients were coded as treated or not treated (pulmtx, pulmntx, canctx, cancntx). For all five hypotheses, treated and untreated samples were combined and dummy coded in order to allow for ease of comparison across conditions. The untreated group was the comparison group, and Deptx, Pulmtx, and Canctx were the variables to be examined in each hypothesis.

Covariates

Because some populations are at higher risk for poor health outcomes than others and thus, higher health care expenditures, it will be important to control for these differences to compare health outcomes among different patient populations (Iezzoni, 2003). Furthermore, data on the working-age population reveal key characteristics that would need to be controlled for in analyses predicting absenteeism (Haveman & Wolfe, 2000). The following variables that are described were included in the regression models (described and depicted in a later section) to control for differences among the study participants. This helped to reduce selection biases in the study design.

Age (Age)

Older persons generally have worse clinical outcomes than younger persons (Iezzoni, 2003); it is therefore important to control for age. This variable was obtained from the MEPS HC full year consolidated files. The individual's age in years at the end of the second year of data collection determined age for this study. In examining the hypotheses for aims one and two, individuals of all ages were included. Because the hypotheses for aim three addressed work with absenteeism as the dependent variable, only the working-age individuals (18 to 65) were included in the analyses, since the outcome variable relates to work.

Sex (Sex)

Sex is an important control variable because men and women face different risks for certain diseases. Among men and women 65 years of age and older, men have higher death rates than women for several chronic conditions (Anderson, 2002). Sex also predicts posthospitalization mortality (Keeler et al., 1990). This variable was obtained from the HC full year consolidated data file and will be dummy coded (0 = male, 1 = female). This variable was included in all five hypotheses.

Race (Racex)

Racial disparities in health care outcomes was also be taken into account in this study because differences in disease prevalence and mortality exist among the races (Iezzoni, 2003). Furthermore, among the working population, the rate of mental and physical disability for African Americans is almost twice than that for whites and Hispanics (Mashaw et al., 1996). The race variable will be obtained from the MEPS HC full year consolidated data file and race will be dummy coded into three separate variables (black, asian, and white) with other as the comparison variable. These variables will be included in all five hypotheses.

Hispanic (Hispan)

This variable was included in the analysis because there are differences in disability rates for Hispanics compared to non-Hispanics (Mashaw et al., 1996). This variable was obtained from the MEPS HC full year consolidated data file and the variable was dummy coded (0 = non-Hispanic, 1 = Hispanic). This variable was included in all five hypotheses.

Years of education (Educyear)

Because of socioeconomic disparities in health status and outcomes, there was a control for income and education factors (Braveman & Tarimo, 2002). More education is associated with fewer disabilities (Wolfe & Haveman, 1990). This variable was obtained from the MEPS HC full year consolidated files and represented number of years of education. This variable was included in the analysis of all five hypotheses.

Total individual income (Ttlp)

As aforementioned, socioeconomic factors was captured with variables representing education and income and was included in the analysis because of socioeconomic health

disparities. This variable is the person's total income in dollars obtained from the HC full year consolidated data file. This variable was included in the analyses for aims one and two.

Family's income as percent of poverty line (Povcat)

This variable represented the family's income as percent of poverty line. Particularly for the working-age population, income for the family may be a stronger consideration for returning to work than individual income (Haveman & Wolfe, 2000). Thus, this variable was included in the analyses for aim three that has absenteeism as the outcome variable. This variable was obtained from the HC full year consolidated data file.

Perceived physical health (Rthlth) and perceived mental health (Mnhlth)

Self-perceived mental health status and self-perceived physical health status are variables defined in MEPS and these are considered risk factors in health care outcomes (Iezzoni, 2003). Respondents were asked to report their self-perceived mental and physical health status on a likert scale of "excellent", "very good", "good", "fair", and "poor." These variables were in the analyses for all five hypotheses and wereobtained from the HC full year consolidated data files.

The need for help with activities of daily living (Adlhlp) and instrumental activities of daily living (Iadlhp)

As aforementioned, physical health status are important risk factors in health care outcomes. Activities of daily living (ADL) refer to typical everyday activities, including self-care activities, necessary for fundamental functioning. In contrast, instrumental activities of daily living (IADL) are those activities that are not fundamental to functioning, but allow one to maintain independence in his or her community (e.g., shopping, meal preparation). These variables were in the analyses for all five hypotheses and were obtained from the HC full year consolidated data files.

Number of medical comorbidities (Comorb)

Medical comorbidites were taken into account because patients with comorbidities tend to have higher risks of death, complications, functional impairments, and higher health service use (Iezzoni, 2003). The variable for comorbidities were determined from the MEPS HC medical conditions file by tallying the number of different ICD-9 codes for each individual. This variable was in the analyses of all five hypotheses.

Insurance status (Insstat)

Health insurance status was an additional variable that was created in order to control for health service utilization. This was a control variable because it is expected that individuals insured throughout the year would have higher expenditures than those intermittently insured and uninsured throughout the year. The MEPS HC full year consolidated file will be used to identify patients who were insured (i.e., insured all months of the year), intermittently insured (i.e., at least one month of the year without health insurance), and uninsured (i.e., no health insurance for all months of the year). This variable was included in the analyses of aims one and two.

Statistical Methods

The distribution of health care expenditures is typically left censored and skewed with a large proportion of zeroes. Because of these properties, estimation using untransformed ordinary least squares (OLS) produces inefficient results. One common method for handling such data is to run a two-part model in which the data are estimated with two methods. Part one involves the estimation of the probability of zero versus non-zero values, and part two involves a separate estimation of the nonzero (positive) values. For part one, the statistical procedure typically employed is the logistic regression for a binary outcome (non zero/zero or use/no use) and the second part generally involves the ordinary least squares (OLS) regression in which expenditures are log-transformed (to accommodate skewness) for the nonzero values (Duan et al., 1984). In this study, the hypotheses that added times 1 and 2 expenditures together as the outcome measure

(hypotheses 1a and 2a) used the two-part model, as there were a large proportion of zeroes and a log-transformed dependent variable (expenditures) successfully corrected for skewed data for total expenditures. For medical and drug expenditures, a different method was used for part II and will be described in a later section.

The two-part model did not fit the data in which expenditures from time 2 was subtracted from time 1 (hypotheses 1b and 2b) because the resultant dependent variables had both positive and negative values (for example, when time 2 expenditures was lower than time 1 for an individual, this resulted in a dependant variable with negative values). Negative values are unable to be transformed to meet OLS assumptions. Furthermore, gamma models are only for non-negative values, which is problematic for the negative values of the dependent variable. An additional theoretical consideration is that the effect of mental health treatment on expenditures would likely be different among those who had increased expenditures than those who had a decrease in expenditures following mental health treatment. Running a single regression combining the two types of change would produce biased results. Thus, a three-part model was used to overcome these aforementioned issues.

Aim 1: Mental Health Treatment and Health Care Expenditures

Hypothesis 1a

To test the hypothesis that patients who received mental health treatment will have lower total health care expenditures and lower medical expenditures than patients who did not receive treatment, and those with mental health treatment will have higher or no difference in prescription drug expenditures compared to those without mental health treatment, a two-part model was used. In part one, a logistic regression modeled whether mental health treatment significantly predicted a change from zero expenditures to positive expenditures. This was modeled using:

(Logistic)$Y_{1+2} = \beta_0 + \beta_1 Deptx_i + \beta_2 Pulmtx_i + \beta_3 Canctx_i + \beta_4 Bothtx_i + \beta_5 Age_i + \beta_6 Sex_i + \beta_7 White_i + \beta_8 Black_i + \beta_9 Asian_i + \beta_{10} Other_i + \beta_{11} Hispan_i + \beta_{12} Educyear_i + \beta_{13} Ttlp_i + \beta_{14} Rthlth_i + \beta_{15} Mnhlth_i + \beta_{16} Comorb_i + \beta_{17} Insstat_i + \beta_{18} Adlhlp_i + \beta_{19} Iadlp_i + \varepsilon_i$

In part two, an Ordinary Least Squares (OLS) model was used for total expenditures. The assumptions of OLS must be met in order to obtain unbiased, consistent, and efficient OLS estimators. The following statistical procedures are accepted econometrics methods to check for OLS assumptions (Gujarati, 2003): The assumption of linearity was examined with the Pregibon's link test, the assumption of normality will be tested with examining plots of the data (the kernel density plot, the standardized normal probability plot "pnorm", and the quantiles of residuals against the quantiles of normal distribution plot "qnorm"), and the Park and Glejser tests tested for heteroskedasticity. Upon testing the assumptions, it was discovered that the dependent variable transformed into the natural log resulted in the normality and linear assumptions being met for the total expenditure variable.

For total expenditures, after log-transformation, the assumption of linearity was met according to the Pregibon's link test. The Kernel density plot (Figure 5-2), "pnorm" (Figure 5-3), and "qnorm" (Figure 5-4) show that the residuals were close to being normally distributed. The Park and Glejser tests deteced heteroskedasticity ($p < 0.01$ for both). Because of heteroskedasticity, subgroup smearing estimators for values of expenditures was employed.

The model to be estimated for part two of the two-part model estimating mental health treatment effects on total expenditures was as follows and the coefficients of interest were β_1, β_2, and β_3:

$$\text{Log}(Y_{1+2}) = \beta_0 + \beta_1\text{Deptx}_i + \beta_2\text{Pulmtx}_i + \beta_3\text{Canctx}_i + \beta_4\text{Bothtx}_i + \beta_5\text{Age}_i + \beta_6\text{Sex}_i + \beta_7\text{White}_i + \beta_8\text{Black}_i + \beta_9\text{Asian}_i + \beta_{10}\text{Other}_i + \beta_{11}\text{Hispan}_i + \beta_{12}\text{Educyear}_i + \beta_{13}\text{Ttlp}_i + \beta_{14}\text{Rthlth}_i + \beta_{15}\text{Mnhlth}_i + \beta_{16}\text{Comorb}_i + \beta_{17}\text{Insstat}_i + \beta_{18}\text{Adlhlp}_i + \beta_{19}\text{Iadlp}_i + \varepsilon_i$$

For medical expenditures and prescription drug expenditures, the OLS assumption of linearity was not achieved (log, square root, cube root, and fourth root transformations did not correct for violations in assumptions). As a result, a generalized linear model (GLM) was used. GLM is a generalization of the OLS regression that does not have distributional assumptions. To use a GLM, a "family" and a "link function" must be identified that fit the data. The family specifies the distribution of the mean-variance relationship, whereas the link function specifies the covariate-mean relationship. An advantage of GLM is that it can give direct predictions of expenditures without the need to make predictions with smearing estimation (Manning, Basu, and Mullahy, 2005).

The generalized Gamma model (GGM) with a log link was shown to fit the data for both medical expenditures and prescription drug expenditures. That is, a modified Park test and a link test showed that the gamma distribution and log link linear relationship fit the data best. The model equation used to estimate medical and prescription drug expenditures was as follows and the coefficients of interest were β_1, β_2, and β_3:

$$(\text{Gamma})(Y_1 + Y_2) = \beta_0 + \beta_1\text{Deptx}_i + \beta_2\text{Pulmtx}_i + \beta_3\text{Canctx}_i + \beta_4\text{Bothtx}_i + \beta_5\text{Age}_i + \beta_6\text{Sex}_i + \beta_7\text{White}_i + \beta_8\text{Black}_i + \beta_9\text{Asian}_i + \beta_{10}\text{Other}_i + \beta_{11}\text{Hispan}_i + \beta_{12}\text{Educyear}_i + \beta_{13}\text{Ttlp}_i + \beta_{14}\text{Rthlth}_i + \beta_{15}\text{Mnhlth}_i + \beta_{16}\text{Comorb}_i + \beta_{17}\text{Insstat}_i + \beta_{18}\text{Adlhlp}_i + \beta_{19}\text{Iadlp}_i + \varepsilon_i$$

Hypothesis 1b

To examine the hypothesis that patients who received mental health treatment will have lower total health care expenditures and lower medical expenditures in time two compared to

their total and medical expenditures in time one ($Y_2 - Y_1$), three-part models were used because expenditures had negative values, along with zero and positive values. In part one, due to more than two categories (negative, zero, positive) a decision was made among using multinomial logit, multinomial probit, and ordered logit. In order to aid in the decision, the goodness of fit Del measure developed by Hildebrand and colleagues (Hildebrand, Liang, and Rosenthal, 1977) was calculated. For each expenditure variable, multinomial logit had a marginally higher Del value, which indicates that it likely has a relatively better fit for the models (see Table 5-3). Despite the Del measure favoring multinomial logit, multinomial probit has an advantage of not relying on the assumption that each category or choice are independent; however, its computationally intensive procedure was unrealistic for the timeline of this study. The model estimated for each of the expenditures is as follows:

(Multinomial Logit)$(Y_{2\text{-}1}) = \beta_0 + \beta_1 Deptx_i + \beta_2 Pulmtx_i + \beta_3 Canctx_i + \beta_4 Bothtx_i + \beta_5 Age_i + \beta_6 Sex_i + \beta_7 White_i + \beta_8 Black_i + \beta_9 Asian_i + \beta_{10} Other_i + \beta_{11} Hispan_i + \beta_{12} Educyear_i + \beta_{13} Ttlp_i + \beta_{14} Rthlth_i + \beta_{15} Mnhlth_i + \beta_{16} Comorb_i + \beta_{17} Insstat_i + \beta_{18} Adlhlp_i + \beta_{19} Iadlp_i + \varepsilon_i$

For parts two and three, assumptions for OLS were checked and log, square root, cube root, and fourth root transformations did not correct for violations in assumptions. Therefore, the generalized linear model (GLM) was used. For each expenditure variable for parts two and three, the generalized Gamma model (GGM) with a log link was shown to fit the data well. That is, a modified Park test and a link test showed that the gamma distribution and log link linear relationship fit the data best.

For part two (estimation of change given negative values), the dependent variables were multipled by -1 in order to create positive values and allow for estimation. The models to be

estimated for each expenditure variable was as follows and the coefficients of interest were β_1, β_2, and β_3:

$$(\text{Gamma})(Y_2 - Y_1 < 0)*(-1) = \beta_0 + \beta_1 Deptx_i + \beta_2 Pulmtx_i + \beta_3 Canctx_i + \beta_4 Bothtx_i + \beta_5 Age_i + \beta_6 Sex_i + \beta_7 White_i + \beta_8 Black_i + \beta_9 Asian_i + \beta_{10} Other_i + \beta_{11} Hispan_i + \beta_{12} Educyear_i + \beta_{13} Ttlp_i + \beta_{14} Rthlth_i + \beta_{15} Mnhlth_i + \beta_{16} Comorb_i + \beta_{17} Insstat_i + \beta_{18} Adlhlp_i + \beta_{19} Iadlp_i + \varepsilon_i$$

For part three (estimation of change given positive values), the models to be estimated for each expenditure variable was as follows and the coefficients of interest were β_1, β_2, and β_3:

$$(\text{Gamma})(Y_2 - Y_1 > 0) = \beta_0 + \beta_1 Deptx_i + \beta_2 Pulmtx_i + \beta_3 Canctx_i + \beta_4 Bothtx_i + \beta_5 Age_i + \beta_6 Sex_i + \beta_7 White_i + \beta_8 Black_i + \beta_9 Asian_i + \beta_{10} Other_i + \beta_{11} Hispan_i + \beta_{12} Educyear_i + \beta_{13} Ttlp_i + \beta_{14} Rthlth_i + \beta_{15} Mnhlth_i + \beta_{16} Comorb_i + \beta_{17} Insstat_i + \beta_{18} Adlhlp_i + \beta_{19} Iadlp_i + \varepsilon_i$$

Predictions based on the two- or three- part equations

In order to determine if predictions from the two- or three- part models were significant overall (in its aggregate), the equations were combined to obtain the estimates of adjusted change in expenditures per person for each treatment group (depression general, pulmonary diagnosis, and cancer diagnosis). For example, the three-part model would be depicted as follows:

$$E(\Delta Y_k \mid Dep) = P(D_k=0 \mid Dep) * E(\Delta Y_k \mid Dep, D_k=0) *(-1) + P(D_k=2 \mid Dep) * E(\Delta Y_k \mid Dep, D_k=2)$$

$$E(\Delta Y_k \mid Pulm) = P(D_k=0 \mid Pulm) * E(\Delta Y_k \mid Pulm, D_k=0) *(-1) + P(D_k=2 \mid Pulm) * E(\Delta Y_k \mid Pulm, D_k=2)$$

$$E(\Delta Y_k \mid Canc) = P(D_k=0 \mid Canc) * E(\Delta Y_k \mid Canc, D_k=0) *(-1) + P(D_k=2 \mid Canc) * E(\Delta Y_k \mid Canc, D_k=2)$$

where $\Delta Y_k = Y_2 - Y_1$.

The significance of the combined equations were estimated by obtaining confidence intervals (CI) via the procedure of bootstrapping. Bootstrapping is a non-parametric method for tests of means (Kennedy 1998). Bootstrapping draws random samples from the data for the

number of times specified (in this study, 1000 iterations were chosen), generating estimations from each sample and each sample is replaced prior to the next drawing. If the 95% CI contains zero then the difference is not significant at the 0.05 level.

Aim 2: Mental Health Treatment and Health Care Utilization

Hypothesis 2a

To test the hypothesis that patients who have received mental health treatment will have lower total office-based provider visits, outpatient hospital visits, inpatient nights, and emergency room visits than patients who have not received mental health treatment, a count data model will be used instead of OLS because count data tends to violate the homoskedasticity assumption, negative predictions can arise, and coefficients may not be meaningful if using OLS. One method is to use a Poisson regression which is a nonlinear analysis that assumes that each observed count is drawn at the same rate. A Poisson regression can be problematic because it assumes that the mean is equal to the variance, it assumes that the probability of the event is independent of how many times the event occurred previously, and it has difficulty modeling data with a large number of zeroes. Due to the limitations of the Poisson regression, the best count model is the negative binomial regression because it does not assume that the incidence rate is the same for all individuals and it is able to fit data with a lot of zeroes. The equations for the models are depicted below with the four separate outcomes – total number of hospital outpatient visits (optotv), total hospital inpatient nights at discharge (ipngtd), total number of all emergency room visits (ertot), and total number of office-based provider visits (obtotv). The coefficients of interest will be β_1, β_2, and β_4:

(1) $f(Y_{1+2}) = [\Gamma(1/\Phi + optotv_i)]/[\Gamma(optotv_i + 1)\ \Gamma(1/\Phi)] \ .\ (1/[1+\Phi\lambda_i])^{1/\Phi} \ .\ (1-[1/(1+ \Phi\lambda_i)])$

optotvi

where $\lambda_i = e^{\beta 0 + \beta 1Deptxi + \beta 2Pulmtxi + \beta 3Canctxi + \beta 4Bothtxi + \beta 5Agei + \beta 6Sexi + \beta 7Whitei + \beta 8Blacki + \beta 9Asiani + \beta 10Otheri + \beta 11Hispani + \beta 12Educyeari + \beta 13Ttlpi + \beta 14Rthlthi + \beta 15Mnhlthi + \beta 16Comorbi + \beta 17Insstati + \beta 18Adlhlpi + \beta 19Iadlpi + \varepsilon i}$

Hypothesis 2b

To test the hypothesis that patients who received mental health treatment will have lower office-based provider visits, outpatient hospital visits, inpatient nights, and emergency room visits in time 2 compared to their office-based provider visits, outpatient hospital visits, inpatient nights, and emergency room visits in time 1 (Y_2-Y_1), three-part models were used because the subtraction of time 1 from time 2 resulted in negative values, along with zero and positive values. Multinomial logits were used for part one due to better Del values (goodness-of-fit). For parts two and three, negative binomial regression were used for the reasons stated in hypothesis 2a. For part two, negative values in the dependent variable (utilization) were multiplied by -1 in order to create positive values for estimation. The coefficients of interest were β_1, β_2, and β_3:

(1) $f(y_i) = [\Gamma(1/\Phi + y_i)]/[\Gamma(y_i + 1)\ \Gamma(1/\Phi)] \ .\ (1/[1+\Phi\lambda_i])^{1/\Phi} \ .\ (1-[1/(1+ \Phi\lambda_i)])^{yi}$

where $\lambda_i = e^{\beta 0 + \beta 1Deptxi + \beta 2Pulmtxi + \beta 3Canctxi + \beta 4Bothtxi + \beta 5Agei + \beta 6Sexi + \beta 7Whitei + \beta 8Blacki + \beta 9Asiani + \beta 10Otheri + \beta 11Hispani + \beta 12Educyeari + \beta 13Ttlpi + \beta 14Rthlthi + \beta 15Mnhlthi + \beta 16Comorbi + \beta 17Insstati + \beta 18Adlhlpi + \beta 19Iadlpi + \varepsilon i}$

and $y_i = [(\text{time } 2) - (\text{time } 1) < 0]*(-1)$

For part three, the negative binomial regression was as follows and the coefficients of interests were β_1, β_2, and β_3:

(2) $f(y_i) = [\Gamma(1/\Phi + y_i)]/[\Gamma(y_i + 1)\ \Gamma(1/\Phi)] \ .\ (1/[1+\Phi\lambda_i])^{1/\Phi} \ .\ (1-[1/(1+ \Phi\lambda_i)])^{yi}$

where $\lambda_i = e^{\beta 0 + \beta 1Deptxi + \beta 2Pulmtxi + \beta 3Canctxi + \beta 4Bothtxi + \beta 5Agei + \beta 6Sexi + \beta 7Whitei + \beta 8Blacki + \beta 9Asiani + \beta 10Otheri + \beta 11Hispani + \beta 12Educyeari + \beta 13Ttlpi + \beta 14Rthlthi + \beta 15Mnhlthi + \beta 16Comorbi + \beta 17Insstati + \beta 18Adlhlpi + \beta 19Iadlpi + \varepsilon i}$

and $y_i = [(\text{time } 2) - (\text{time } 1) > 0]$

Predictions based on the three equations

In order to determine if predictions from the three-part models are significant overall (in its aggregate), the equations were combined to obtain the estimates of adjusted change in utilization per person for each treatment group (depression general, pulmonary diagnosis, and cancer diagnosis), as was done in hypotheses 1a and 2a. For aim two, this procedure was only done with the three part model (hypothesis 2b) because hypothesis 2a was estimated with a single equation.

Aim 3: Mental Health Treatment and Absenteeism

Hypothesis 3

To test the hypothesis that patients who received mental health treatment will have lower total days missed from work (misstot) than those who did not receive mental health treatment, the negative binomial regression will once again be used for the reasons stated in hypothesis 2a. The equation for the model is depicted below and the coefficients of interest will be β_1, β_2, and β_3.:

(1) $f(misstot_i) = [\Gamma(1/\Phi + misstot_i)]/[\Gamma(misstot_i + 1)\ \Gamma(1/\Phi)] \ .\ (1/[1+\Phi\lambda_i])^{1/\Phi} \ .\ (1-[1/(1+\Phi\lambda_i)])^{misstoti}$

where $\lambda_i = e^{\beta 0 + \beta 1Deptxi + \beta 2Pulmtxi + \beta 3Canctxi + \beta 4Bothtxi + \beta 5Agei + \beta 6Sexi + \beta 7Whitei + \beta 8Blacki + \beta 9Asiani + \beta 10Otheri + \beta 11Hispani + \beta 12Educyeari + \beta 13Ttlpi + \beta 14Rthlthi + \beta 15Mnhlthi + \beta 16Comorbi + \beta 17Insstati + \beta 18Adlhlpi + \beta 19Iadlpi + \varepsilon i}$

Selection bias and selection correction modeling

As depicted in chapter four, the conceptual model for the analyses for aim three illustrates a selection bias. That is, individuals' mental health status is not only affected by treatment, it determines whether or not one seeks mental health treatment in the first place. This introduces a problem with comparing treated versus untreated groups because the two groups may be fundamentally different. This study observes mental health status through the use of the variable

representing self-perceived mental health status (mthlth); however, this undoubtedly does not capture the entirety of mental health status. If mental health status is not fully accounted for, this may produce a spurious correlation between mental health treatment and absenteeism. Furthermore, resultant coefficients in the model would not accurately reflect the size of the relationship (coefficients would be biased). In order to correct for the selectivity bias and to attempt to more fully control for mental health status, a regression that accounts for observable confounders and unobservable confounders by the use of instrumental variables was used (Gujarati, 2003). An instrumental variable estimation relies on identifying one or more variables that affect the independent variable of interest (mental health treatment), but does not independently affect the dependent variable (absenteeism). That is, the instrumental variable must influence mental health treatment and only affects absenteeism through the treatment. The variable chosen for this is insurance. Having insurance has been found to relate to treatment seeking (Staniec & Webb, 2007), and insurance is not directly related to absenteeism (Lofland & Frick, 2006).

Table 5-1. Clinical classification codes and diagnostic categories

Medical condition	Classification code	Clinical classification software diagnosis category
Pulmonary conditions	127	Chronic obstructive pulmonary disease and bronchiectasis
	128	Asthma
	129	Aspiration pneumonitis, food/vomitus
	130	Pleurisy, pneumothorax, pulmonary collapse
	131	Respiratory failure, insufficiency, arrest (adult)
	132	Lung disease due to external agents
	133	Other lower respiratory disease
	134	Other upper respiratory disease
Cancer	11-45	Cancer of head and neck; esophagus; stomach; colon; rectum and anus; liver and intrahepatic bile duct; pancreas; other GI organs, peritoneum; bronchus, lung; other respiratory and intrathoracic; bone and connective tissue; melanomas of skin; other non-epithelial cancer of skin; breast; uterus; cervix; ovary; other female genital organs; prostate; testis; other male genital organs; bladder; kidney and renal pelvis; other urinary organs; brain and nervous system; thyroid; Hodgkin's disease; non-Hodgkin's lymphoma; leukemias; multiple myelom; other and unspecified primary; secondary malignancies; malignant neoplasm without specification of site; neoplasms of unspecified nature or uncertain behavior; maintenance chemotherapy, radiotherapy

Table 5-2. Antidepressant medication names.

Drug class	Generic name	Brand name
Antidepressant	Imipramine	Tofanil
	Desipramine	Norpramin
	Amitriptyline	Elavil
	Nortriptyline	Aventyl, Pamelor
	Protriptyline	Vivacil
	Trimipramine	Surmontil
	Doxepin	Sinequan, Adapin
	Clomipramine	Anafranil
	Maprotiline	Ludiomil
	Amoxapine	Asendin
	Trazodone	Desyrel
	Fluoxetine	Prozac
	Bupropion	Wellbutrin
	Sertraline	Zoloft
	Paroxetine	Paxil
	Venlafaxine	Effexor
	Nefazodone	Serzone
	Fluvoxamine	Luvox
	Mirtazapine	Remeron
	Citalopram	Celexa
	Escitalopram	Lexapro
	Duloxetine	Cympbalta
	Atomoxetine	Strattera
	Phenelzine	Nardil
	Tranylcypromine	Parnate
	Selegiline	Emsam (patch)
	Clonozepam	Klonopin
	Propranolol	Inderal
	Atenolol	Tenormin

Table 5-3. Del values indicating goodness-of-fit of regression models for expenditures.

		Del
Total expenditures	Multinomial logit	0.0685
	Multinomial probit	0.0676
	Ordered logit	0.0618
Medical expenditures	Multinomial logit	0.0770
	Multinomial probit	0.0705
	Ordered logit	0.0562
Drug expenditures	Multinomial logit	0.1298
	Multinomial probit	0.1252
	Ordered logit	0.1094

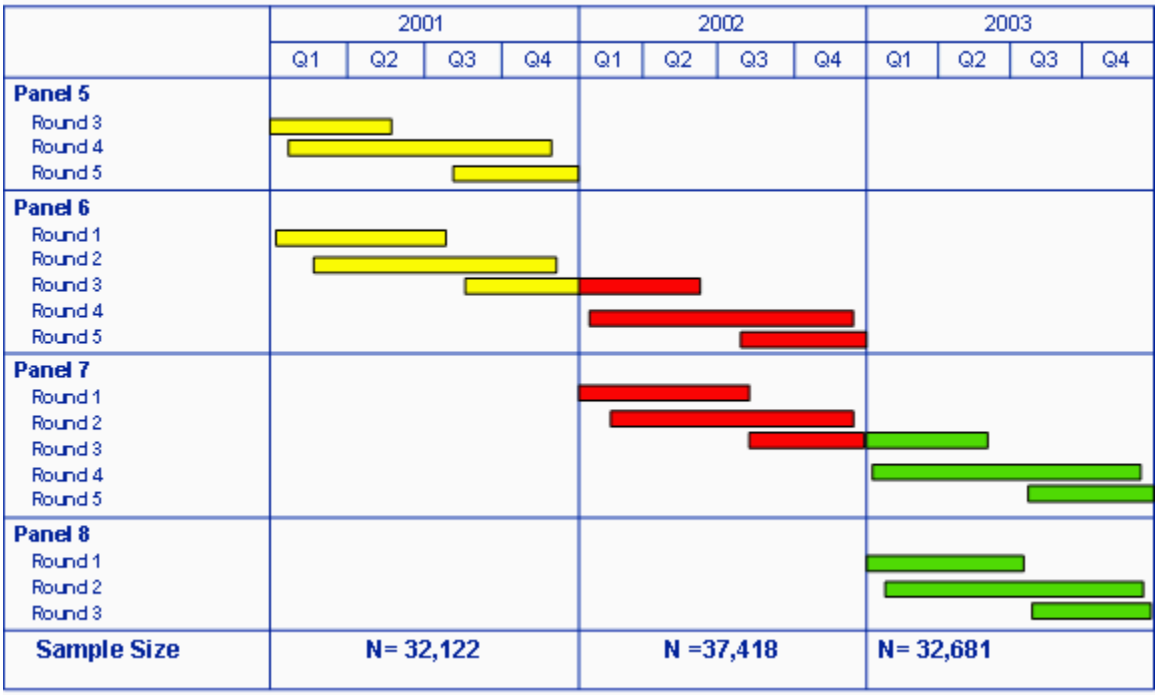

Figure 5-1. Overlapping panel design of MEPS.

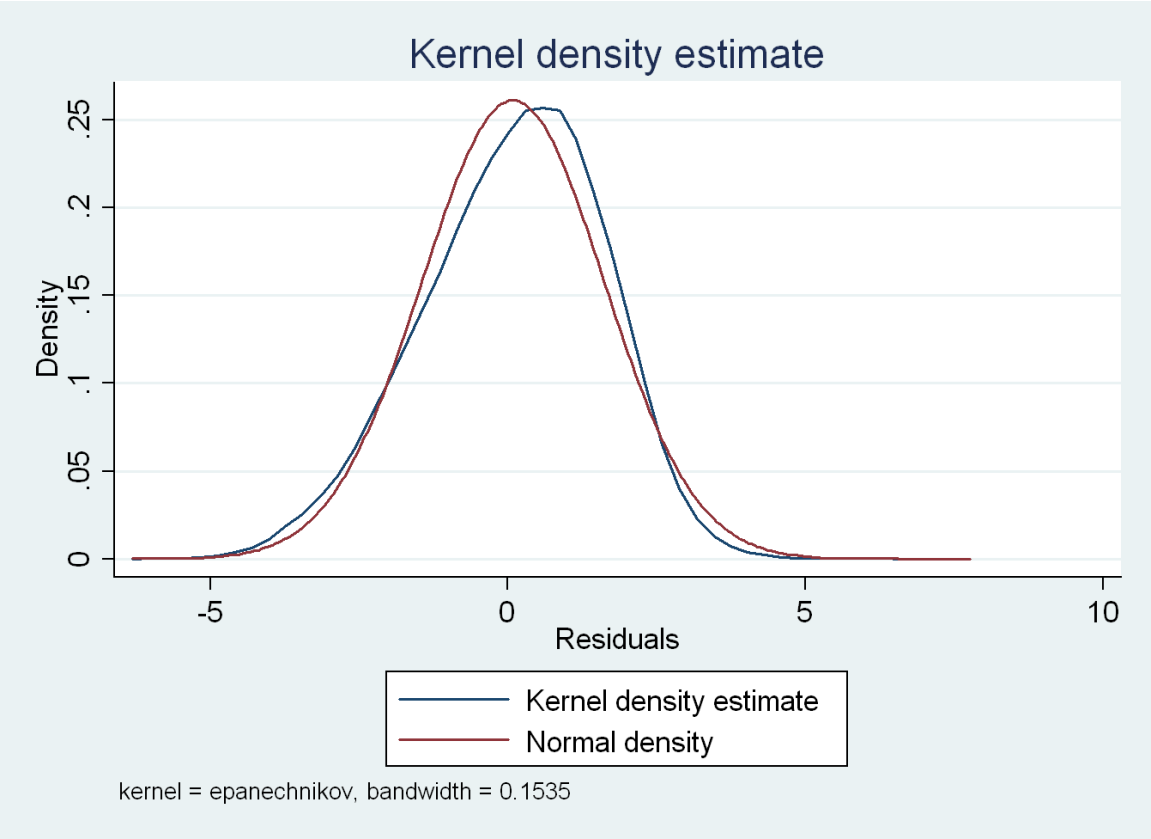

Figure 5-2. Kernel density plot for total expenditures

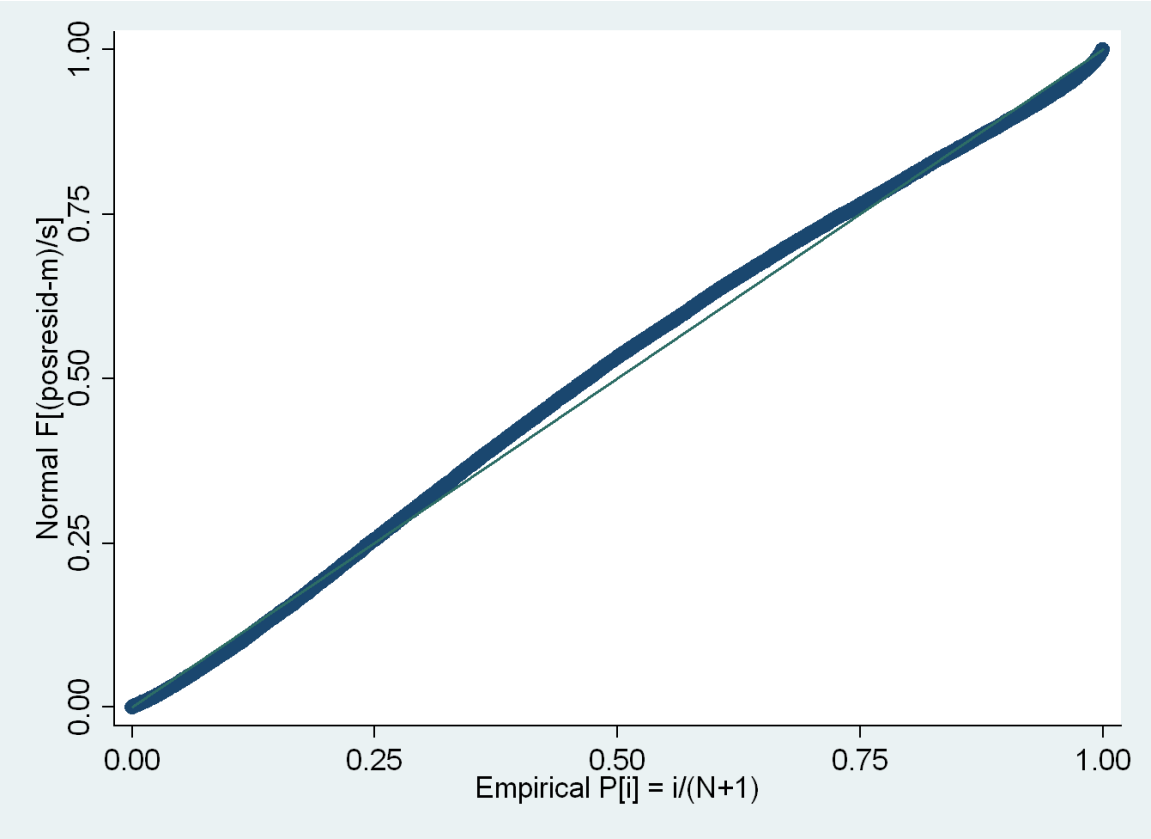

Figure 5-3. Standardized normal probability plot for total expenditures

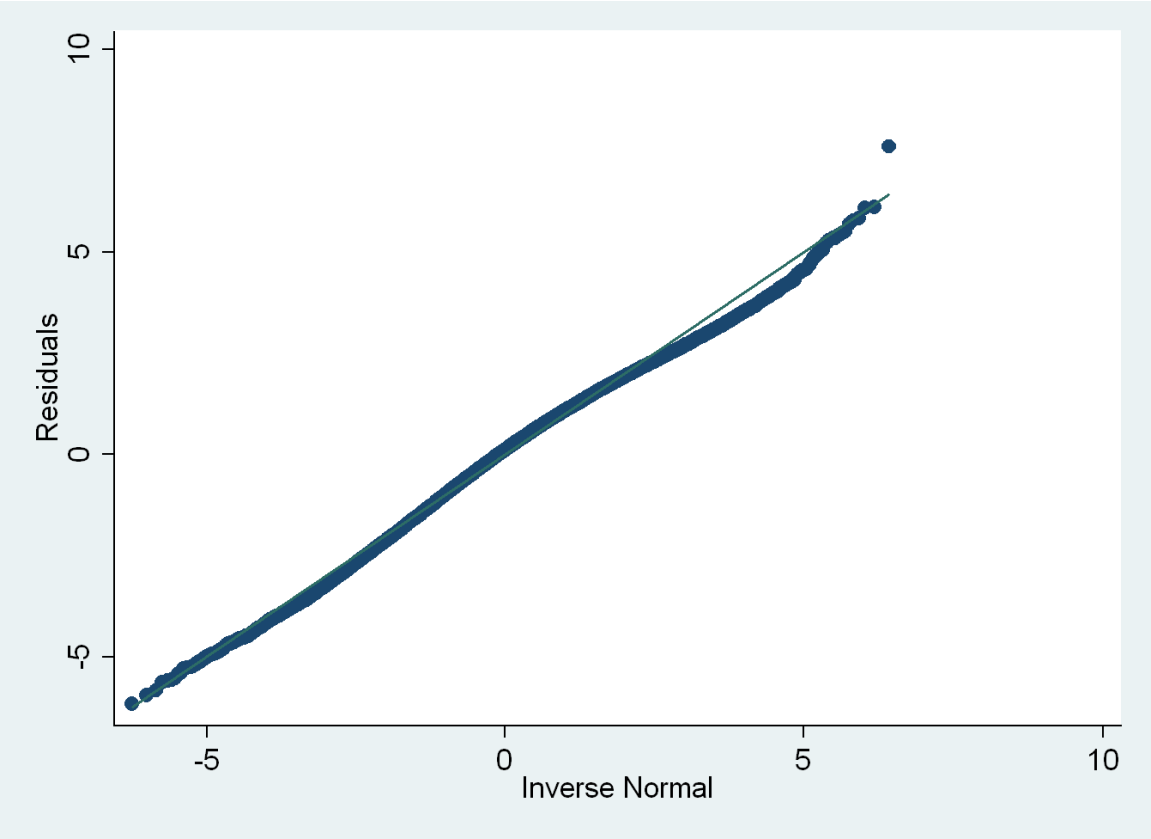

Figure 5-4. Quantiles of residuals against the quantiles of normal distribution plot for total expenditures

CHAPTER 6
RESULTS

Overview

This section describes the overall sample characteristics and the results of chi-square tests to determine whether there were differences in individual characteristics among the samples of interest (depression general, pulmonary diagnosis, and cancer diagnosis). Descriptive statistics are followed by the statistical results from each aim. Statistical results are organized by outcome measure: total expenditures, medical expenditures, prescription drug expenditures, emergency room visits, inpatient visits, outpatient visits, office-based provider visits, and work absenteeism. The pulmonary and cancer groups are reported both in comparison to an aggregated no treatment general group (Tables 6-1 to 6-26) and to the no treatment pulmonary or cancer groups (Tables 6-27 to 6-37).

Description of the Sample

The sample included 6,028 individuals with depression. Within the sample, 4,024 individuals received mental health treatment, while 2,004 participants did not receive mental health treatment. Among those receiving treatment, 1,119 had a comorbid pulmonary diagnosis and 194 individual had a comorbid cancer diagnosis. None of the remaining 2,488 depressed and treated participants had either a cancer or pulmonary comorbidity. The sample consisted of 69.14% females and 30.86% males. The majority of the sample was White (84.52%). The average age of participants was 45.13 with 11.59 years of education. The average yearly income was almost $20,000. Table 6-1 presents the percentages of the sample within each category or characteristic, along with chi-square values. Table 6-2 provides the averages, standard deviations, and ranges of the sample characteristics with continuous values.

For each characteristic, chi-square values indicate that there were significant differences among the study groups ($p<0.000$) (Table 6-1). Among the treated groups, individuals most likely to get treated were between the ages of 45 and 64. For the untreated group, the age group most likely to forgo treatment are those between 25 and 44. For females, treatment seeking was highest for depressed females with a comorbid pulmonary condition and they were more likely to seek treatment than forgo treatment. Men were relatively more likely to forgo treatment. With respect to race, White participants in the depression general group were most likely to seek treatment. Among Black participants, the highest proportion of individuals were in the no treatment group. Among Asian participants, treatment-seeking was more likely among those with a cancer comorbidity. There was also a relatively high percentage of Hispanic participants in the no treatment group compared to treated Hispanic participants. Among the poor, near poor, and low income participants, the proportion of individuals forgoing treatment was higher than the treatment groups within the same poverty categories. Middle income and high income participants had the highest percentages of individuals in treatment groups (pulmonary diagnosis and cancer diagnosis, respectively). Insured participants were most likely to seek treatment. With regards to self-perceived physical and mental health status, those who were rated as having "good" physical health status were most likely to forgo treatment compared to those who sought treatment and were rated "good." However, among those who did seek treatment, the highest percentage of individuals were in the "good" category. Individuals with cancer who rated their physical health as "excellent" were the least likely to seek mental health treatment. Furthermore, participants with ADL and IADL needs with a cancer diagnosis were most likely to seek treatment compared to others with similar needs. However, more people without ADL or IADL

needs tend to seek treatment than those with such needs. Finally, participants with 3 comorbid conditions and a pulmonary diagnosis were most likely to seek treatment.

In summary, individuals who were most likely to seek treatment were White individuals aged 45-64 with high income, "good" mental health status, and three comorbid conditions. Individuals least likely to seek mental health treatment appear to be children under age 12, males, Asians, those in the "near poor" category, the uninsured, and those in "excellent" self-perceived physical and mental health.

Total Expenditures

Two-Part Model ($Y_1 + Y_2$)

The weighted percentages of participants who had zero vs. positive expenditures for the two-part model is represented in Table 6-3. Overall, the percentage of participants who had zero expenditures was 27.31% and the percentage who had positive expenditures was 72.69%. The coefficients, standard errors, and p-values of significance tests from the regression are depicted in Table 6-4 (Part I), Table 6-5 presents the coefficients, standard errors, and p-values of significance tests from the regressions in part II, and Table 6-6 presents the bootstrapped results.

Part I

A logistic regression was run to predict the probability of having zero or non-zero values for each treatment group, relative to the no treatment group. The predicted probabilities of each group to have expenditures greater than zero were 74.74% for the depression general group, 69.05% for the pulmonary group, 66.88% for the cancer group, and 67.54% for the no treatment group. Holding all other variables constant, the probabilities for each treatment group did not differ significantly from the no treatment group. A comparison of the pulmonary treatment group with the pulmonary no treatment group revealed that the pulmonary treatment group was

less likely to have any expenditures than the no treatment pulmonary group (p=0.001). The cancer treatment group did not differ from the no treatment cancer group (0.060).

Part II

A log-transformed OLS regression was performed on part II of the two-part model to determine if there was a significant difference in expenditures between treatment and non-treatment among those who had positive expenditures during the study period. The mean predicted expenditures for the depression general, pulmonary, and cancer groups were $14,398.59, $15,800.25, and $18,422.04, respectively. Results demonstrate that each treatment group had significantly higher expenditures than the mean predicted expenditures of the group that did not have any mental health treatment ($8,897.61) (p=0.000). When the no treatment pulmonary group was compared directly to the treated pulmonary group, the treated group had higher expenditures than the no treatment group (p=0.000), whereas the cancer treated and untreated groups were not significantly different (p=0.291).

Bootstrapping prediction

Using each of the two equations from the two-part model, the combination of the equations were used to predict the overall amount of change in expenditures for each treatment group and to determine whether or not there was a significant overall effect of mental health treatment on expenditures. Bootstrapped results show that the overall total expenditures for the treatment groups were significantly higher than the no treatment group and both medical conditions were also higher than the untreated pulmonary or cancer groups.

Summary

Treatment groups were not more likely to have any expenditures than the non-treatment group. Among those who had expenditures greater than zero, those with mental health treatment

were more likely to experience an increase in expenditures regardless of treatment group. However, the cancer treated group when compared to the untreated cancer group, did not yield significant results. The increase in total expenditures held true when aggregating the zero and non-zero groups to estimate expenditures (i.e., there was an overall increase in total expenditures for each treatment group).

Three-Part Model ($Y_2 - Y_1$)

The weighted percentages of participants who experienced each type of change in total expenditures for the three treatment groups are presented in Table 6-7. Overall, the percentages of participants who had a decrease, no change, and increase in total expenditures with mental health treatment were 38.57%, 27.31%, and 34.12%, respectively. Table 6-8 shows the results from Part I , Table 6-9 depicts the results from Parts II and III, and Table 6-10 displays the bootstrapped results.

Part I

A multinomial logit regression was used to predict the probability of having a negative change, no change, or positive change in expenditures for each treatment group, relative to the no treatment group. The predicted probabilties for the depression general, pulmonary, cancer, and no treatment groups to experience a decrease in expenditures were 37.86%, 33.80%, 28.38%, and 43.63%, respectively. The predicted probabilties for the depression general, pulmonary, cancer, and no treatment groups to experience an increase in expenditures were 36.88%, 35.25%, 38.55% and 29.38%, respectively. Holding all other variables constant, compared to the no treatment group, the depression general group was 1.39 times as likely to experience a positive change in expenditures (p=0.000). In contrast, depressed treated participants with a pulmonary diagnosis were 69.6% more likely to experience a negative change (decrease) in expenditures relative to the no treatment general group (p=0.002), as well as in comparison to the no treatment

cancer group (p=0.000). Depressed treated participants with a cancer diagnosis were 61.3% more likely to experience a negative change in expenditures when compared to the no treatment general group, but not the no treatment cancer group (p=0.072).

Part II

A GGM regression with a log link function was used to determine the amount of negative change in expenditures given a negative change for each treatment group. The predicted mean expenditures for the depression general, pulmonary, cancer, and no treatment groups were $-2264.89, $-1965.70, $-2416.43, and $-1906.14, respectively. Each treatment group (depression general, pulmonary diagnosis, cancer diagnosis) experienced a significant increase in the amount of negative change in expenditures compared to the no treatment group (p=0.000, p=0.026, and p=0.000, respectively) and the cancer group experienced the largest change. However, when the untreated pulmonary or cancer groups were isolated to compare to the pulmonary or cancer treated groups, there were no significant decreases in expenditures (p=0.520 and p=0.526).

Part III

A GGM regression with a log link function was used to determine the amount of positive change in expenditures given a positive change for each treatment group. The predicted mean expenditures for the depression general, pulmonary, cancer, and no treatment groups were $1840.681, $1616.279, $2270.57, and $1115.305, respectively. Controlling for all other variables, each treatment group experienced a significant increase in the amount of positive change in expenditures relative to the no treatment group (p=.010, p=0.032, and p=0.013, respectively) with the cancer group experiencing the largest change in expenditures. When the pulmonary and cancer no treated groups were isolated, only the pulmonary treatement group had a significant increase in expenditures relative to the no treatment pulmonary group (p=0.035).

Bootstrapping prediction

Using each of the three equations from the three-part model, the combination of the equations were used to predict the overall amount of change in expenditures for each treatment group and to determine whether or not there was a significant overall effect of mental health treatment on expenditure change. Bootstrapped results show that for each treatment group, there was not a significant change in expenditures when the negative change, no change, and positive change groups were aggregated and compared to the no treatment general group. Both the pulmonary and cancer groups had an overall significant increase in expenditures overall when compared with the no treatment pulmonary or cancer groups.

Summary

Individuals in the depression general group were more likely to experience an increase in expenditures with treatment, whereas the pulmonary and cancer diagnoses groups were more likely to experience a decrease in total expenditures with treatment. This held true when the pulmonary no treatment group was compared to the pulmonary treatment group. When those with negative change and positive change were examined separately, each negative change group had a greater decrease in expenditures with treatment and each positive change group had a greater increase in expenditures with treatment. When isolating the treatment groups into medical condition, only the pulmonary treatment group with positive expenditures had a significant increase in expenditures. However, when combining the negative, no change, and positive change groups together, there was no overall significant differences in expenditures when comparing to the no treatment general group. In the pulmonary and cancer conditions, however, there was a significant increase in total expenditures when compared with the corresponding no treatment medical condition group.

Medical Expenditures

Two-Part Model ($Y_1 + Y_2$)

The weighted percentages of participants who had zero vs. positive expenditures for the two-part model is represented in Table 6-11. Overall, the percentage of participants who had zero expenditures was 13.12% and the percentage who had positive expenditures was 86.88%. The coefficients, standard errors, and p-values of significance tests from the regression are depicted in Table 6-4 for Part I, Table 6-5 presents the coefficients, standard errors, and p-values of significance tests from the regressions in Parts II, and Table 6-6 shows the results from the boostrapped predictions.

Part I

A logistic regression was run to predict the probability of having zero or non-zero values for each treatment group, relative to the no treatment group. The predicted probabilities of each group to have expenditures greater than zero were 88.43%, 86.91%, 83.37%, and 73.61% for the depression general, pulmonary, cancer, and no treatment groups, respectively. Holding all other variables constant, the treated depression general group was significantly more likely to experience medical expenditures greater than zero than the no treatment group (p=0.000). The treated group with a pulmonary diagnosis and the treated group with a cancer diagnosis did not show a significant difference in the probability to have any expenditures compared with the untreated general group (p=0.185 and p=0.495, respectively); however, comparing the pulmonary no treatment group to the pulmonary group revealed that the treated group was less likely to experience expenditures greater than zero (p=0.016).

Part II

A GGM regression with a log link function was performed on part II of the two-part model to determine if there was a significant difference in expenditures between treatment and non-

treatment among those who had positive expenditures during the study period. The predicted mean expenditures for each group were $9,344.22, $10,323.20, $13,312.50, and $6,291.30 for the depression general, pulmonary, cancer, and no treatment groups, respectively. Results demonstrate that for those who had some expenditures during the study period, each treatment group had significantly higher medical expenditures than the group who did not have any mental health treatment (p=0.000) and this still held true with the pulmonary treated versus pulmonary untreated group (p=0.000), but not for treated versus untreated cancer groups (p=0.291).

Bootstrapping prediction

Using each of the two equations from the two-part model, the combination of the equations were used to predict the overall amount of change in expenditures for each treatment group and to determine whether or not there was a significant overall effect of mental health treatment on expenditures. Bootstrapped results show that for the depression general treatment group, there was an overall significant positive change in expenditures with treatment when the zero and positive value groups were aggregated. For the treatment group with a pulmonary diagnosis or cancer diagnosis, there was an overall increase in expenditures when these groups were compared to the untreated pulmonary and cancer groups.

Summary

The depression general group was more likely to have medical expenditures from mental health treatment. The pulmonary treatment group was less likely to have expenditures compared to the no treatment pulmonary group. Amongst those with a non-zero (positive) expenditures, each treatment group was more likely to have an increase in medical expenditures, except the cancer treatment group compared to the no treatment cancer group. Each group had an overall significant increase in medical expenditures from mental health treatment.

Three-Part Model ($Y_2 - Y_1$)

The weighted percentages of participants who experienced each type of change in total expenditures for the three treatment groups are presented in Table 6-12. Overall, the percentages of participants who had a decrease, no change, and increase in medical expenditures with mental health treatment were 45.50%, 6.80%, and 47.69%, respectively. Table 6-8 shows the results from Part I , Table 6-9 depicts the results from Parts II and III, and Table 6-10 displays the bootstrapped results.

Part I

A mulitnomial logit regression was used to predict the probability of having a negative change, no change, or positive change in expenditures for the depression general group and the pulmonary diagnosis group, relative to the no treatment group. Because the cancer diagnosis group had no participants with zero (no change), they were excluded from part I. The predicted probabilties for the depression general, pulmonary, and no treatment groups to experience a decrease in expenditures were 40.86%, 44.57%, and 46.89%, respectively. The predicted probabilties for the depression general, pulmonary, and no treatment groups to experience an increase in expenditures were 38.93%, 46.75%, and 43.69%, respectively. Holding all other variables constant, compared to the no treatment group, the depression general group was 1.91 times more likely to experience a negative (decrease) change in expenditures (p=0.000), as well as 2.23 times more likely to experience a positive change (increase) in expenditures (p=0.000) compared to the no treatment group. Similarly, the pulmonary diagnosis group was simultaneously 5.76 times more likely to experience an negative change (decrease) in expenditures and a 7.43 times more likely to experience a positive change in expenditures (p=0.000) relative to the no treatment general group. Furthermore, when the pulmonary group

was compared to the no treatment pulmonary group, there was a significant decrease in expenditures for those who showed a decrease over time (p=0.000).

Part II

A GGM regression with a log link function was used to determine the amount of negative change in expenditures given a negative change for each treatment group (cancer diagnosis was included in this part). The predicted mean expenditures for each treatment group (depression general, pulmonary diagnosis, cancer diagnosis) were $-2,275.40, $-1,993.68, $-2,855.93, and $-1,626.54, respectively. Each treatment group experienced a significant increase in the amount of negative change in expenditures compared to the no treatment group (p=0.000, p=0.010, and p=0.000, respectively) and the cancer group experienced the largest change.

Part III

A GGM regression with a log link function was used to determine the amount of positive change in expenditures given a positive change for each treatment group. The predicted mean expenditures for the depression general, pulmonary, cancer, and no treatment groups were $2,405.45, $2,540.70, $4,200.70, and $1,990.04, respectively. Controlling for all other variables, the cancer diagnosis group experienced a significant increase in the amount of positive change in expenditures relative to the no treatment group (p=0.000), whereas the depression general group and the pulmonary diagnosis group did not show a significant increase in positive expenditures (p=0.562 and p=0.450).

Bootstrapping prediction

Using each of the three equations from the three-part model, the combination of the equations were used to predict the overall amount of change in expenditures for each treatment

group and to determine whether or not there was a significant overall effect of mental health treatment on expenditures. Bootstrapped results show that for each treatment group, there was not a significant change in expenditures when the negative change, no change, and positive change groups were aggregated and compared to the no treatment general group. However, when the medical groups were compared directly to its corresponding no treatment medical group, both the pulmonary and cancer treatment groups had a significant overall increase in expenditures over time.

Summary

Both the depression general group and the pulmonary diagnosis groups were likely to experience a change (positive or negative) in medical expenditures from mental health treatment. Of the participants who experienced a negative change in medical expenditures, each treatment group (depression general, pulmonary, and cancer) experienced a greater decrease in expenditures than no treatment. Only the cancer group amongst those with a positive change showed a significant increase in medical expenditures with treatment. Comparing the pulmonary and cancer treatment groups to the corresponding no treatment medical group, there was no significant increase nor decrease in expenditures. The pulmonary and cancer treatment groups showed an overall increase in medical expenditures with mental health treatment compared to the pulmonary and cancer no treatment groups.

Prescription Drug Expenditures

Two-Part Model ($Y_1 + Y_2$)

The weighted percentages of participants who had zero vs. positive expenditures for the two-part model is represented in Table 6-13. Overall, the percentage of participants who had zero expenditures was 11.61% and the percentage who had positive expenditures was 88.39%. The coefficients, standard errors, and p-values of significance tests from the regression are

depicted in Table 6-4 for Part I, Table 6-5 presents the coefficients, standard errors, and p-values of significance tests from the regressions in Parts II, and Table 6-6 shows the results from the boostrapped predictions.

Part I

A logistic regression was run to predict the probability of having zero or non-zero values for each treatment group, relative to the no treatment group. The predicted probability of having any expenditures for the depression general, pulmonary, cancer, and no treatment groups were 92.4%, 89.4%, 85.4%, and 79.9%, respectively. Statistical results indicate that the depression general group and the pulmonary diagnosis group probabilities were significantly different than the no treatment group. That is, holding all other variables constant, the treated depression general group was 92% more likely to have any drug expenditures than the no treatment group (p=0.000) and the treated group with a pulmonary diagnosis was 51.9% more likely to have any drug expenditures than the no treatment group (p=0.000). When the pulmonary treatment group was compared to the no treatment pulmonary group, the treated group was significantly less likely to have expenditures greater than zero (p=0.050).

Part II

A GGM regression with a log link function was performed on part II of the two-part model to determine if there is a significant difference in expenditures between treatment and non-treatment among those who had positive expenditures during the study period. The predicted mean expenditures for the depression general, pulmonary, cancer, and no treatment groups were $4,189.64, $5,199.13, $4,126.83, and $1,897.36, respectively. Statistical results demonstrate that for those who had some expenditures during the study period, each of the treatment groups had significantly higher medical expenditures than the general group that did not have any mental

health treatment (p=0.000) and the pulmonary group was more likely to have higher drug expenditures than the no treatment pulmonary group (p=0.000).

Bootstrapping prediction

Using each of the two equations from the two-part model, the combination of the equations were used to predict the overall amount of change in expenditures for each treatment group and to determine whether or not there was a significant overall effect of mental health treatment on expenditures. Bootstrapped results show that for each treatment group comparing to the no treatment general group, there was not an overall significant change in drug expenditures when the zero and positive value groups were aggregated. However, when the treated pulmonary or cancer groups were compared directly to the no treatment pulmonary or cancer groups, there was a significant increase in the treatment groups.

Summary

Depression general and pulmonary diagnosis groups were most likely to have positive drug expenditures with mental health treatment compared to no treatment. When only those with drug expenditures greater than zero were examined, all three treatment groups had a significant increase in expenditures associated with mental health treatment. However, there was not a significant overall difference in drug expenditures for the depression general group, but an increase in drug expenditures for the pulmonary and cancer treatment groups.

Three-Part Model ($Y_2 - Y_1$)

The weighted percentages of participants who experienced each type of change in drug expenditures for the three treatment groups are presented in Table 6-14. Overall, the percentages of participants who had a decrease, no change, and increase in drug expenditures with mental health treatment were 44.31%, 5.29%, and 50.40%, respectively. Table 6-8 shows the results

from Part I , Table 6-9 depicts the results from Parts II and III, and Table 6-10 displays the bootstrapped results.

Part I

A mulitnomial logit regression was used to predict the probability of having a negative change, no change, or positive change in expenditures for the depression general group and the pulmonary diagnosis group, relative to the no treatment group. Because the cancer diagnosis group had no participants with zero (no change), they were excluded from part I. The predicted probabilties for the depression general, pulmonary, and no treatment groups to experience a decrease in expenditures were 40.43%, 41.51%, and 39.48%, respectively. The predicted probabilties for the depression general, pulmonary, and no treatment groups to experience an increase in expenditures were 54.95%, 56.72%, and 31.75%, respectively. The depression general and pulmonary groups were significantly different than the no treatment group. That is, holding all other variables constant, compared to the no treatment group, the depression general group was 8.83 times more likely to experience a negative change (decrease) in expenditures (p=0.000), as well as 14.68 times more likely to experience a positive change (increase) in expenditures (p=0.000) compared to the no treatment group. Similarly, the depressed treatment group with a pulmonary diagnosis were simultaneously 24.81 times more likely to experience a negative change (decrease) in expenditures and a 41.35 times more likely to experience a positive change (increase) in expenditures (p=0.000) relative to the no treatment group.

Part II

A GGM regression with a log link function was used to determine the amount of negative change in expenditures given a negative change for each treatment group. The predicted mean expenditures for the depression general, pulmonary, cancer, and no treatment groups were $-

551.18, $-693.08, $-429.86, and $-398.34, respectively. Each treatment group (depression general, pulmonary diagnosis, cancer diagnosis) experienced a significant increase in the amount of negative change in expenditures compared to the no treatment group (p=0.000, p=0.000, and p=0.001, respectively) and the cancer group experienced the most change. When comparing the no treatment pulmonary group to the treated pulmonary group, there was a significant decrease for the treated group (p=0.000), whereas the cancer treatment group did not show a significant decrease compared to the no treatment cancer group (p=0.846).

Part III

A GGM regression with a log link function was used to determine the amount of positive change in expenditures given a positive change for each treatment group. The predicted mean expenditures for the depression general, pulmonary, cancer, and no treatment groups were $608.16, $800.53, $725.88, and $228.35, respectively. Controlling for all other variables, among those who experienced a positive change, each treatment group experienced a significant increase in the amount of positive change in expenditures relative to the no treatment general group (p=0.000). Both the pulmonary and cancer treatment groups showed a significant increase in drug expenditures when compared to the no treatment pulmonary and cancer groups (p =0.001).

Bootstrapping prediction

Using each of the three equations from the three-part model, the combination of the equations were used to predict the overall amount of change in expenditures for each treatment group and to determine whether or not there was a significant overall effect of mental health treatment on expenditures. Bootstrapped results show that for each treatment group compared to the no treatment general group, there was not a significant change in expenditures when the

negative change, no change, and positive change groups were aggregated. When the pulmonary and cancer groups were compared to the corresponding untreated medical group, there was an overall significant increase for the pulmonary treatment group, whereas there was a significant decrease in the cancer treatment group.

Summary

Both depression general and pulmonary diagnosis groups were more likely to experience a change (positive or negative) in drug expenditures relative to the no treatment group. Additionally, each group (depression general, pulmonary, and cancer) with positive or negative drug expenditures had increasingly positive or negative changes, respectively, associated with mental health treatment, with the exception of the cancer treatment group compared to the no treatment cancer group. There was a significant overall increase in drug expenditures for the pulmonary and cancer treatment groups compared to the no treatment medical groups.

Emergency Room Visits

Negative Binomial Regression ($Y_1 + Y_2$)

For total emergency room visits, a negative binomial regression was estimated in order to determine if the treated groups had higher emergency room visits than the no treatment group. Table 6-15 depicts the incidence rate ratios, standard errors, and p-value results. Table 6-16 shows the predicted average number of visits for each group. The depression general group had a mean of 0.72, the pulmonary diagnosis group had a mean of 1.11, the cancer diagnosis group had a mean of 0.98 visits, and the no treatment group had 0.64 mean visits. Results indicate that for each treatment group, emergency room visits were more likely relative to the no treatment group (p=0.000, p=0.000, and p=0.025). The incidence rates indicated that the depression general group was 1.18 times higher, the pulmonary diagnosis group was 1.23 times higher, and the cancer diagnosis group was 1.21 times higher than the no treatment general group. When

comparing to the no treatment cancer group, the treated cancer group had an incident rate 1.32 times higher than the no treatment cancer group (p=0.050), whereas there was no difference between the treated and untreated pulmonary group (0.991).

Three-Part Model ($Y_2 - Y_1$)

The weighted percentages of participants who experienced each type of change in emergency room visits for the three treatment groups are presented in Table 6-17. Overall, the percentages of participants who had a decrease, no change, and increase in emergency room visits with mental health treatment were 16.92%, 59.94%, and 23.14%, respectively. Table 6-18 shows the results from Part I , Table 6-19 depicts the results from Parts II and III, and Table 6-20 displays the bootstrapped results.

Part I

A mulitnomial logit regression was used to predict the probability of having a negative change, no change, or positive change in visits for the depression general group, the pulmonary diagnosis group, and the cancer diagnosis group relative to the no treatment group. The predicted probabilities of having a negative change in emergency room visits were 20.30%, 18.38%, 16.24%, and 17.03% for the depression general, pulmonary, cancer, and no treatment general groups, respectively. The predicted probabilities of having a positive change in emergency room visits for each group were 20.46%, 19.70%, 18.49%, and 17.06% for the respective groups. Statistical results indicate that the depression general group was the only treatment group with significant differences from the no treatment group. That is, holding all other variables constant, compared to the no treatment group, the depression general group was simultaneously more likely to experience a negative change (decrease) in expenditures (p=0.001), as well as more likely to experience a positive change (increase) in expenditures (p=0.007) compared to the no treatment group. Furthermore, the treated pulmonary group

compared to the untreated pulmonary group was more likely to experience a decrease in emergency room visits. All other estimates were non-significant.

Part II

A negative binomial regression was used to determine the amount of negative change in expenditures given a negative change for each treatment group. The predicted mean number of emergency room visits for each group (depression general, pulmonary, cancer, and no treatment) were -0.30, -0.27, -0.24, and -0.23, respectively. Each treatment group (depression general, pulmonary diagnosis, cancer diagnosis) that experienced a negative change in expenditures were not significantly different from the no treatment general group (p=0.086, p=0.175, and 0.505, respectively). However, the cancer diagnosis treatment group with a decrease in visits over time had a higher incidence rate than the no treatment cancer group (p=0.028).

Part III

A negative binomial regression was used to estimate the amount of positive change in expenditures given a positive change for each treatment group. The predicted mean number of visits for each group were 0.28, 0.31, 0.19, and 0.23 for the depression general, pulmonary, cancer, and no treatment groups, respectively. Controlling for all other variables, among those who experienced a positive change, the only treatment group that experienced a significant increase in the amount of positive change in expenditures relative to the no treatment general group was the pulmonary diagnosis group (p=0.049). The cancer treatment group had a significant increase in expenditures compared to the no treatment cancer group (p=0.001).

Bootstrapping prediction

Using each of the three equations from the three-part model, the combination of the equations were used to predict the overall amount of change in utilization for each treatment

group and to determine whether or not there was a significant overall effect of mental health treatment on utilization. Bootstrapped results show that for each treatment group comparing to the general no treatment grouop, there was not a significant change in visits when the negative change, no change, and positive change groups were aggregated. However, when the medical groups were compared to the no treatment medical groups, the pulmonary and cancer treatment groups had more emergency room visits overall than the no treatment pulmonary or cancer group.

Summary

Total emergency room visits are greater with each treated group compared to the untreated general group, but the depression general group was more likely to have a change in emergency room visits (positively or negatively) over time. The pulmonary treatment group was more likely to have a decrease in emergency room visits. Of participants experiencing a positive change with mental health treatment, the pulmonary and cancer diagnoses groups experienced a significant increase with treatment. Nevertheless, the overall difference, combining negative, no change, and positive change, was non-significant for each treatment group when compared with the no treatment general group. The medical condition treatment groups did show greater utilization than the no treatment medical groups.

Inpatient Visits

Negative Binomial Regression ($Y_1 + Y_2$)

For total inpatient visits, a negative binomial regression was estimated in order to determine if the treated groups were more or less likely to undergo inpatient visits. Table 6-15 depicts the incidence rate ratios, standard errors, and p-value results. Table 6-16 shows the predicted average number of visits for each group and the depression general group had an average of 2.78, the pulmonary diagnosis group had an average of 3.06, the cancer diagnosis

group had an average of 5.98 visits, and the no treatment group had an average of 7.52 visits. Results indicate that for the depression general and the cancer diagnosis treatment group, inpatient visits were more likely relative to the no treatment group (p=0.024 and p=0.002). The incidence rates indicated that the depression general group was 1.40 times higher and the cancer diagnosis group was 2.25 times higher than the no treatment group. However, both the pulmonary and cancer diagnosis treatment groups did not show significant results for total inpatient visits when compared to the pulmonary and cancer diagnosis untreated groups (p=0.588 and p=0.550, respectively).

Three-Part Model ($Y_2 - Y_1$)

The weighted percentages of participants who experienced each type of change in inpatient visits for the three treatment groups are presented in Table 6-21. Overall, the percentages of participants who had a decrease, no change, and increase in inpatient visits with mental health treatment were 11.15%, 69.84%, and 19.01%, respectively. Table 6-18 shows the results from Part I , Table 6-19 depicts the results from Parts II and III, and Table 6-20 displays the bootstrapped results.

Part I

A mulitnomial logit regression was used to predict the probability of having a negative change, no change, or positive change in visits for the depression general group, the pulmonary diagnosis group, and the cancer diagnosis group relative to the no treatment group. The predicted probabilities of having a negative change in inpatient visits were 12.53%, 11.71%, 17.83%, and 10.21% for the depression general, pulmonary, cancer, and no treatment groups, respectively. The predicted probabilities of having a positive change in inpatient visits for each group were 14.79%, 19.12%, 25.28%, and 12.56% for the respective groups. Statistical results indicate that holding all other variables constant, compared to the no treatment group, the

depression general group and the cancer diagnosis group were more likely to experience a negative change (decrease) in utilization (p=0.010 and p=0.004, respectively). The pulmonary diagnosis group and the cancer diagnosis group were more likely to experience a positive change (increase) in utilization (p=0.012 and 0.003, respectively) compared to the no treatment group. All other differences were non-significant. When the pulmonary treatment group was compared to the pulmonary no treatment groups, the results were not significant. The cancer treatment group was more likely to experience an increase in inpatient visits compared to the no treatment cancer group (p=0.000).

Part II

A negative binomial regression was used to determine the amount of negative change in utilization given a negative change for each treatment group. The predicted mean number of inpatient visits for each group (depression general, pulmonary, cancer, and no treatment) were -1.25, -0.75, -1.48, and -1.05, respectively. Each treatment group (depression general, pulmonary diagnosis, cancer diagnosis) that experienced a negative change in utilization was not significantly different than the no treatment group (p=0.053, p=0.347, and 0.191, respectively). However, the pulmonary treatment group had a slower decrease in expenditures than the no treatment pulmonary group (p=0.023).

Part III

A negative binomial regression was used to estimate the amount of positive change in utilization given a positive change for each treatment group. The predicted mean number of visits for each group were 1.01, 1.83, 2.34, and 1.12 for the depression general, pulmonary, cancer, and no treatment groups, respectively. Controlling for all other variables, among those who experienced a positive change, each treatment group (depression general, pulmonary

diagnosis, cancer diagnosis) that experienced a positive change in utilization did not experience a significant change in the amount of positive change (p=0.380, p=0.750, and 0.182, respectively) and this held true when the treated medical groups were compared to the untreated medical groups.

Bootstrapping prediction

Using each of the three equations from the three-part model, the combination of the equations were used to predict the overall amount of change in utilization for each treatment group and to determine whether or not there was a significant overall effect of mental health treatment on utilization. Bootstrapping results show that for the depression general treatment group, there was not a significant change in inpatient visits when the negative change, no change, and positive change groups were aggregated. However, for the pulmonary diagnosis group and the cancer diagnosis group, there was an overall increase in inpatient visits compared to the no treatment general group. The cancer treatment group had more inpatient visits than the no treatment cancer group.

Summary

The depression general group and the cancer diagnosis group had an increased incidence of inpatient visits than the untreated group, and the pulmonary diagnosis group approached significance. The cancer diagnosis group was more likely to experience any change (positive or negative) in visits over time, whereas the pulmonary diagnosis group was more likely to experience an increase in inpatient visits and the depression general group were more likely to experience a decrease in visits from mental health treatment. However, there were no differences in visits amongst the negative or positive change groups compared to the general treatment group, but the pulmonary treatment group compared to the untreated pulmonary group

showed a lower incidence rate. The overall difference in visits combining each type of change (negative, none, positive) indicate that the pulmonary and cancer diagnoses groups had higher utilization than the no treatment general group. The cancer treatment group also had more inpatient visits than the no treatment cancer group.

Outpatient Visits

Negative Binomial Regression ($Y_1 + Y_2$)

For total outpatient visits, a negative binomial regression was estimated in order to determine if the treated groups were more or less likely to undergo outpatient visits. Table 6-15 depicts the incidence rate ratios, standard errors, and p-value results. Table 6-16 shows the predicted average number of visits for each group and the depression general group had an average of 2.00, the pulmonary diagnosis group had an average of 3.00, the cancer diagnosis group had an average of 5.21 visits, and the no treatment group had an average of 4.01 visits. Results indicate that for each treatment group, outpatient visits were more likely relative to the no treatment group (p=0.000, p=0.043, and p=0.000). The incidence rates indicated that the depression general group was 1.45 times higher, the pulmonary diagnosis group was 1.43 times higher, and the cancer diagnosis group was 2.29 times higher than the no treatment group. The pulmonary treatment group had an incidence rate 1.35 times higher than the no treatment pulmonary group (p=0.008).

Three-Part Model ($Y_2 – Y_1$)

The weighted percentages of participants who experienced each type of change in outpatient visits for the three treatment groups are presented in Table 6-22. Overall, the percentages of participants who had a decrease, no change, and increase in outpatient visits with mental health treatment were 17.90%, 58.15%, and 23.95%, respectively. Table 6-18 shows the

results from Part I , Table 6-19 depicts the results from Parts II and III, and Table 6-20 displays the bootstrapped results.

Part I

A mulitnomial logit regression was used to predict the probability of having a negative change, no change, or positive change in visits for the depression general group, the pulmonary diagnosis group, and the cancer diagnosis group relative to the no treatment group. The predicted probabilities of having a negative change in outpatient visits were 19.86%, 20.96%, 23.86%, and 16.32% for the depression general, pulmonary, cancer, and no treatment groups, respectively. The predicted probabilities of having a positive change in outpatient visits for each group were 20.17%, 20.50%, 32.63%, and 17.53% for the respective groups. Statistical results indicate that holding all other variables constant, compared to the no treatment group, each treatment group was more likely to experience both positive or negative changes in expenditures when compared to the no treatment group (p=0.000). However, when the pulmonary and cancer groups were compared to its corresponding no treatment groups, results were non-significant.

Part II

A negative binomial regression was used to determine the amount of negative change in utilization given a negative change for each treatment group. The predicted mean number of outpatient visits for each group (depression general, pulmonary, cancer, and no treatment) were -0.63, -0.96, -1.45, and -0.65, respectively. Amongst the individuals experiencing a negative change in utilization, the depression general group was the only group to experience a significant increase in the amount of negative change (p=0.008). The medical groups compared to the untreated medical groups did not show a significant difference.

Part III

A negative binomial regression was used to estimate the amount of positive change in utilization given a positive change for each treatment group. The predicted mean number of visits for each group were 0.94, 0.69, 0.96, and 0.48 for the depression general, pulmonary, cancer, and no treatment groups, respectively. Amongst the individuals experiencing a positive change in utilization, each treatment group experienced a significant increase in the amount of positive change relative to the no treatment group (p=0.000, p=0.000, and p=0.014). The medical groups compared to the untreated medical groups did not show a significant difference.

Bootstrapping prediction

Using each of the three equations from the three-part model, the combination of the equations were used to predict the overall amount of change in utilization for each treatment group and to determine whether or not there was a significant overall effect of mental health treatment on utilization. Bootstrapping results show that for each treatment group compared to the no treatment general group, there was not a significant change in outpatient visits when the negative change, no change, and positive change groups were aggregated. The pulmonary treatment group had fewer outpatient visits than the no treatment pulmonary group and the cancer treatment group had more outpatient visits than the no treatment cancer group.

Summary

For total outpatient visits, each treatment group experienced a greater incidence of visits with mental health treatment. Each treatment group was also more likely to experience a change (positive or negative) in visits than the no treatment general group, except the medical groups compared to the untreated medical groups did not show a significant difference. Only the

participants in the depression general group that had either a positive or negative change in visits over time showed a significant increase or decrease in visits, respectively. However, there was no significant overall change in visits when the negative, no change, and positive change were aggregated when groups were compared to the no treatment general group. When the medical condition treatment groups were compared to their corresponding medical condition no treatment group, the pulmonary treatment group had fewer outpatient visits and the cancer treatment group had more outpatient visits overall.

Office-Based Provider Visits

Negative Binomial Regression ($Y_1 + Y_2$)

For total outpatient visits, a negative binomial regression was estimated in order to determine if the treated groups were more or less likely to have any outpatient visits. Table 6-15 depicts the incidence rate ratios, standard errors, and p-value results. Table 6-16 shows the predicted average number of visits for each group and the depression general group had an average of 23.07, the pulmonary diagnosis group had an average of 31.60, the cancer diagnosis group had an average of 30.91 visits, and the no treatment group had an average of 12.60 visits. Results indicate that for each treatment group, office-based provider visits were more likely experienced relative to the no treatment group (p=0.000). The incidence rates indicated that the depression general group was 1.88 times higher, the pulmonary diagnosis group was 2.07 times higher, and the cancer diagnosis group was 1.96 times higher than the no treatment general group. When compared to the corresponding untreated medical groups, the pulmonary treated group had an incidence rate 1.54 times higher and the cancer treated groups had an incidence rate 1.32 times higher.

Three-Part Model ($Y_2 - Y_1$)

The weighted percentages of participants who experienced each type of change in office-based provider visits for the three treatment groups are presented in Table 6-23. Overall, the percentages of participants who had a decrease, no change, and increase in emergency room visits with mental health treatment were 41.61%, 10.77%, and 47.63%, respectively. Table 6-18 shows the results from Part I , Table 6-19 depicts the results from Parts II and III, and Table 6-20 displays the bootstrapped results.

Part I

A mulitnomial logit regression was used to predict the probability of having a negative change, no change, or positive change in visits for the depression general group, the pulmonary diagnosis group, and the cancer diagnosis group relative to the no treatment group. The predicted probabilities of having a negative change in office-based provider visits were 43.10%, 40.49%, 39.57%, and 46.32% for the depression general, pulmonary, cancer, and no treatment groups, respectively. The predicted probabilities of having a positive change in emergency room visits for each group were 48.96%, 51.02%, 55.13%, and 36.90% for the respective groups. Statistical results indicate that holding all other variables constant, compared to the no treatment group, each treatment group was less likely to experience both positive and negative changes in expenditures when compared to the no treatment group (p=0.000). When the no treatment pulmonary group was compared to the treated pulmonary group, there was a decreased likelyhood of an increase in office-based provider visits over time (p=0.014).

Part II

A negative binomial regression was used to determine the amount of negative change in utilization given a negative change for each treatment group. The predicted mean number of office-based provider visits for each group (depression general, pulmonary, cancer, and no

treatment) were -3.68, -3.62, -4.26, and -3.33, respectively. Amongst the individuals experiencing a negative change in utilization, each treatment group experienced a significant increase in the amount of negative change (p=0.011, p=0.003, and p=0.000), and this held true when the cancer treatment group was compared to the untreated cancer group (p=0.046). The incidence rates indicated that the depression general group was 1.24 times more likely to experience an office-based provider visits, the pulmonary diagnosis group was 1.47 times more likely, and the cancer diagnosis group was 1.43 times more likely to experience an office-based provider visit relative to the no treatment general group.

Part III

A negative binomial regression was used to estimate the amount of positive change in expenditures given a positive change for each treatment group. The predicted mean number of visits for each group were 4.09, 4.54, 4.93, and 2.45 for the depression general, pulmonary, cancer, and no treatment groups, respectively. Amongst the individuals experiencing a negative change in utilization, each treatment group experienced a significant increase in the amount of negative change (p=0.000, p=0.000, and p=0.014). The incidence rates indicated that the depression general group was 1.35 times more likely to experience an office-based provider visits, the pulmonary diagnosis group was 1.48 times more likely, and the cancer diagnosis group was 1.56 times more likely to experience an office-based provider visit relative to the no treatment group. The pulmonary treatment group had a higher incidence of office-based provider visits than the no treatment pulmonary group p=(0.040).

Bootstrapping prediction

Using each of the three equations from the three-part model, the combination of the equations were used to predict the overall amount of change in utilization for each treatment

group and to determine whether or not there was a significant overall effect of mental health treatment on utilization. Bootstrapped results show that for each treatment group, there was not a significant change in office-based provider visits when the negative change, no change, and positive change groups were aggregated.

Summary

For total office-based provider visits, each treatment group had a greater number of visits associated with mental health treatment. An examination of a difference in visits over time revealed that each group was less likely to experience a change over time (positive or negative) with mental health treatment. Amongst those who had a positive or negative change, they were shown to experience an increased respective positive or negative change with treatment. However, combining the negative, no change, and positive changes together reveal that there was not a significant overall difference in office-based provider visits within the groups.

Work Absenteeism

Table 6-24 and Table 6-25 shows the individual characteristics of the work sample. The work sample consisted of depressed individuals aged 18-65 who were employed during each round of the study timeframe. The total sample consisted of 3,930 participants, 1,399 did not receive mental health treatment and 2,531 received mental health treatment. Males consisted of 31.17% of the sample and females constituted 68.83% of the sample. The average age of the work sample was 43.61 years and the majority were White (88.24%). Chi-square results indicate that participant groups were significantly different on each study characteristic examined in this study, with the exception that ADL and IADL needs were similar across the treatment and non-treatment groups. Participants most likely to seek treatment were female, white, high income, and insured individuals aged 45-64. The highest proportion of individuals who sought treatment

rated their physical health as “very good” and mental health as “good” and had 3 comorbid conditions. Table 6-26 depicts the statistical results on the work sample as discussed next.

Negative binomial regression

A negative binomial regression was used to determine whether those treated for depression in the work sample were more likely to show a decrease in work absenteeism. The regression was weighted, but did not include a selection correction that would be needed to correct for any fundamental differences between treated vs. untreated participants. The uncorrected regression showed that treated depression general participants were more likely to experience an increase in work absenteeism rates than the no treatment group (p=0.047). Participants in the treated pulmonary diagnosis group and the treated cancer diagnosis group did not show significant differences from the no treatment general group (p=0.166 and p=0.434, respectively), and this result was consistent when the pulmonary and cancer treatment groups were compared to the untreated pulmonary and cancer groups.

Poisson regression

In order to correct for the selection bias as discussed in Chapter 5 (page 52), an instrumental variable poisson regression (“ivpois” in Stata) was used to examine whether those treated for depression in the work sample were more likely to show a decrease in work absenteeism. The instrumental variable poisson regression was used because other options (e.g., heckman two-step) relied on the assumption of a normal distribution of error terms, which did not fit the data. A poisson regression is commonly used for count data and when a negative binomial instrumental regression is unavailable. Unfortunately, the option for “ivpois” in Stata do not allow for weighting of the data, so the results do not provide a nationally representative estimate of the US non-institutionalized, civilian population. Nevertheless, the results corroborate the uncorrected negative binomial regression when groups were compared to the no

treatment general group and the no treatment medical groups. That is, the depression general group was most likely to experience an increase in work absenteeism rates (p=0.004), whereas the pulmonary diagnosis and cancer diagnosis groups did not yield significant results (p=0.107 and p=0.324, respectively).

Post Hoc (Sensitivity) Analyses

Psychotherapy vs. Antidepressants

The main analyses combined psychotherapy and antidepressants in order to define mental health treatment. In order to determine if there was a significant difference between psychotherapy and antidepressant therapy on total and medical expenditures, further analyses were done. Psychotherapy and antidepressant therapy (treatment type) were separated for each of the treatment groups (depression general, pulmonary, and cancer) and compared with the no treatment group.

For total expenditures, it appears that the main results in which the depression general group had higher expenditures with treatment and more likely to show an increase in total expenditures over time are due to both psychotherapy and antidepressant medication. However, the increased reduction in total expenditures over time for the depression general group was due to antidepressant medication. For the pulmonary diagnosis group, the decreased likelihood of experiencing a reduction in expenditures was due to medication. For the cancer diagnosis group, antidepressant medication appears to be the driver of increased cost when expenditures are totalled across time periods, whereas individuals with cancer experiencing a reduction in expenditures over time was less likely with antidepressants, but more likely with psychotherapy.

For medical expenditures, antidepressant medication was the culprit of significant results for the depression general group. That is, individuals in the depression general group taking antidepressant medication were more likely to have any expenditures, show a change in

expenditures over time. For the pulmonary diagnosis group, psychotherapy played the prominent role. Despite medication increasing the likelihood of change over time for pulmonary patients, amongst individuals who had any medical expenditures or experienced a reduction, psychotherapy acted to reduce the amount of negative change and increase medical expenditures. For the cancer diagnosis group, antidepressant medication had the effect of minimizing the magnitude of reduction and increasing medical expenditures.

Mild vs. Severe Depression

MEPS included a measure screening for depression, the Patient Health Questionnaire (PHQ-2), in its 2004 and 2005 survey. The PHQ-2 contains the stem question, "Over the last 2 weeks, how often have you been bothered by any of the following problems?" and the two problems are "little interest or pleasure in doing things" and "feeling down, depressed, or hopeless" (Kroenki, Spitzer, & Williams, 2003). Each problem is rated as "not at all," "several days," "more than half the days," and "nearly everyday," resulting in a score from 0-6. On the PHQ-2 scale, a 3 or higher on the PHQ-2 is considered depression. In order to determine if differing levels of depression severity may have an impact on results, the sample with PHQ-2 data was used. A 3 or 4 on the PHQ-2 was considered moderate depression and a 5 or 6 on the PHQ-2 was considered severe depression for this analysis. Due to inadequate sample size, the pulmonary and cancer groups were not included in the analysis. Only the depression general group was examined. Post-hoc results indicate that the only difference between the moderate and severe groups was that amongst those who experienced a reduction in total expenditures over time, the severe depression group had a greater reduction in expenditures than the no treatment group ($p=0.043$).

Full-Time vs. Part-Time Work

In this study, full-time and part-time workers were not differentiated. Thus, for this post-hoc analysis, it was determined whether there was a significant difference between full- and part-time workers. A negative binomial regression revealed that there were no significant differences between full- and part- time workers, except for individuals with cancer. Results indicate that treated cancer patients working part-time had a greater incidence rate of work absenteeism than individuals who did not receive mental health treatment ($p=0.02$).

Table 6-1. Demographic characteristics of study samples by treatment group for expenditures/utilization equations

Variables	Depression General Treatment (N=2488) %	Pulmonary Comorbid Treatment (N=1199) %	Cancer Comorbid Treatment (N=194) %	No Treatment (N=2004) %	Total (N=6028) %	Chi2 test p-value
Age						
0-5	0.12	0	0	0.45	0.22	0.000
6-12	1.77	2.25	0	2.69	2.09	
13-17	5.27	4.59	1.03	3.89	4.43	
18-24	6.67	5.09	3.61	13.07	8.23	
25-44	33.72	30.94	21.65	39.12	34.17	
45-64	38.87	41.70	44.85	29.49	36.60	
65+	13.59	15.43	28.35	11.28	14.27	
Gender						
Female	69.65	74.90	69.07	65.02	69.14	0.000
Male	30.35	25.10	30.93	34.98	30.86	
Race						
White	87.02	83.90	85.57	81.34	84.52	0.000
Black	8.72	9.92	7.73	12.92	10.32	
Asian	1.57	1.08	2.06	2.00	1.59	
Other	2.69	5.10	4.64	3.74	3.57	
Ethnicity						
Hispanic	14.67	11.93	9.28	25.75	17.47	0.000
Non-Hispanic	85.33	88.07	90.72	74.25	82.53	
Poverty category						
Poor/negative	20.94	22.94	20.62	24.60	22.61	0.000
Near poor	6.31	5.75	4.12	7.09	6.44	
Low income	15.27	15.01	13.92	18.76	16.36	
Middle income	27.65	30.78	24.74	28.19	28.35	
High income	29.82	25.52	36.60	21.36	26.24	
Insurance status						
Uninsured	9.69	5.42	7.22	20.01	12.08	0.000
Intermittent	14.23	10.93	13.92	19.76	15.39	
Insured	76.09	83.65	78.87	60.23	72.53	
Physical health status						
Excellent	10.13	5.75	3.61	13.12	9.89	0.000
Very good	27.48	20.18	23.20	24.15	23.04	
Good	33.20	31.19	26.80	33.88	32.78	
Fair	19.17	22.94	23.71	18.26	19.79	
Poor	10.81	17.60	13.40	7.49	11.60	

Table 6-1. Continued

Variables	Depression General Treatment (N=2488) %	Pulmonary Comorbid Treatment (N=1199) %	Cancer Comorbid Treatment (N=194) %	No Treatment (N=2004) %	Total (N=6028) %	Chi2 test p-value
Mental health status						
Excellent	9.53	9.51	6.19	15.02	11.18	0.000
Very good	20.70	18.68	19.59	21.76	20.49	
Good	36.94	36.78	38.14	36.58	36.78	
Fair	20.50	23.02	18.56	17.81	20.14	
Poor	10.09	9.67	8.25	5.74	8.49	
Comorbidity count						
1	55.99	0	0	41.57	36.93	0.000
2	44.01	41.37	57.22	41.87	42.15	
3	0	58.63	42.78	15.82	19.34	
4	0	0	0	0.75	1.58	
Need help with IADL						
Yes	10.81	12.93	15.46	6.54	10.22	0.000
No	89.19	87.07	84.54	93.46	89.78	
Need help with ADL						
Yes	5.79	7.34	10.82	3.24	5.64	0.000
No	94.21	92.66	89.18	96.76	94.36	

Table 6-2. Central tendency of demographics for sample included in expenditures/utilization equations

Variables	Depression general treatment (N=2488) %	Pulmonary comorbid treatment (N=1199) %	Cancer comorbid treatment (N=194) %	No treatment (N=2004) %	Total (N=6028) %
Age					
Average	45.50	47.01	55.05	41.57	45.13
Standard deviation	17.79	17.40	16.55	18.11	18.10
Minimum	5	6	13	4	4
Maximum	85	85	85	85	85
Years of education					
Average	11.78	11.67	12.64	11.14	11.59
Standard deviation	3.55	3.59	3.20	3.64	3.59
Minimum	0	0	0	0	0
Maximum	17	17	17	17	17
Income					
Average	21232.42	19691.56	22375	18107.94	19963.55
Standard deviation	25038.11	22830.40	28156.22	21865.90	23698.17
Minimum	-40337	-333	-28961	-90050	-90050
Maximum	182836	200722	171953	163684	200722
Comorbidity count					
Average	1.44	2.59	2.43	1.76	1.86
Standard deviation	0.50	0.49	0.50	0.74	0.78
Minimum	1	2	2	1	1
Maximum	2	3	3	4	4

Table 6-3. Proportions of each type of change in total expenditures by treatment group (weighted)

	Depression general (%)	Pulmonary diagnosis (%)	Cancer diagnosis (%)	Total (%)
Zero expenditures	25.72	27.52	32.44	27.31
Non-zero expenditures	74.28	72.48	68.56	72.69
Total	100.00	100.00	100.00	100.00

Table 6-4. Logit regression predicting probability of experiencing each type of change in expenditures (part I of two-part model)

		Relative risk of having positive change vs. no change		
		Coef.	s.e.	p-value
Total expenditures	No treatment	Reference		
	Depression general	0.114	0.066	0.084
	Pulmonary diagnosis	-0.155	0.079	0.051
	Cancer diagnosis	-0.132	0.146	0.364
Medical expenditures	No treatment	Reference		
	Depression general	0.288**	0.078	0.000
	Pulmonary diagnosis	0.130	0.098	0.185
	Cancer diagnosis	-0.187	0.274	0.495
Drug expenditures	No treatment	Reference		
	Depression general	0.920**	0.107	0.000
	Pulmonary diagnosis	0.519**	0.128	0.000
	Cancer diagnosis	0.116	0.269	0.666

**Significant at 0.05 level

Table 6-5. Ordinary least squares regression (OLS) or generalized linear model (GLM) predicting amount of change in expenditures given positive change (Part II of two-part model)

		Amount of change		
		Coef.	s.e.	p-value
Total expenditures	No treatment	Reference		
	Depression general	0.785**	0.069	0.000
	Pulmonary diagnosis	0.845**	0.050	0.000
	Cancer diagnosis	0.985**	0.119	0.000
Medical expenditures	No treatment	Reference		
	Depression general	0.300**	0.066	0.000
	Pulmonary diagnosis	0.400**	0.052	0.000
	Cancer diagnosis	0.654**	0.087	0.000
Drug expenditures	No treatment	Reference		
	Depression general	0.792**	0.074	0.000
	Pulmonary diagnosis	1.008**	0.058	0.000
	Cancer diagnosis	0.777**	0.136	0.000

**Significant at 0.05 level

Table 6-6. Bootstrapping prediction of expenditure change after two-part model (OLS)

		N	Mean	S.D.	95%CI
Total expenditures	Depression general	1000	12235.52**	10536.79	(12165.27, 15104.86)
	Pulmonary diagnosis	1000	10657.36**	9250.19	(10168.78, 12472.32)
	Cancer diagnosis	1000	12673.82**	10992.70	(10496.44, 16412.93)
Medical expenditures	Depression general	1000	9344.22**	6922.44	(8398.14, 10365.60)
	Pulmonary diagnosis	1000	10323.20	7647.69	(9440.85, 11605.71)
	Cancer diagnosis	1000	13312.50	9862.24	(10879.77, 16254.00)
Drug expenditures	Depression general	1000	4189.64	2926.54	(3936.48, 4478.54)
	Pulmonary diagnosis	1000	5199.13	3631.69	(4789.87, 5666.10)
	Cancer diagnosis	1000	4126.83	2882.66	(3558.48, 4718.46)

**Significant at 0.05 level

Table 6-7. Proportions of each type of change in total expenditures by treatment group (weighted)

	Depression general (%)	Pulmonary diagnosis (%)	Cancer diagnosis (%)	Total (%)
Decreased	37.66	35.45	29.38	38.57
No change	25.72	27.52	31.44	27.31
Increased	36.62	37.03	39.18	34.12
Total	100.00	100.00	100.00	100.00

Table 6-8. Multinomial logit regression predicting probability of experiencing each type of change in expenditures (part I of three-part model)

		Relative risk of having negative change vs. no change			Relative risk of having positive change vs. no change		
		RRR	s.e.	p-value	RRR	s.e.	p-value
Total expenditures	No treatment	Reference					
	Depression general	0.941	0.079	0.469	1.391**	0.104	0.000
	Pulmonary diagnosis	0.696**	0.062	0.000	1.099	0.093	0.263
	Cancer diagnosis	0.613**	0.094	0.002	1.276	0.242	0.200
Medical expenditures	No treatment	Reference					
	Depression general	1.911**	0.188	0.000	2.228**	0.179	0.000
	Pulmonary diagnosis	5.755**	1.505	0.000	7.434**	2.167	0.000
Drug expenditures	No treatment	Reference					
	Depression general	8.829**	0.774	0.000	14.675**	0.918	0.000
	Pulmonary diagnosis	24.810**	8.084	0.000	41.352**	13.262	0.000

**Significant at 0.05 level

Table 6-9. Generalized linear regression (GLM) predicting amount of change in expenditures given negative or positive change (parts II and III of three-part model)

		Amount of negative change			Amount of positive change		
		Coef.	s.e.	p-value	Coef.	s.e.	p-value
Total expenditures	No treatment	Reference					
	Depression general	0.378**	0.081	0.000	0.299**	0.115	0.010
	Pulmonary diagnosis	0.272**	0.121	0.026	0.239**	0.111	0.032
	Cancer diagnosis	0.628**	0.127	0.000	0.544**	0.218	0.013
Medical expenditures	No treatment	Reference					
	Depression general	0.388**	0.109	0.000	0.070	0.120	0.562
	Pulmonary diagnosis	0.286**	0.110	0.010	0.053	0.118	0.45
	Cancer diagnosis	0.619**	0.091	0.000	0.558**	0.143	0.000
Drug expenditures	No treatment	Reference					
	Depression general	0.539**	0.0739	0.000	0.608**	0.063	0.000
	Pulmonary diagnosis	0.823**	0.053	0.000	0.834**	0.064	0.000
	Cancer diagnosis	0.401**	0.115	0.001	0.695**	0.103	0.000

**Significant at 0.05 level

Table 6-10. Bootstrapping prediction of expenditure change after three-part model (GLM)

		N	Mean	S.D.	95%CI
Total expenditures	Depression general	1000	46.21	1161.41	(-487.20, 967.06))
	Pulmonary diagnosis	1000	265.00	1086.23	(-391.34, 925.66)
	Cancer diagnosis	1000	979.70	1788.33	(-1088.26, 2746.94)
Medical expenditures	Depression general	1000	130.04	1103.48	(-2107.51, 684.36)
	Pulmonary diagnosis	1000	547.03	1247.29	(-1040.33, 1742.27)
	Cancer diagnosis	1000	1344.78	-194.24	(-1825.03, 7134.67)
Drug expenditures	Depression general	1000	56.97**	336.14	(-501.202, -56.364)
	Pulmonary diagnosis	1000	107.45**	439.18	(-970.617, -28.874)
	Cancer diagnosis	1000	296.01	403.31	(-917.411, 330.244)

**Significant at 0.05 level

Table 6-11. Proportion of each type of change in medical expenditures by treatment group (weighted)

	Depression general (%)	Pulmonary diagnosis (%)	Cancer diagnosis (%)	Total (%)
Zero expenditures	12.74	6.51	9.79	13.12
Non-zero expenditures	87.26	93.49	90.21	86.88
Total	100.00	100.00	100.00	100.00

Table 6-12. Proportion of each type of change in medical expenditures by treatment group (weighted)

	Depression general (%)	Pulmonary diagnosis (%)	Cancer diagnosis (%)	Total (%)
Decreased	46.38	43.12	44.85	45.50
No change	6.15	0.50	0	6.80
Increased	47.47	56.38	55.15	47.69
Total	100.00	100.00	100.00	100.00

Table 6-13. Proportion of each type of change in drug expenditures by treatment group (weighted)

	Depression general (%)	Pulmonary diagnosis (%)	Cancer diagnosis (%)	Total (%)
Zero expenditures	7.92	6.17	9.79	11.61
Non-zero expenditures	92.08	93.83	90.21	88.39
Total	100.00	100.00	100.00	100.00

Table 6-14. Proportion of each type of change in drug expenditures by treatment group (weighted)

	Depression general (%)	Pulmonary diagnosis (%)	Cancer diagnosis (%)	Total (%)
Decreased	42.04	41.62	40.21	44.31
No change	1.33	0.17	0	5.29
Increased	56.63	58.22	59.79	50.40
Total	100.00	100.00	100.00	100.00

Table 6-15. Negative binomial regression predicting amount of change in utilization with treatment

		Negative binomial results		
		IRR	s.e.	p-value
Emergency room visits	No treatment	Reference		
	Depression general	1.174**	0.030	0.000
	Pulmonary diagnosis	1.229**	0.056	0.000
	Cancer diagnosis	1.213**	0.104	0.025
Inpatient visits	No treatment	Reference		
	Depression general	1.402**	0.209	0.024
	Pulmonary diagnosis	1.312	0.190	0.062
	Cancer diagnosis	2.250**	0.588	0.002
Outpatient visits	No treatment	Reference		
	Depression general	1.452**	0.136	0.000
	Pulmonary diagnosis	1.427**	0.250	0.043
	Cancer diagnosis	2.293**	0.491	0.000
Office-based provider visits	No treatment	Reference		
	Depression general	1.882**	0.108	0.000
	Pulmonary diagnosis	2.068**	0.082	0.000
	Cancer diagnosis	1.959**	0.109	0.000

**Significant at 0.05 level

Table 6-16. Negative binomial regression predicting amount of visits for samples with and without treatment

		Predicted visits for treatment sample			Predicted visits for sample without treatment		
		N	Mean	SD	N	Mean	SD
Emergency room visits	Depression general	2425	0.720	0.349	3418	0.845	0.492
	Pulmonary diagnosis	1171	1.107	0.526	4672	0.716	0.382
	Cancer diagnosis	176	0.980	0.513	5667	0.787	0.439
Inpatient visits	Depression general	2425	2.784	3.582	3418	2.661	4.373
	Pulmonary diagnosis	1171	3.058	3.662	4672	2.625	4.154
	Cancer diagnosis	176	5.975	7.461	5667	2.611	3.869
Outpatient visits	Depression general	2425	2.001	1.156	3418	2.219	1.884
	Pulmonary diagnosis	1171	2.998	1.609	4672	1.911	1.555
	Cancer diagnosis	176	5.205	2.714	5667	2.033	1.481
Office-based provider visits	Depression general	2425	23.072	7.473	3418	20.415	13.185
	Pulmonary diagnosis	1171	31.600	9.709	4672	18.990	10.140
	Cancer diagnosis	176	30.907	8.945	5667	21.226	11.190

Table 6-17. Proportion of each type of change in emergency room visits by treatment group (weighted)

	Depression general (%)	Pulmonary diagnosis (%)	Cancer diagnosis (%)	Total (%)
Decreased	17.44	18.02	20.10	16.92
No change	60.25	53.96	54.12	59.94
Increased	22.31	28.02	25.77	23.14
Total	100.00	100.00	100.00	100.00

Table 6-18. Multinomial logit regression predicting probability of experiencing each type of change in utilization (part I of three-part model)

		Relative risk of having negative change vs. no change			Relative risk of having positive change vs. no change		
		Coef.	s.e.	p-value	Coef.	s.e.	p-value
Emergency room visits	No treatment	Reference					
	Depression general	0.265**	0.078	0.001	0.259**	0.096	0.007
	Pulmonary diagnosis	0.072	0.111	0.517	0.189	0.117	0.106
	Cancer diagnosis	0.261	0.156	0.094	0.049	0.171	0.773
Inpatient visits	No treatment	Reference					
	Depression general	0.220**	0.085	0.010	0.267	0.137	0.053
	Pulmonary diagnosis	0.320	0.170	0.061	0.494**	0.196	0.012
	Cancer diagnosis	0.545**	0.188	0.004	0.675**	0.223	0.003
Outpatient visits	No treatment	Reference					
	Depression general	0.314**	0.068	0.000	0.311**	0.058	0.000
	Pulmonary diagnosis	0.391**	0.105	0.000	0.320**	0.084	0.000
	Cancer diagnosis	0.906**	0.196	0.000	1.005**	0.190	0.000
Office-based provider visits	No treatment	Reference					
	Depression general	-0.346**	0.051	0.000	-1.095**	0.113	0.000
	Pulmonary diagnosis	-0.474**	0.096	0.000	-1.066**	0.198	0.000
	Cancer diagnosis	-0.518**	0.127	0.000	-1.743**	0.250	0.000

**Significant at 0.05 level

Table 6-19. Negative binomial regression predicting amount of change in utilization given negative or positive change (parts II and III of three-part model)

		Amount of negative change			Amount of positive change		
		IRR	s.e.	p-value	IRR	s.e.	p-value
Emergency room visits	No treatment	Reference					
	Depression general	0.915	0.047	0.086	1.008	0.043	0.842
	Pulmonary diagnosis	0.961	0.028	0.175	1.083**	0.044	0.049
	Cancer diagnosis	1.033	0.050	0.505	0.906	0.083	0.283
Inpatient visits	No treatment	Reference					
	Depression general	1.201	0.113	0.053	0.854	0.153	0.380
	Pulmonary diagnosis	0.824	0.169	0.347	0.951	0.150	0.750
	Cancer diagnosis	0.830	0.118	0.191	1.524	0.481	0.182
Outpatient visits	No treatment	Reference					
	Depression general	0.706**	0.917	0.008	1.554**	0.154	0.000
	Pulmonary diagnosis	0.945	0.251	0.830	1.245	0.174	0.117
	Cancer diagnosis	1.230	0.276	0.358	1.144	0.131	0.242
Office-based provider visits	No treatment	Reference					
	Depression general	1.243**	0.105	0.011	1.352**	0.088	0.000
	Pulmonary diagnosis	1.465**	0.184	0.003	1.476**	0.067	0.000
	Cancer diagnosis	1.426**	0.137	0.000	1.564**	0.283	0.014

**Significant at 0.05 level

Table 6-20. Bootstrapping prediction of expenditure change after three-part model (GLM)

		N	Mean	S.D.	95%CI
Emergency room visits	Depression general	1000	.0796	0.137	(-0.009, 0.114)
	Pulmonary diagnosis	1000	0.0328	0.129	(-0.035, 0.134)
	Cancer diagnosis	1000	-0.069	0.135	(-0.218, 0.079)
Inpatient visits	Depression general	1000	-0.453	1.136	(-0.546, 0.354)
	Pulmonary diagnosis	1000	0.733**	0.941	(0.084, 1.324)
	Cancer diagnosis	1000	2.526**	2.418	(0.354, 5.461)
Outpatient visits	Depression general	1000	0.271	0.327	(-0.033, 0.567)
	Pulmonary diagnosis	1000	-0.232	0.234	(-0.617, 0.167)
	Cancer diagnosis	1000	-0.423	0.341	(-1.493, 0.646)
Office-based provider visits	Depression general	1000	0.452	1.475	(-0.257, 1.068)
	Pulmonary diagnosis	1000	0.827	1.670	(-0.226, 1.869)
	Cancer diagnosis	1000	0.578	1.823	(-2.625, 3.753)

**Significant at 0.05 level

Table 6-21. Proportion of change in inpatient hospital visits by treatment group (weighted)

	Depression general (%)	Pulmonary diagnosis (%)	Cancer diagnosis (%)	Total (%)
Decreased	11.21	13.01	16.49	11.15
No change	70.18	64.30	55.15	69.84
Increased	18.61	22.69	28.35	19.01
Total	100.00	100.00	100.00	100.00

Table 6-22. Proportion of change in outpatient hospital visits by treatment group (weighted)

	Depression general (%)	Pulmonary diagnosis (%)	Cancer diagnosis (%)	Total (%)
Decreased	17.64	23.35	25.77	17.90
No change	58.32	49.29	32.47	58.15
Increased	24.04	27.36	41.75	23.95
Total	100.00	100.00	100.00	100.00

Table 6-23. Proportion of change in office-based provider visits by treatment group (weighted)

	Depression general (%)	Pulmonary diagnosis (%)	Cancer diagnosis (%)	Total (%)
Decreased	41.40	39.12	39.69	41.61
No change	7.68	6.26	3.61	10.77
Increased	50.92	54.63	56.70	47.63
Total	100.00	100.00	100.00	100.00

Table 6-24. Work sample demographic characteristics of study samples by treatment group

Variables	Depression general treatment (N=1703) %	Pulmonary comorbid treatment (N=681) %	Cancer comorbid treatment (N=98) %	No treatment (N=1399) %	Total (N=3930) %	Chi2 test p-value
Age						
18-24	4.99	3.38	4.08	9.86	6.36	0.000
25-44	45.63	46.99	25.51	51.89	47.33	
45-64	48.85	48.90	66.33	37.67	45.65	
65	0.53	0.73	4.08	0.57	0.66	
Gender						
Female	71.34	77.53	69.39	61.33	68.83	0.000
Male	28.66	22.47	30.61	38.67	31.17	
Race						
White	91.60	87.67	89.80	84.06	88.24	0.000
Black	5.05	6.61	0	10.08	6.97	
Asian	1.29	1.17	6.12	2.14	1.68	
Other	2.06	4.55	4.08	3.72	3.11	
Ethnicity						
Hispanic	10.16	8.52	6.12	24.37	14.76	0.000
Non-Hispanic	89.84	91.48	93.88	75.63	85.24	
Poverty category						
Poor/negative	4.87	5.29	1.02	10.44	6.77	0.000
Near poor	4.29	1.76	0	4.79	3.92	
Low income	10.16	9.84	17.35	18.16	13.26	
Middle income	32.06	37.74	23.47	34.60	33.79	
High income	48.62	45.37	58.16	32.02	42.26	
Insurance status						
Uninsured	7.81	5.43	10.20	19.87	11.76	0.000
Intermittent	9.28	6.90	5.10	12.65	9.95	
Insured	82.91	87.67	84.69	67.48	78.30	
Physical health status						
Excellent	14.86	9.25	10.20	14.80	13.61	0.000
Very good	33.59	31.86	43.88	30.38	32.16	
Good	36.76	42.00	27.55	38.46	38.45	
Fair	10.63	13.07	14.29	12.79	11.93	
Poor	4.17	3.82	4.08	3.57	3.84	
Mental health status						
Excellent	13.68	13.07	13.27	17.87	14.94	0.016
Very good	27.95	26.14	28.57	26.59	27.10	
Good	42.10	43.61	41.84	39.31	41.55	
Fair	12.98	15.42	14.29	13.30	13.59	
Poor	3.29	1.76	2.04	2.93	2.82	

Table 6-24. Continued

Variables	Depression general treatment (N=1703) %	Pulmonary comorbid treatment (N=681) %	Cancer comorbid treatment (N=98) %	No treatment (N=1399) %	Total (N=3930) %	Chi2 test p-value
Comorbidity count						
1	54.26	0	0	43.46	38.98	0.000
2	45.74	36.71	55.10	41.67	42.39	
3	0	63.29	44.90	14.30	17.71	
4	0	0	0	0.57	0.92	
Need help with IADL						
Yes	1.70	1.91	3.06	1.07	1.53	0.264
No	98.30	98.09	96.94	98.93	98.47	
Need help with ADL						
Yes	1.06	0.59	1.02	0.50	0.76	0.413
No	98.94	99.41	98.98	99.50	99.24	

Table 6-25. Central tendency of demographic characteristics for work sample

Variables	Depression general treatment (N=1703) %	Pulmonary comorbid treatment (N=681) %	Cancer comorbid treatment (N=98) %	No treatment (N=1399) %	Total (N=3930) %
Age					
Average	43.61	43.96	48.68	40.67	42.83
Standard deviation	10.68	10.26	10.99	11.50	11.07
Minimum	18	18	21	18	18
Maximum	68	65	65	65	65
Years of education					
Average	13.33	13.53	14.35	12.64	13.16
Standard deviation	2.70	2.67	2.19	2.96	2.81
Minimum	0	0	9	0	0
Maximum	17	17	17	17	17
Income					
Average	39388.03	37807.12	41485.37	32315.13	36711.43
Standard deviation	29491.63	25318.92	36145.71	26431.24	28086.65
Minimum	-19010	-333	-28961	-90050	-90050
Maximum	182836	171953	145489	163684	182836
Comorbidity count					
Average	1.46	2.63	2.45	1.72	1.81
Standard deviation	0.50	0.48	0.50	0.72	0.75
Minimum	1	2	2	1	1
Maximum	2	3	3	4	4

Table 6-26. Negative binomial regression predicting amount of change in work absenteeism rates with treatment

	Negative binomial regression, weighted, no selection correction			Poisson regression, unweighted, with selection correction		
	IRR	s.e.	p-value	Coef.	s.e.	p-value
No treatment	Reference					
Depression general	1.344	0.170	0.021	0.277	0.105	0.009
Pulmonary diagnosis	1.101	0.143	0.461	0.072	0.117	0.538
Cancer diagnosis	1.384	0.379	0.237	0.296	0.285	0.300

Table 6-27. Logit regression predicting probability of experiencing each type of change in expenditures when expenditures added over time (part I of two-part model)

		Relative risk of having positive change vs. no change		
		Coef.	s.e.	p-value
Total Expenditures	Pulmonary diagnosis	-0.340**	0.102	0.001
	Cancer diagnosis	-0.587*	0.306	0.060
Medical Expenditures	Pulmonary diagnosis	-0.488**	0.199	0.016
	Cancer diagnosis	-0.619	0.328	0.064
Drug Expenditures	Pulmonary diagnosis	-0.429**	0.217	0.050
	Cancer diagnosis	-0.619	0.328	0.064

**Significant at 0.05 level

Table 6-28. Part II of two-part model predicting amount of change in expenditures for medical treated and untreated groups when expenditures added over time

		Amount of change		
		Coef.	s.e.	p-value
Total Expenditures	Pulmonary diagnosis	0.402**	0.069	0.000
	Cancer diagnosis	0.117	0.110	0.291
Medical Expenditures	Pulmonary diagnosis	0.198**	0.073	0.008
	Cancer diagnosis	-0.007	0.136	0.962
Drug Expenditures	Pulmonary diagnosis	0.685**	0.059	0.000
	Cancer diagnosis	0.344	0.223	0.129

**Significant at 0.05 level

Table 6-29. Bootstrapping prediction of expenditure change after two-part model (OLS) for medical treated and untreated groups when expenditures added over time

		N	Mean	S.D.	95%CI
Total Expenditures	Pulmonary diagnosis	1000	18654.66**	11388.29	(13865.27, 14082.20)
	Cancer diagnosis	1000	34157.13**	14562.34	(17892.00, 18255.92)
Medical Expenditures	Pulmonary diagnosis	1000	19028.22**	13642.63	(11133.90, 11307.05)
	Cancer diagnosis	1000	32122.92**	16567.99	(2809.19, 3045.90)
Drug Expenditures	Pulmonary diagnosis	1000	5603.02**	3264.87	(1000.22, 1258.18)
	Cancer diagnosis	1000	7552.97**	2807.70	(1022.96, 1190.62)

**Significant at 0.05 level

Table 6-30. Part I of three-part model for medical groups compared to no treated medical groups for difference in expenditures over time

		Relative risk of having negative change vs. no change			Relative risk of having positive change vs. no change		
		RRR	s.e.	p-value	RRR	s.e.	p-value
Total Expenditures	Pulmonary diagnosis	0.630**	0.071	0.000	0.812	0.101	0.097
	Cancer diagnosis	0.499	0.189	0.072	0.612	0.179	0.099
Medical Expenditures	Pulmonary diagnosis	5.16e-07**	3.91e-07	0.000	6.49e-07**	0.041	0.000
Drug Expenditures	Pulmonary diagnosis	No participants in no change group to make estimation					

**Significant at 0.05 level

Table 6-31. Parts II and III of three-part model for medical treated groups compared to untreated medical groups for difference in expenditures over time

		Amount of negative change			Amount of positive change		
		Coef.	s.e.	p-value	Coef.	s.e.	p-value
Total expenditures	Pulmonary diagnosis	0.088	0.136	0.520	0.260**	0.122	0.035
	Cancer diagnosis	-0.196	0.308	0.526	-0.081	0.177	0.650
Medical expenditures	Pulmonary diagnosis	0.044	0.140	0.756	0.175	0.118	0.142
	Cancer diagnosis	0.039	0.187	0.835	-0.115	0.203	0.574
Drug expenditures	Pulmonary diagnosis	0.561**	0.055	0.000	0.482**	0.075	0.000
	Cancer diagnosis	-0.045	0.229	0.846	0.634**	0.179	0.001

**Significant at 0.05 level

Table 6-32. Bootstrapping prediction of expenditure change after three-part model comparing medical treated and untreated groups for difference in expenditures over time

		N	Mean	S.D.	95%CI
Total Expenditures	Pulmonary diagnosis	1000	385.55**	1359.14	(-160.97, -32.38)
	Cancer diagnosis	1000	1750.35**	5698.06	(-4000.71, -2839.37)
Medical Expenditures	Pulmonary diagnosis	1000	813.34**	2162.07	(-1497.90, -1257.72)
	Cancer diagnosis	1000	3548.98**	10413.89	(278.57, 741.64)
Drug Expenditures	Pulmonary diagnosis	1000	56.17**	56.17	(-898.05, -818.74)
	Cancer diagnosis	1000	-123.28**	781.84	(-940.98, -870.18)

**Significant at 0.05 level

Table 6-33. Negative binomial regression of medical treated and untreated groups predicting amount of change in utilization with treatment when utilization added over time

		Negative binomial results		
		IRR	s.e.	p-value
Emergency Room Visits	Pulmonary diagnosis	0.999	0.072	0.991
	Cancer diagnosis	1.324**	0.186	0.050
Inpatient Visits	Pulmonary diagnosis	1.133	0.261	0.588
	Cancer diagnosis	1.133	0.235	0.550
Outpatient Visits	Pulmonary diagnosis	1.351**	0.151	0.008
	Cancer diagnosis	1.159	0.493	0.729
Office-Based Provider Visits	Pulmonary diagnosis	1.539**	0.077	0.000
	Cancer diagnosis	1.321**	0.130	0.006

**Significant at 0.05 level

Table 6-34. Part I of three-part model for medical treated and untreated groups for difference in utilization over time

		Relative risk of having negative change vs. no change			Relative risk of having positive change vs. no change		
		Coef.	s.e.	p-value	Coef.	s.e.	p-value
Emergency Room Visits	Pulmonary diagnosis	0.394**	0.200	0.049	0.309	0.181	0.087
	Cancer diagnosis	-0.021	0.352	0.953	0.152	0.349	0.663
Inpatient Visits	Pulmonary diagnosis	0.106	0.222	0.631	0.222	0.190	0.244
	Cancer diagnosis	0.458	0.472	0.332	1.577**	0.403	0.000
Outpatient Visits	Pulmonary diagnosis	0.242	0.178	0.175	0.265	0.176	0.133
	Cancer diagnosis	-0.243	0.389	0.532	-0.170	0.355	0.631
Office-Based Provider Visits	Pulmonary diagnosis	-0.249	0.148	0.091	-0.616**	0.251	0.014
	Cancer diagnosis	-0.067	0.311	0.829	0.762	0.744	0.306

**Significant at 0.05 level

Table 6-35. Parts II and III of three-part model for medical treated and untreated groups for difference in utilization over time

		Amount of negative change			Amount of positive change		
		IRR	s.e.	p-value	IRR	s.e.	p-value
Emergency Room Visits	Pulmonary diagnosis	0.986	0.095	0.881	1.050	0.088	0.559
	Cancer diagnosis	1.276**	0.142	0.028	1.509**	0.181	0.001
Inpatient Visits	Pulmonary diagnosis	0.551**	0.145	0.023	1.386	0.274	0.100
	Cancer diagnosis	0.924	0.181	0.685	1.072	0.352	0.833
Outpatient Visits	Pulmonary diagnosis	1.080	0.214	0.699	1.300	0.253	0.178
	Cancer diagnosis	0.865	0.394	0.750	1.411	0.276	0.078
Office-Based Provider Visits	Pulmonary diagnosis	1.229	0.147	0.086	1.232**	0.125	0.040
	Cancer diagnosis	1.472**	0.285	0.046	1.192	0.227	0.356

**Significant at 0.05 level

Table 6-36. Three-part model bootstrapping prediction for medical treated and untreated groups for difference in utilization over time

		N	Mean	S.D.	95%CI
Emergency Room Visits	Pulmonary diagnosis	1000	0.161**	0.281	(-0.190, -0.182)
	Cancer diagnosis	1000	0.109**	0.501	(-1.548, -1.137)
Inpatient Visits	Pulmonary diagnosis	1000	0.451	2.044	(-0.047, 0.042)
	Cancer diagnosis	1000	2.157**	8.136	(-1.405, -1.051)
Outpatient Visits	Pulmonary diagnosis	1000	-0.114**	0.791	(-0.561, -0.494)
	Cancer diagnosis	1000	0.015**	4.133	(-1.701, -1.448)
Office-Based Provider Visits	Pulmonary diagnosis	1000	1.258	2.411	(-0.015, 0.142)
	Cancer diagnosis	1000	0.647**	5.578	(-1.119, -0.740)

**Significant at 0.05 level

Table 6-37. Negative binomial regression for medical treated and untreated groups predicting amount of change in work absenteeism rates with treatment

	Negative binomial regression, weighted, no selection correction			Poisson regression, unweighted, with selection correction		
	IRR	s.e.	p-value	Coef.	s.e.	p-value
Pulmonary diagnosis	1.006	0.146	0.966	0.005	0.115	0.966
Cancer diagnosis	1.070	0.361	0.843	0.102	0.291	0.726

CHAPTER 7
DISCUSSION

Overview

This study hypothesized a decrease in total and medical expenditures for individuals with a comorbid medical condition (pulmonary or cancer) who sought mental health treatment. It was also hypothesized that the depression general group that did not have a specific comorbidity of a pulmonary or cancer diagnosis (but may have other comorbidities) would show either an increase in expenditures or no change in expenditures over time. In this study, it was suggested that isolating individuals with expensive chronic medical conditions would reveal a medical cost offset effect that is otherwise masked when individuals with varying risk factors are pooled together. The medical cost offset hypothesis that mental health treatment can reduce or prevent usual cost to the health care system would be supported if total or medical expenditures are reduced for groups who seek mental health treatment. Analysis of medical expenditures is critical to the analysis of medical cost offset. Medical expenditures excludes the cost of psychological care. Observing a reduction in medical expenditures demonstrates a medical cost offset effect. Prescription drug expenditures were examined because increased care is thought to increase cost and mental health care was not excluded from this possibility. It was hypothesized that there would be either no difference or an increase in prescription drug expenditures with mental health treatment.

This study also examined whether mental health treatment affects health care utilization. Examination of health care utilization in light of total or medical expenditures should shed some light on which factors drive increased or decreased cost. In this study, it was hypothesized that there would be a reduction in utilization, as a medical cost offset effect could be observed through several different medical services.

This study adopted a broad perspective on the potential benefits of mental health treatment. Work absenteeism was also examined to add a perspective beyond the health care system and provide a broader view of societal and personal cost as a result of missed days from work. The following discussion will summarize the findings of this study.

Summary and Interpretation of Findings

Treatment groups compared to no treatment general group

Total expenditures for each treatment group were higher overall compared to the no treatment general group. Medical expenditures were higher for only the depression general group. These results suggested that in the depression general group, more care simply costed more. The higher medical expenditures suggest that aggregating individuals with various comorbidities into one group to examine medical cost offset results in a lack of an offset effect. For the pulmonary and cancer treatment groups, mental health treatment added cost to the total expenditures, but when the cost of psychological care was partialed out, medical expenditures remained the same, suggesting that psychological care at minimum does not increase the use of other medical services for these groups. These results are contrary to a medical cost offset effect, supporting the notion that additional care simply costs more.

Other results indicated when expenditures were added over time, the depression general group was more likely to have medical or drug expenditures, and the pulmonary group was also more likely to have drug expenditures. The results for drug expenditures confirm the study hypothesis that there would be no change or an increase in drug expenditures with mental health treatment. With rising prices of pharmaceuticals and increased drug use in the population (Scherer, 2004), this is not surprising. Furthermore, each group (depression general, pulmonary, and cancer) that had total, medical, and drug expenditures greater than zero had significantly higher expenditures than the no treatment group. Thus, those who utilize services tend to have

rising cost with mental health treatment. Post-hoc analyses reveal that the main culprit of rising total cost seemed to be antidepressant medication, as opposed to psychotherapy. Once again, this is likely due to the pricing and amount of medication use.

When the change in expenditures over two time periods was examined, the results revealed that each treatment group exhibited a change (positive, negative, or both) with mental health treatment, indicating a notable impact of mental health treatment on expenditure trends over time. Isolating only those with negative (decrease) or positive (increase) change, each treatment group with a negative change showed a significant decrease in total, medical, and drug expenditures over time compared to no treatment and there was a significant increase for each group with a positive change in expenditures, except for the depression general and pulmonary groups with respect to medical expenditures. In general, those who have a change in expenditures over time tend to show a larger magnitude of change when mental health care is added to the mix of medical services. It may be the case that these individuals have characteristics or unobserved factors that drive this change over time and the seeking of mental health treatment may simply be a reflection of these factors. The exception to mental health treatment impacting change was for the depression general and pulmonary treatment groups that showed an increase in medical expenditures over time. Taking into account the result that individuals with depression typically have higher expenditures, it appears that for the depression general and pulmonary groups, mental health treatment may be preventing an increase in medical expenditures. This conjecture is strengthened by the overall results (adding negative, positive, and no change groups together) indicating that there is no significant change in total, medical, or drug expenditures over time, positive or negative, with mental health treatment. The study time

frame and examining change with only two time points may have prevented the detection of an overall change.

One consistent finding is that treated cancer patients who had a reduction in total, medical, or drug expenditures over time had the greatest reduction in expenditures compared to the other treated groups. This suggests that particular medical groups may show differential benefit from mental health treatment and further suggests that teasing apart different medical conditions may be beneficial to future cost offset studies.

Breaking down type of medical service, total utilization of emergency room visits, inpatient visits, outpatient visits, and office-based provider visits tends to be higher for each treatment group than the no treatment group. In the context of the study result that total expenditures are greater with mental health treatment, it appears that each of these utilization measures contribute to the increase. When examining change in emergency room visits over time, mental health treatment had an impact on change for each treatment group for each measure of utilization, except for emergency room visits. That is, the pulmonary and cancer groups had no change in emergency room visits over time. However, emergency room visits also did not show an overall difference in visits for those receiving mental health treatment.

It appears that despite no difference in overall change in expenditures, the treated groups with a pulmonary or cancer diagnosis showed significant change in inpatient hospital stays overall. This is not surprising because these comorbid medical conditions are among the top five most expensive medical conditions (Soni, 2007) and their medical needs may require inpatient services. For the remaining health care utilization measures, outpatient hospital visits and office-based provider visits, there was no overall difference in visit counts over time. Because mental health treatment, particularly psychotherapy, is typically in an outpatient or office-based setting,

the lack of an increase in these measures may suggest a potential (but statistically unobserved) medical cost offset effect.

Finally, with respect to work absenteeism, it appears that the treated aggregated depression general group had more days missed from work than their non-treated counterparts and those with a comorbid pulmonary or cancer diagnosis. This suggests that not only may aggregating depressed individuals into a group mask a medical cost offset effect and even show an increase in total expenditures, there may be a corresponding effect on work absenteeism. That is, collapsing everyone who is depressed into one group regardless of other medical or psychological conditions may inadvertently create an impression that there is no societal benefit (from a cost perspective) of mental health treatment. It is noteworthy that the expensive medically comorbid groups with a pulmonary or cancer diagnosis showed no significant increase in medical expenditures nor work absenteeism counts. It may be that the benefits of mental health treatment on health care expenditures and work-related outcomes are most robust for those with chronic medical conditions.

Medical treatment groups compared to medical no treatment groups

When the pulmonary and cancer treatment groups were compared to the pulmonary and cancer no treatment groups, overall results argue against a medical cost offset effect. For both medical groups, every category of expenditures (total, medical, and drug) was higher overall than the corresponding medical no treatment group when expenditures were totalled over time. When change in expenditures was examined, each type of expenditures showed a significant increase over time for the treatment groups compared to the no treatment medical groups, with the exception of the cancer treatment group that showed a significant decrease in drug expenditures relative to the no treatment cancer group.

In terms of utilization added over time, there was a significant increase in utilization for emergency room visits for the cancer treated group and there was a significant overall increase in emergency visits over time for the cancer treatment group compared to the no treatment cancer group, which suggests that individuals with cancer who seek out mental health treatment may also be in more advanced stages with their cancer. Other results show an increase in outpatient visits for the pulmonary treated group relative to the no treatment pulmonary group, and an increase office-based provider visits for both medical treated groups compared to the no treatment medical groups. This result is consistent with the fact that mental health treatment is most often in these settings.

When change in utilization was examined over time, the cancer treatment group had higher utilization rates for each utilization measure compared to the no treatment cancer group. Thus, it appears that the increase in total expenditures with treatment for the cancer group was due to an increase in emergency room, inpatient, outpatient, and office-based provider visits. For the pulmonary treatment group, only emergency room visits were higher than the no treatment pulmonary group, whereas outpatient visits were lower for the treatment group than the no treatment group. There was no difference in inpatient or office-based provider visits between the pulmonary treatment and no treatment groups. The pulmonary group utilization results suggest that an increase in emergency room visits is driving the increased cost and mental health treatment may be shifting care away from outpatient settings.

Study Limitations

Despite the longitudinal nature of this study, the two-and-a-half year timeframe may not be sufficient to examine real change over time. Simon and Katzelnick (1997) suggested a cost offset effect may require several years before it can be observed. Furthermore, the length of

mental health treatment prior to participation in this study could not be determined. It is possible individuals in the treated group did not receive an effective "dosage" of treatment.

Second, the study results that showed different patterns among those who experienced a negative, no change, or positive change in expenditures suggest that the groups may have fundamental differences not captured by this study. For example, negative change individuals tended to have an increased negative change with mental health treatment, whereas individuals with positive change tend to have an increased positive change with treatment. This finding might also suggest differences in the quality of treatment received. The quality of mental treatment could not be determined in this study. Quality of treatment could help determine the relationship between treatment effectiveness and health care expenditures or utilization.

Third, identifying individuals using ICD-9 codes has limited reliability and validity, particularly due to participants reporting their own diagnoses. On a related note, the severity of depression could not be determined with accuracy in this study, which reduced precision in the analysis and may have masked any nuances among differing degrees of severity. Lastly, there was a reduction in precision of the analysis because antidepressant medication was collapsed with psychotherapy to create the mental health treatment variable.

Implications

Mental health treatment and mental health disorders have historically carried a social stigma. With the biomedical model dominating health care, mental health is traditionally underemphasized in health care. The medical cost offset effect, if demonstrated, would be a strong argument for increased attention to, and treatment of, mental health disorders. Particularly with the demonstrated cost and impairment of depression comparable to other medical disorders (e.g., Murray & Lopez, 1996), mental health care is increasingly given more importance in recent years. Despite the difficulty of demonstrating a medical cost offset effect,

the data quantifying the negative impact of depression on a personal and societal level cannot be ignored.

The medical cost offset effect is a particularly compelling concept for mental health professionals. The medical cost offset effect provides a way to quantify the value of mental health care. If the medical cost offset effect were a robust and consistent phenomenon, psychologists and other mental health professionals could use the effect to justify payment for services to third-party payers and policymakers. The cost offset also provides a compelling argument for the integration of phsyical and mental health care. However, this study, along with most recent published studies have not supported the existence of a medical cost offset effect. The medical cost offset effect may have dwindled with the institution of cost control efforts during the last decade of the 20th century. The managed care era spanned from approximately 1980 to 2000; however, the use of health maintenance organizations increased dramatically in the 1990s (Robinson, 2004). During this time, health care spending was reduced by reductions in fees and payment rates. These changes reduced the opportunity for cost savings from other methods.

Despite the difficulties with demonstrating a medical cost offset effect, it remains a noteworthy phenomenon to examine because of consistent increases in the cost of medical care and a potentially changing political climate in the near future. As this study demonstrated with differential results for individuals with comorbid medical conditions and the aggregated general depression group, future studies may benefit from increasing the specificity of the populations under study. That is, the medical cost offset effect is likely to be the most applicable when one can determine the specific comorbid medical conditions that interact to drive costs. The challenge of defining the nature of this interaction is great. In this study, however, when the

medical groups were compared to the no treatment medical groups (instead of the general no treatment group), the medical offset did not matreialize suggesting a medical cost offset effect for expensive medical groups may not be meaningful. In fact, this study strengthens the idea that more care simply costs more and individuals with a chronic medical condition who seek mental health care are no exception to this.

The search for a medical cost offset may focus outcome researchers on the wrong issue. The medical cost offset justifies treatment based on cost savings alone. Treatment should be validated on the effectiveness of the intervention, improved quality of life, and functioning. There are serious implications for health care if each treatment must demonstrate a cost offset in order to be deemed valuable. If insurance companies or policymakers focus solely on the bottom line, the quality of health care will likely suffer. Thus, it is important to continually keep patient quality of life as an important outcome and marker of success. Cost-effectiveness analyses comparing interventions in terms of a cost to effectiveness ratio, and cost-benefit analysis, which estimates value by weighing the benefits of a treatment to the cost of the treatment (Santerre & Neun, 2007), is more in line with the goal of quality health care. Future studies should focus more on effectiveness and benefit to the patient.

In this study, medication was a significant driver of health care expenditures. The proportion of depressed individuals on antidepressant medication in the sample was higher than the proportion undergoing psychotherapy. Previous research has demonstrated that the combination of psychotherapy and antidepressant medication is superior to either psychotherapy or medication alone (Freedland et al., 2004). This combined approach was not most frequent treatment approach among individuals in this study.

The reduction in work days was also examined in this study. Future studies should expand the societal benefit analysis even further to include areas such as cost to other public programs, the losses and difficulties experienced by family of individuals needing mental health care, lost income, and diminished worforce productivity when at work.

Recent studies have failed to demonstrate the medical cost offset effect. Despite this failure, work to estimate medical cost offset effects should not be abandonned. On the contrary, it is important to recognize the magnitude of change in the financing health services has far outpaced research examining the interaction among clinical services and cost. More efforts to better understand these relationships are needed to update the literature and examine trends over time. Such efforts must also give weight to the assessment of quality of care and how quality compares to the cost of care.

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BIOGRAPHICAL SKETCH

Andrea Lee, born in Vancouver, British Columbia, Canada, had a desire to become a psychologist at the age of 14. She itched to graduate high school in order to study psychology. She earned a Bachelor of Arts Honor's degree in psychology from Simon Fraser University in Burnaby, British Columbia in 2003. Over the years, she refined her interest in psychology to encompass clinical psychology and health psychology. Her overwhelming desire to help others on an individual level was eventually supplemented by a desire to make a difference on a population level. This interest in population level changes was the beginning of her desire for knowledge in health policy. The obvious next step for her was to pursue a doctoral degree in psychology. She was delighted to discover that not only could she be trained superbly in the areas of clinical psychology and health psychology at the University of Florida, she would also be able to gain valuable exposure to health policy. Thus, the Department of Clinical and Health Psychology at the University of Florida became the obvious choice for her graduate studies. Since her matriculation at the University of Florida in 2004, she has gained the knowledge and skills that will allow her to attempt to make the kind of difference she has dreamed of since her teenage years. Prior to graduating with her doctoral degree, she will be heading to the University of Manitoba to complete a year-long pre-doctoral internship. Whatever may become of Andrea's future and career, she hopes to positively contribute to the already outstanding reputation of the University of Florida's Department of Clinical and Health Psychology.