The Economic Cost of Depressive Disorders: Evidence from a Large Midwest Public University

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THE ECONOMIC COST OF DEPRESSIVE DISORDERS: EVIDENCE FROM A LARGE MIDWEST PUBLIC UNIVERSITY

by

Alketa Hysenbegasi

A Dissertation
Submitted to the
Faculty of The Graduate College
in partial fulfillment of the
requirements for the
Degree of Doctor Philosophy
Department of Economics

Western Michigan University
Kalamazoo, Michigan
August 2001
This dissertation aims to estimate the total cost of depression and the benefits of its treatment per diagnosed depressed student in Western Michigan University. To accomplish this, first, I measure the overall impact of depression and the effectiveness of its treatment on the student school performance. The empirical evidence show that diagnosed depression decreases student GPA by 0.48 points (almost a half grade), but this impairment is reduced by treatment about 0.43 points. Further, I develop and validate different measurements of student school performance and I observe that the negative effect of diagnosed depression and the positive effect of treatment are underestimated when the subjective measurement of student school performance is employed.

Second, the student’s activities also extend outside the academic environment. The empirical evidences show that depressive disorders reduce significantly employment probabilities by 0.49 and work hours supply per week by 1.66 hours among University students. This negative impairment of depressive disorders on employment status is compensated by the positive effect of treatment for depression. I also find evidence of small reduction in the absenteeism rate for working students. An interesting finding is that student productivity is significantly reduced by the depressive disorders and is robust to
alternative specifications whether the student was working at home or at an employment site. Treatment for depression induces a reduction in depressive severity which is reflected in the improvement of student productivity.

Finally, I compute the overall annual cost of depression and net benefits of its treatment to the student population. The average cost of diagnosed depression per student is $2,826.57 which consists of 41% treatment cost and 59% morbidity cost. I find that the main driver of treatment cost is counseling cost while the main drivers of indirect cost are school performance and presenteeism. The analysis indicates the effectiveness of treatment in preventing student GPA from falling, saving hours of work scheduled to work and increasing student performance at work and home. Treatment benefits exceeds the direct cost of depression by $96.42. Thus, the total net cost of depression is reduced to $232,592.25 or $1,659.88 per diagnosed depressed student.
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CHAPTER I

INTRODUCTION

One main goal of the health economist is to estimate the direct and indirect costs of chronic diseases such as cardiovascular diseases, respiratory ailments, gastrointestinal disorders, and mental disorders. While the direct costs which consist of the costs of inpatient, outpatient and pharmaceutical care, are relatively easy to calculate, the indirect costs are 'hidden' costs to employers, employees and society. They may account for a very large proportion of the total cost of disease. They include: the loss of production due to absence from paid work, reduction in productivity of sick individuals at paid work and reduction in household production due to disease. Besides these common components, researchers have started to consider the indirect costs incurred by the family members and/or friends who take care of the sick people (Liljas, 1998).

Depression is a common disorder that creates health problems in ten percent of the population annually (Claxton, Chawla, & Kennedy, 1999). Statistics have shown that one in eight persons will experience a depression disorder during his/her lifetime. In the case of severe symptoms of depression, the effects are significant on all aspects of the individual's life, including clinical and functional status, quality of life and financial well being (Greenberg, Stiglin, Finkelstein, & Berndt, 1993b). Recently, it has been found that the economic toll of depression is high relative to that associated with other acute and
chronic diseases (Greenberg, Stiglin, Finkelstein, & Berndt, 1993a). The World Bank has estimated that depression will be the second leading (after cardiovascular diseases) cause of high disability in the work force by the year 2020 (Birnbaum, Cremieux, Greenberg, & Kessler, 1999; Murray & Lopez, 1996). Researchers argue that the economic burden of depression is mostly attributed to indirect costs such as losses arising from absenteeism, lowered productivity, safety risks, accidents, suicide and ineffective treatment of the disease (Broadhead, Blazer, George, & Tze, 1990; Conti & Burton, 1994; Greenberg et al., 1993b).

Using the human capital approach, Greenberg et al. (1993b) estimated that the annual cost of depression in 1990 in the US was $43.7 billion (0.7 percent of US gross domestic product in 1990), where $12.4 billion (28%) is attributed to direct costs, $7.5 billion (17%) to mortality cost and $23.8 billion (55%) to indirect costs. They pointed out that this is still an underestimate of the total cost of depression since it does not include the costs arising from substance abuse, smoking, and other mental disorders that are associated with depression.

Depression imposes financial costs on family and friends beyond the costs described above. It is frequently unrecognized by primary care physicians because they usually diagnose physical disorders and ignore ‘hidden’ mental disorders. In addition, there are many individuals who experience depressive symptoms but do not seek medical help. These facts show that the economic burden of depression would be even higher if the analyses took into account those people who experienced depressive symptoms but have never sought medical help or never been diagnosed. Thus, the major goal of
employers to manage this high cost is to provide patients with early appropriate interventions and to return them to normal function including a restoration of work performance.

While Greenberg et al. (1993b) showed that depression is very costly to society overall, other studies have estimated the costs of depression to a firm or group of firms in a particular industry. These microeconomic studies have investigated the impact of major depression and its treatment on worker performance and computed the cost associated with this disease. Kessler et al. (1999) used a two-phase regression analysis to estimate the effects of major depression and depressive symptoms on short-term disability. They found that the odds of having short-term disability are higher among depressed workers than among other workers in the National Comorbidity Survey and the Midlife Development Survey. In their microeconomic analysis of impairment caused by depression in the workplace, Burton and Conti (1994) estimated that the average length of a short-term disability due to a diagnosed depressive disorder was 40 days among workers at First Chicago Corporation. For mental health disorders excluding depression, the average length of short-term disability was 32 days and for non-mental health disorders it was 29 days. Thus, depression has the highest short-term disability cost among other chronic illnesses.

Brinbaum et al. (1999) analyzed long-term disability due to depression in employees of Fortune 100 manufacturers. They found that the treatment cost for depressed workers was 4.2 times higher than for those of workers who experienced long-term disability due to other diseases. Because of this high cost of depression due to absenteeism, researchers emphasize strongly the necessity of treatment. Claxton et al.
(1999) observed the effect of drug therapy on monthly absenteeism due to depression. They found that monthly absenteeism increased steadily before treatment and dropped significantly after the initiation of treatment.

The above studies have considered only the worker's forgone productivity and income due to absenteeism but ignored impairment of productivity while at work which makes the total cost of depression underestimated. Measuring worker's productivity while on job is a difficult task. Those who have attempted to measure on-job productivity in depression and other disease states have used subjective instruments collecting workers' self-reports (Berndt, Finkelstein, Greenberg, Keller, & Russell, 1998; Chilcott & Shapiro, 1996; Ferrari, 1998). Very few studies have been conducted to validate these self-reports against an objective measurement. The most easily quantifiable objective measure of job productivity would be in "piece work" manufacturing where workers are paid on the basis of the number of items they produce. In modern assembly line manufacturing and the increasingly service sector oriented economy, the opportunities to access an objective measure of this type are extremely limited.

Recently, Burton, Conti, Chen, Schultz, and Edington (1999) introduced the worker productivity index (WPI) which measures the time away from work due to disease and time lost because of a failure to maintain the productivity standard. Their study was conducted at a large Midwestern US credit card operation providing telephone customer service. They concluded that the employees with health problems such as mental health disorders, respiratory ailments, gastrointestinal disorders and injuries, are less productive in their jobs than their healthy colleagues. Depression was also the most
common category of disease and its cost was the highest in terms of total time lost from work compared to other diseases. Another attempt to measure the impairment caused by depression on job performance is a five-year ongoing study conducted by Ronald Kessler that seeks to collect objective data on productivity. It studies worker productivity in a large grocery store chain and airline reservation companies to test the impact of depressive disorders in the workplace and assess the value of treatment.

However, so far, there is no completed study that investigates the economic impact of depression on worker performance which considers both subjective and objective measures of productivity. This is because objective measures of productivity are difficult to collect and they are available only for some categories of occupations. Most of the studies mentioned above have relied on self-reported data of productivity that may bias the estimated cost of depression. Another feature of the above micro studies is that they usually investigate only one cost component of depression such as the cost due to absenteeism, the cost due to presenteeism, the cost due to prescription medication etc. Although Greenberg et al. (1993b) tried to include all the possible cost components in his macro estimation of depression cost, his calculated cost is underestimated due to ignoring the economic cost induced by non-diagnosed individuals.

The main objective of this dissertation is to estimate the total cost of depression and the benefits of its treatment per diagnosed depressed student. To accomplish this, I need to estimate the direct and indirect costs of diagnosed depression. While the direct  

\footnote{There are no results yet from this study. For a detailed description of the past and current studies on the impact of depression on the job productivity see Vernarce (2000).}
cost is straightforward to calculate by considering the cost of counseling and drug therapy, the indirect cost component is more complex for reasons mentioned in the previous paragraphs. In this dissertation, I consider college students who are involved in academic and non-academic activities. There are two reasons for choosing this population group. First, depression is usually called the “youth disease” because its highest prevalence is among young people aged 18-34 years (National Institute of Mental Health) and because most of them have their first symptoms before they are 15 years old (Berndt, Bir, Bush, Frank, & Normand, 2000). Second, students belong to a unique set of individuals whose quantity and quality of work is regularly evaluated. This evaluation is conducted by their instructors and is reflected in the grade they receive for a course. While there is some subjective evaluation associated with grading essays, projects, presentations, etc. which are common for graduate classes, undergraduate course grades are largely based upon exams that consist mostly of non-essay questions. Thus, undergraduate GPA is a reasonably objective measurement of student “on job performance” versus graduate GPA and is used within this dissertation to evaluate the validity of students’ (“workers”) self-reported productivity. In addition, the graduate students have significant age, school and work experience differences from the undergraduate students, therefore, they are excluded from the analysis. In the remainder of this chapter, I summarize briefly the contents of each chapter of the dissertation.

My analysis uses data regarding students of Western Michigan University covering a 28 month period. The data were obtained from the Sindecuse Health Center and the Registrar’s Office at Western Michigan University, which were linked with those
extracted from a survey delivered to students of the University. A detailed description of the data collection and construction is outlined in Chapter II.

One main objective of this study is to evaluate the indirect cost of a student's depression during his/her academic career. In the third chapter of this dissertation, I present a model of the relationship between depression disorders and the student's school performance. The reduction in student performance due to depression while enrolled in school is one of the major outcomes of the disorder. It reflects absence from learning opportunities, a decrease in the level of information absorbed, and/or a decrease in their ability to demonstrate learning. Additionally, depression can have a disruptive influence on students' future careers by delaying entry into the job market or inhibiting the job search process. In this chapter, I investigate the effect of student health status and other factors on student school performance which is measured by student GPA. An important issue discussed here is the effectiveness of depression treatment. I expect that treatment for depression leads to changes in student health status which will be followed by positive changes in the student school performance. I apply the model to a panel data that consists of student school performance, health status, individual and school characteristics. Further, I develop and validate an alternative measurement of student performance which was obtained from a survey that was administered to all students in the sample.

The activities of University students also extend outside the academic environment. Usually students work part-time or full-time during the academic year or summer vacations. Some of them work to obtain professional experience and others work to fulfill their financial needs. Depression disorders might affect student ability to work and
to perform household duties. In the fourth chapter of this dissertation, I investigate the possible impact of depressive disorders on a student's decision to participate in the labor force and the number of work hours they perform. In addition, I estimate the degree of impairment caused by depression on student work productivity and household activities. Different econometric techniques are applied to the equations of student employment, work hours, absenteeism, work and home performance and longitudinal data are employed to estimate these impairments.

While the indirect cost components of depression are addressed in Chapters III and IV of this dissertation, the direct cost components are estimated in Chapter V. In this chapter, I compute the total cost of diagnosed depression and benefits of its treatment per episode within the student population from a societal point of view. To evaluate this cost, I use information on the total outpatient and pharmaceutical expenditures for depressed students collected from the Sindecuse Health Center. Also, knowing the effect of depression on student performance in and out of school, the cost of study (tuition, books and supplies) and the wage rate of working students, I calculate the total indirect cost of depression due to less performance at school, work and home, missed hours of work, and reduced scheduled work hours. The analysis estimates the total cost of diagnosed depression associated with a population of university students, and allows me to evaluate the beneficial impact of medical intervention in reducing the high costs associated with depression and other impairments on the student's labor outcomes. This project may support further research that can demonstrate the value of counseling and health services on school performance versus alternative uses of University funding.
CHAPTER II

THE DATA COLLECTION AND DESCRIPTION

The Data Collection

The data needed to meet the study's objectives were obtained from a sample of 314 students of Western Michigan University who were diagnosed with depression based on ICD-9 codes (i.e., 296.2x and 296.3x) from January 1998 to April 2000 at the Sindecuse Health Center and a matched control group of 892 students. Each student treated for depression was matched with three 'non-depressed' controls\(^2\). The controls were randomly selected from the pool of all University students and were matched on gender, curriculum, graduate versus undergraduate, class level, and their GPA\(^3\) for the term prior to the date of their first depression visit of their matched subjects. These students are called 'non-depressed' controls because they have not been diagnosed and treated for depression at the Health Center. However, this does not exclude the possibility that some of them may have experienced depressive symptoms but never been treated for depression, or been diagnosed and treated for depression at the Counseling and

\(^2\)Number 'three' was arbitrary chosen. I intended to have a significant number of one to one matched pairs. However, taking into consideration that some of the controls would not meet the criteria for being a perfect match or may not respond to the survey, I decided to increase the initial number of matched controls to three.

\(^3\)The matching on GPA has been made on the range of ±0.25.
Testing Center or off campus (i.e., not at the Health Center). Information from a survey was used to further classify the students who were diagnosed or not with depression (for details see next section).

To check whether the sample of depressed students is a representative sample of the Western Michigan University students, in Table 1, I provide some descriptive statistics for two groups of students: 314 students diagnosed with depression at the Sindecuse Health Center from January 1, 1998 to April 30, 2000 and a weighted sample of WMU students across the study period. I find that the proportion of females for the depressed group is higher relative to that for the University. The graduate students and also students from Engineering College, Business College and Others are under represented within the group of depressed students. The statistics in Table 1 show that proportions of freshmen, sophomore, junior and students from Art College who were diagnosed with depression are higher than those for the WMU sample.

For both groups of students (treated and controls), the Registrar’s Office provided additional information which consisted of: SAT and/or ACT scores, student’s University entry date, student’s current class level, current college within the University, current curriculum, total credit hours attempted, total credit hours earned, current GPA, gender, age and graduation date if the student had graduated. In addition, the Registrar’s Office provided GPAs, credit hours attempted and earned for each of 9 terms (from Winter 1998 to Winter 2000).

The Health Center provided the health information for the treated group and the control group. The following information was collected for each student: chronic
Table 1

Descriptive Statistics for Depressed Students and a Weighted Sample of WMU Students

<table>
<thead>
<tr>
<th>Variables</th>
<th>Means and Proportions</th>
<th>WMU students</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Diagnosed depressed students (n=314)</td>
<td></td>
</tr>
<tr>
<td>1. Age</td>
<td>23.87</td>
<td>24.13</td>
</tr>
<tr>
<td>2. Female</td>
<td>0.75</td>
<td>0.55</td>
</tr>
<tr>
<td>3. ACT score</td>
<td>23.07</td>
<td>22.2</td>
</tr>
<tr>
<td>4. Graduate students</td>
<td>0.07</td>
<td>0.22</td>
</tr>
<tr>
<td>5. Freshmen</td>
<td>0.24</td>
<td>0.19</td>
</tr>
<tr>
<td>6. Sophomore</td>
<td>0.22</td>
<td>0.17</td>
</tr>
<tr>
<td>7. Junior</td>
<td>0.24</td>
<td>0.18</td>
</tr>
<tr>
<td>8. Senior</td>
<td>0.23</td>
<td>0.24</td>
</tr>
<tr>
<td>9. Engineering College</td>
<td>0.04</td>
<td>0.10</td>
</tr>
<tr>
<td>10. Business College</td>
<td>0.15</td>
<td>0.18</td>
</tr>
<tr>
<td>11. Education College</td>
<td>0.20</td>
<td>0.18</td>
</tr>
<tr>
<td>12. Art College</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>13. Health College</td>
<td>0.05</td>
<td>0.06</td>
</tr>
<tr>
<td>14. Arts and Sciences</td>
<td>0.29</td>
<td>0.29</td>
</tr>
<tr>
<td>15. Others*</td>
<td>0.09</td>
<td>0.16</td>
</tr>
</tbody>
</table>

a) This includes University curriculums and Continuing Education majors.


disease history (migraine, asthma, diabetes, allergies) and current insurance status. Additional information for the students in the treatment group included their diagnosis date for depression, date of last visit for depression, depression history, number of office visits, number of office visits with counseling at this center, total charge for office visits, information about treatment drugs such as name, total quantity dispensed and total charge. It is clear that for those students who never used the University’s health facilities, the above information is not available.
The second stage of the data collection involved the delivery of a survey to 314 students treated for depression and their controls (892). The survey contained 68 questions which were organized in 7 sections: school status, employment status, demographic characteristics, health care evaluation, health status, productivity impairment related to depression and productivity impairment related to other health disorders (see the second form of questionnaire in Appendix A). Because the students in the treated group were diagnosed with depression in different academic years, three forms of the survey were developed. The questions in these three forms are the same but they cover different time periods:

1. The first form was designed to collect information from January 1, 1998 to December 31, 1998 and was delivered to those students who were first diagnosed with depression in 1998 and their controls.

2. The second form was designed to collect information from January 1, 1999 to December 31, 1999 and was delivered to those students who were first diagnosed with depression in 1999 and their controls.

3. The third form was designed to collect information from May 1, 1999 to April 30, 2000 and was delivered to those students who were first diagnosed with depression in Winter 2000 and their controls.

The Analysis Sample

A total of 450 completed surveys were returned for a response rate of 37%. There were 36 graduates and 414 undergraduates. As mentioned in the previous chapter,
graduate students were excluded from the analysis, thus the total sample consists of 414 undergraduate students. Figure 1 provides details regarding subsets of this sample that were used for analytical purposes. These students are first classified into two groups: 167 students diagnosed with depression by a health professional at the Health Center, Counseling and Testing Center or off campus, and the 247 students not diagnosed with depression who serve as controls. The group of depressed students can be divided further into two subgroups: 121 students who were diagnosed with depression at the Health Center, and 46 students who were diagnosed with depression at the Counseling Center or off campus. Students can see a psychiatrist, medical doctor or physician assistant at the Health Center for their depressive disorders. Usually, drug therapy and sometimes counseling is suggested to them. At the Counseling Center, students can meet with a licensed psychologist or graduate students from the department of psychology to have counseling sessions which usually last one hour. I collected detailed health information on the first subgroup of students which includes the diagnosis date, prescription medication taken for depression, number of office visits and number of visits with counseling at the Health Center. Within the first subgroup, 92 students obtained at least one prescription which usually consisted of SSRI (selective serotonin reuptake inhibitor) products such as Prozac®, Paxil®, Zoloft®, Luvox®, and Celexa® or older generic antidepressants such as Imipramine® and Pamelor® that belong to the TCA (tricyclic amine) group. The majority of depressed students (60) had some counseling sessions with psychiatrists or psychologists, while 32 students followed drug therapy only. There are 29 students who, although diagnosed with depression and prescribed medication by a health
Figure 1. Subsets of the Analysis Sample.
professional, failed to purchase medication. It is possible that some of them could not afford the cost of medication due to the lack of insurance coverage and others believed that with help of parents and/or friends they could manage the depressive disorder without the medications. Of these, 18 participated in some form of counseling at school or off campus, but 11 students did not follow any treatment.

A second subgroup of students (46) were identified with depressive disorders based on information from a survey. Some of them (30) claimed that they obtained treatment at the Counseling Center or off campus, while the remaining (16) did not pursue any kind of treatment. Due to non-availability of information about their medication and diagnosis date, this subgroup of students (46) has been excluded from my sample in the analysis described in upcoming chapters.

Within the control group (247), it may be that some students experienced symptoms of depression, but never saw a health professional for these disorders. For this reason, in the survey, I constructed an evaluation for the mood disorders based on DSM-IV criteria in order to identify those students. This evaluation consisted of a series of questions that asked students whether they experienced various symptoms of depression in the past 12 months. Because there were liability concerns caused by posing the question

---

4 The DSM-IV criteria considers nine symptoms for evaluation of mood disorders. An individual must experience at least five of the following symptoms, where one of symptoms is depressed mood or loss of interest or pleasure, in order to be diagnosed with depression.

1. Depressed mood most of the day, nearly every day (feel sad or empty).
2. Loss of interest or pleasure in all, or almost all, activities most of the day, nearly every day.
3. Significant weight loss (when not dieting) or weight gain; or decrease or increase in appetite nearly every day.
4. Insomnia or excessive sleep nearly every day.
5. An increase or decrease of activity noticeable by others nearly every day.
6. Fatigue or loss of energy nearly every day.

---
regarding suicide attempt and my inability to follow up within this anonymous patient group, in this analysis I consider the first eight symptoms of depression listed in footnote 4. If the student experienced at least four of these symptoms, where one of symptoms is depressed mood or loss of interest or pleasure, then the student is considered a potential depressed subject. There are 38 students within the control group who met this criterion for being depressed and they are considered as a separate group in my analysis.

To summarize, my analysis sample consists of three groups of students: 121 students diagnosed with depression by a health professional at the Health Center, 38 potentially depressed students, and 209 students who were not diagnosed with depression. In the next section, I provide some descriptive statistics and compare these subgroups' demographic and school characteristics.

Descriptive Statistics

Table 2 displays the means and proportions of demographic and school characteristics for four groups of students: 171 students diagnosed with depression who did not complete the survey, 121 students diagnosed with depression who completed the survey, 38 potentially depressed students and 209 controls. The demographic in the first two columns show that the mean age for the first group of students is higher while the proportion of female students is smaller relative to that of the second group. According to the

7. Feeling of worthlessness or guilt nearly every day.
8. Diminished ability to think or concentrate, or indecisiveness, nearly every day.
9. Recurrent thoughts of death, recurrent suicidal ideation without a specific plan, or a suicide attempt or a specific plan for committing suicide.
Table 2

Demographic and School Characteristics for Depressed Students and Controls

<table>
<thead>
<tr>
<th>Variables</th>
<th>Means and Proportions</th>
<th>P-values for t-test and chi-square test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Depressed students who did not complete the survey (n=171)</td>
<td>Depressed students who completed the survey (n=121)</td>
</tr>
<tr>
<td>1. Age</td>
<td>23.96</td>
<td>22.67</td>
</tr>
<tr>
<td>2. Female</td>
<td>0.68</td>
<td>0.85</td>
</tr>
<tr>
<td>3. White (race)</td>
<td>-</td>
<td>0.92</td>
</tr>
<tr>
<td>4. ACT score</td>
<td>23.03</td>
<td>23.06</td>
</tr>
<tr>
<td>5. Freshmen</td>
<td>0.25</td>
<td>0.27</td>
</tr>
<tr>
<td>6. Sophomore</td>
<td>0.23</td>
<td>0.25</td>
</tr>
<tr>
<td>7. Junior</td>
<td>0.26</td>
<td>0.25</td>
</tr>
<tr>
<td>8. Senior</td>
<td>0.26</td>
<td>0.23</td>
</tr>
<tr>
<td>9. Engineering College</td>
<td>0.06</td>
<td>0.03</td>
</tr>
<tr>
<td>10 Business College</td>
<td>0.18</td>
<td>0.13</td>
</tr>
<tr>
<td>11. Education College</td>
<td>0.20</td>
<td>0.25</td>
</tr>
<tr>
<td>12. Art College</td>
<td>0.12</td>
<td>0.08</td>
</tr>
<tr>
<td>13. Health College</td>
<td>0.04</td>
<td>0.08</td>
</tr>
<tr>
<td>14. Arts and Sciences</td>
<td>0.32</td>
<td>0.33</td>
</tr>
<tr>
<td>15. Others</td>
<td>0.09</td>
<td>0.10</td>
</tr>
</tbody>
</table>
p-values of student t-tests listed in last four columns of Table 2, the demographic across the three groups of students (depressed, potentially depressed and controls) are similar with exception of ACT score which is significantly higher for the 121 depressed students. The p-values of chi-square tests show that there is no difference in the distribution of student levels and colleges across all groups of students.

The mean age of the 121 diagnosed depressed students is 22.67; 85% are female and 92% are white. The mean of their ACT scores is 23.06. The proportion of undergraduate students diagnosed with depression by four class levels is: 27% freshmen, 25% sophomore, 25% juniors, and 23% seniors. In the sample, the depressed students are from different colleges, but the majority come from the College of Arts and Sciences (33%) and the College of Education (25%).

Table 3 provides statistics on the self-reported symptoms of depression. On average, students who were diagnosed with depression from a health professional or those potentially depressed reported more than five symptoms of depression and 66%-69% of them respectively claimed to have experienced similar symptoms before age of 18 years old. This is expected because recurrence is common for non-chronic episode of depression, particularly among non-treated cases. Half of the people who experience a first depressive episode will have a second one, and those with two consecutive episodes have a high probability of experiencing additional episodes of depression (Berndt et al., 2000). Students who experienced depressive symptoms were asked in the survey about the causes of these symptoms. Statistics in Table 3 show the majority of depressed students (58%-66% respectively) reported a relationship problem as the main cause of their
<table>
<thead>
<tr>
<th>Variables</th>
<th>Percentage</th>
<th>P-values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Depressed students who completed the survey (n=121)</td>
<td>Potentially depressed students (n=38)</td>
</tr>
<tr>
<td>1. Symptoms before age of 18 years old</td>
<td>69%</td>
<td>66%</td>
</tr>
<tr>
<td>2. Number of depressive symptoms</td>
<td>5.61</td>
<td>5.13</td>
</tr>
<tr>
<td>3. Symptoms caused by relationship problems</td>
<td>66%</td>
<td>58%</td>
</tr>
<tr>
<td>4. Symptoms caused by low school performance</td>
<td>48%</td>
<td>50%</td>
</tr>
<tr>
<td>5. Symptoms caused by family problems</td>
<td>48%</td>
<td>39%</td>
</tr>
<tr>
<td>6. Symptoms caused by financial problems</td>
<td>45%</td>
<td>45%</td>
</tr>
<tr>
<td>7. Symptoms caused by other problems</td>
<td>50%</td>
<td>53%</td>
</tr>
<tr>
<td>8. Parents' history of depression</td>
<td>59%</td>
<td>39%</td>
</tr>
<tr>
<td>9. Parents' history of anxiety</td>
<td>32%</td>
<td>29%</td>
</tr>
<tr>
<td>10. Parents' history of substance abuse</td>
<td>21%</td>
<td>24%</td>
</tr>
</tbody>
</table>
symptoms. Also low school performance, family and financial problems were reported to have a negative impact on their mental health status. On average, the depressed students indicated more than one cause of their depressive symptoms. It seems that a portfolio of these problems are responsible for student depression and not just one problem.

It is interesting to observe that more than half of the students diagnosed with depression by a health professional claimed that their parents had a history of depression. This evidence may support the medical statement that depression can have genetic causes as well (Biederman, Farone, & Keenan, 1991). A significant proportion of depressed students (29%-32% respectively) also claimed that their parents had a history of anxiety and substance abuse which also can be seen as causes of their depressive symptoms. The means and percentages reported in Table 3 are not significantly different between two groups of depressed students (except variable 8), but are significantly different from those of controls (see the respective p-values in the last three columns).
CHAPTER III

THE IMPACT OF DEPRESSION ON SCHOOL PERFORMANCE OF UNIVERSITY STUDENTS

There is a strong correlation between an individual's health status and his/her performance of activities during his/her lifetime. This relationship has been widely analyzed in the past ten years with the intention of revealing the total costs of chronic diseases and the necessity of treatment. Much emphasis has been put on chronic depression, because a high proportion of its cost results from the loss of productivity due to absenteeism and poor performance on the job (usually called 'presenteeism'). This cost is not directly observable and may be hidden from the individual and his/her employer. The previous work on the economics of depression have restricted the sample of analysis to wage earners with depressive disorders (see Berndt et al., 1998; Birnbaum et al., 1999; Burton et al., 1999; Druss, Rosenheck, & Sledge, 2000; Rizzo, Abbott, & Pashko, 1996). Their evidence indicated that the economic consequences of chronic depression are large and multidimensional. But the poor health status of individuals with chronic or acute depressive disorders affects their performance not only on job but also on other activities such as school, social activities and household production.

In this analysis, I use a student population with the intention of investigating the impact of depression and its treatment on school performance. I consider that the students who experience depressive disorders incur penalties due to lower performance in
school caused by less studying, less concentration in class, missing classes, assignments, exams, failing or dropping classes. This should be reflected in the student's low GPA and may impose some potential financial losses such as reduced learning, delaying graduation (money spent on tuition and other school supplies), entering the job market late (labor income loss) or not finding the desired job (income lost due to a lower paid job).

It is hypothesized that student performance is an outcome that can be correlated with several factors such as the student ability, major, number of credit hours taken per semester, class attendance, amount of study time, number of work hours, and others. If students are suffering from depression, they will experience the usual symptoms of this mental illness such as less concentration in class or during studying, low energy, lack of or excessive sleep. These symptoms will affect the school factors mentioned above. Often depression is associated with other mental or physical disorders such as anxiety, substance abuse, muscles pains, etc. All these disorders may cause a reduction in the student class grade, which reflects lower school performance overall.

Descriptive Statistics

To get a preliminary idea of the relationship between students' depression disorders and their school performance, I looked at the GPA difference between students with depressive disorders and their controls. I selected 75 pairs from the sample of 368 students, where one was diagnosed with depression and the other was not. These students were matched based on the criteria mentioned in Chapter II. Table 4 presents the means of GPA for the 75 depressed students in the matched semester (the semester
Table 4
Matched Pair Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Number of subjects</th>
<th>Means</th>
<th>P-values of ( t )-test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Depressed students</td>
<td>Controls</td>
</tr>
<tr>
<td>1. GPA(_t) in the matched term</td>
<td>75</td>
<td>3.2055</td>
<td>3.0572</td>
</tr>
<tr>
<td>2. GPA(_t) in the current term</td>
<td>75</td>
<td>2.9583</td>
<td>3.0836</td>
</tr>
<tr>
<td>3. (GPA(<em>t) - GPA(</em>{t-1})) difference</td>
<td>75</td>
<td>-0.2472</td>
<td>0.0264</td>
</tr>
<tr>
<td>4. ATHR(_t) in the matched term</td>
<td>75</td>
<td>12.1733</td>
<td>11.8933</td>
</tr>
<tr>
<td>5. ATHR(_t) in the current term</td>
<td>75</td>
<td>12.5600</td>
<td>13.2533</td>
</tr>
<tr>
<td>6. (ATHR(<em>t) - ATHR(</em>{t-1})) difference</td>
<td>75</td>
<td>0.3866</td>
<td>1.3600</td>
</tr>
<tr>
<td>7. EHR(_t) in the matched term</td>
<td>75</td>
<td>12.4933</td>
<td>11.9733</td>
</tr>
<tr>
<td>8. EHR(_t) in the current term</td>
<td>75</td>
<td>12.1866</td>
<td>13.0533</td>
</tr>
<tr>
<td>9. (EHR(<em>t) - EHR(</em>{t-1})) difference</td>
<td>75</td>
<td>-0.3067</td>
<td>1.0800</td>
</tr>
</tbody>
</table>

prior to the date of their first visit for depression) and the current semester (the semester when they had their first visit for depression). These means are 3.2055 and 2.9583 respectively, and are not statistically different from those of controls. Table 4 also presents the mean difference (GPA\(_t\) - GPA\(_{t-1}\)) for both group of students which represents the decrease in the mean GPA of students during the current semester relative to the previous or matched semester. For the group of depressed students, this difference clearly shows a decrease in the student GPA during the semester when they were diagnosed with
depression (this number is statistically different from zero with p-value equals to 0.0153).

On the other hand, there is no significant difference in the mean GPA for non-depressed controls during the matched and current semesters (p-value equals to 0.7612). The difference in difference of mean GPAs \([\text{GPA}^D_t - \text{GPA}^D_{t-1}) - (\text{GPA}^{ND}_t - \text{GPA}^{ND}_{t-1})]\) represents the decrease in the mean difference of depressed students’ GPA relative to their controls. A student t-test shows that this difference in difference of mean GPAs is significant with a p-value 0.0398.

In addition, Table 4 provides the means of attempted (ATHR) and earned (EHR) credit hours for students in both groups. These means show that there is no significant difference in the attempted and earned credit hours between both groups of students in the matched semester or current one. The difference in difference of mean ATHRs (EHRs) represents the decrease in the mean difference of depressed students’ attempted (earned) credit hours relative to their controls. This statistic is significant only for the earned credit hours per semester (p-value equals to 0.0571) and not for the attempted credit hours (p-value equals to 0.1499).

Table 5 presents school absenteeism due to depression and other health disorders for three groups of students: students clinically diagnosed with depression, students who self-reported depression and controls. On average, students diagnosed with depression reported missing 15 classes, 5 assignments, 1 exam, and 4 social activities per semester due to their health disorders. Also, on average, potentially depressed students missed 11 classes, 4 assignments and 4 social activities per semester due to their health disorders. These figures are very close to those of clinically diagnosed depressed students,
Table 5

School Absenteeism Due to Depression and Other Health Disorders

<table>
<thead>
<tr>
<th>Variables</th>
<th>Means</th>
<th>P-values of t-tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Depressed students (n=121)</td>
<td>Potentially depressed students (n=38)</td>
</tr>
<tr>
<td>1. Missed classes due to depression and other health disorders</td>
<td>14.64</td>
<td>11.32</td>
</tr>
<tr>
<td>2. Dropped classes due to depression and other health disorders</td>
<td>0.74</td>
<td>0.39</td>
</tr>
<tr>
<td>3. Missed exams due to depression and other health disorders</td>
<td>1.36</td>
<td>0.50</td>
</tr>
<tr>
<td>4. Missed assignments due to depression and other health disorders</td>
<td>5.45</td>
<td>4.39</td>
</tr>
<tr>
<td>5. Missed social activities due to depression and other health disorders</td>
<td>4.46</td>
<td>4.34</td>
</tr>
</tbody>
</table>
suggesting that the two groups of depressed students have similar status regarding their health disorders. In addition, the means for both groups of depressed students are statistically significantly higher than those of controls.

In the survey, I also included a question asking students to assess the impact of their depressive and other health disorders on school performance. I constructed a scale where 0% represents no impairment due to depression and 100% total impairment. Table 6 reports the mean impairment of depressive disorders on student school performance during the month when they were diagnosed with depression and also six months before and after. These means exhibit an inverted U-shaped pattern that takes the maximum value (46.28%) during the month when students were diagnosed with depression. It is still high one month prior to their first visit (41.44%) and one month after their diagnosis date (42.77%). After three months, impairment fades falling to values between 15% and 20%. This pattern supports my hypothesis that after treatment for depression, many students return to their normal status. In the next section, I extend this descriptive analysis further and evaluate the negative effect of depression and positive effect of treatment on student performance econometrically.

Econometric Methodology

For analysis purposes, the student GPA is tracked up to four times\(^5\) (i.e., in every term) over an academic year. This time span is long enough to allow me to investigate

\(^5\)The academic year at Western Michigan University is divided into four terms: Fall and Winter semesters, Spring and Summer sessions.
Table 6

Impairment Caused by Depression on Student School Performance

<table>
<thead>
<tr>
<th>Months</th>
<th>Depressed students</th>
<th>Means (%)</th>
<th>P-values*</th>
</tr>
</thead>
<tbody>
<tr>
<td>M-6</td>
<td>42</td>
<td>28.21</td>
<td>0.0436</td>
</tr>
<tr>
<td>M-5</td>
<td>36</td>
<td>31.11</td>
<td>0.1446</td>
</tr>
<tr>
<td>M-4</td>
<td>39</td>
<td>33.46</td>
<td>0.2582</td>
</tr>
<tr>
<td>M-3</td>
<td>54</td>
<td>33.98</td>
<td>0.0911</td>
</tr>
<tr>
<td>M-2</td>
<td>82</td>
<td>33.48</td>
<td>0.0120</td>
</tr>
<tr>
<td>M-1</td>
<td>95</td>
<td>41.44</td>
<td>0.2625</td>
</tr>
<tr>
<td>M+9</td>
<td>105</td>
<td>46.28</td>
<td></td>
</tr>
<tr>
<td>M+1</td>
<td>97</td>
<td>42.77</td>
<td>0.4193</td>
</tr>
<tr>
<td>M+2</td>
<td>69</td>
<td>37.32</td>
<td>0.0809</td>
</tr>
<tr>
<td>M+3</td>
<td>44</td>
<td>32.84</td>
<td>0.2275</td>
</tr>
<tr>
<td>M+4</td>
<td>21</td>
<td>16.19</td>
<td>0.0223</td>
</tr>
<tr>
<td>M+5</td>
<td>22</td>
<td>15.45</td>
<td>0.0015</td>
</tr>
<tr>
<td>M+6</td>
<td>21</td>
<td>19.05</td>
<td>0.0029</td>
</tr>
</tbody>
</table>

Note: a) These are p-values of the t-tests for the mean differences in reported impairment caused by depression on school performance between months M and M+i or M and M-i; b) M represents the month the student was diagnosed with depression.

student school performance across different semesters and any change in major, working or living status as a result of depression disorders. Because of the small number of matched pairs, I extend the analysis to the total panel of 368 Western Michigan University undergraduate students who completed the survey over four different semesters (Fall, Winter, Spring, and Summer) in one academic year. As described in Chapter II, this sample contains three groups of students: 121 students diagnosed with depression at the Sindecuse Health Center, 38 students who are potentially depressed, and a pure control group consisting of 209 students without a diagnosis or indication of depression. Among
121 students diagnosed with depression, 58 students claimed low school performance as one cause of their depressive symptoms, but no one reported that as the only cause. On average these students claimed two other causes along with this cause. It seems that a mixture of these problems are responsible for student's depression and not just one problem. Thus, it seems reasonable to assume that the causality goes from the health disorders to the student school performance. I estimate a regression with student GPA as the dependent variable and the following vectors as sets of regressors: (a) $X$ - a vector of factors that represents student health status, (b) $W$ - a vector of student specific characteristics, and (c) $Z$ - a vector of student school characteristics.

I proceed to consider each set of these regressors separately. First, I identify students who were diagnosed with depression by a health professional at the Health Center. In each case, a doctor or a therapist recommended treatment (drug therapy and/or counseling) that very few of them failed to follow. In the absence of a proxy for the severity of the depression, I construct a dummy variable $\text{DEP}_{si}$ that takes the value 1 if the student 'i' was diagnosed with depression in semester 's' or if this semester was within a 180 day interval from the diagnosis date. It takes the value zero for the semesters before the diagnosis date and after a period of 180 days from the diagnosis date. For the starting and ending semester it takes a value between 0 and 1 depending on the date the student was diagnosed with depression and the last date he/she experienced the depressive symptoms. Based on health guidelines, the period that an individual may experience depressive symptoms can be 4-6 months (American Psychiatric Association, 1994). In this analysis, I constructed a conservative proxy for depression by assuming these students have
depressive symptoms for 6 months (180 days). Note that this proxy takes the value 0 in all semesters for the undiagnosed students. I believe that students who were diagnosed with depression and were recommended treatments are the most severe cases.

I construct a second dummy variable SELFDEP* to represent those in the control group who are potentially depressed. This variable takes the value 1 if the student 'i' on the semester 's' met the criteria for depression mentioned in Chapter II and takes the value 0 otherwise. The above dummy variables define two groups of students: the first group consists of diagnosed students for whom a treatment was recommended (121 students) and the second group consists of students from controls who are potentially depressed (38 students).

Depression treatment consists of drug therapy provided by the Health Center and sometimes interacted with psychotherapy offered at this Center or at the Counseling Center. Because the information on counseling therapy is not adequate, the treatment variable used in this analysis mostly reflects drug therapy that student obtained from the Health Center. However, this Center did not provide information about the duration of treatment and daily dosage for each medication bought by students. Using the information regarding medication name, diagnosis date, number of prescriptions and the total drug dispense released by the Health Center and also the information on daily dosage for each medication obtained from the Physicians' Desk Reference (1999), I calculated the number of days each student have been taken drug therapy. This was used to determine the months when students were taking treatment for depression. Thus, the treatment variable used in this analysis is given as: $\text{TREAT}_{is} = (k/n)_s$ where 'k' is the number of
months that the student took medication for depression during semester ‘s’ and ‘n’ is the number of months for semester ‘s’. The literature regarding depression treatment state that treatment starts to be effective after 6 weeks (Perry, Alexander, & Liskow, 1997). Thus, the starting date for treatment is shifted 6 weeks when the treatment proxy is constructed. This variable represents compliance with treatment and takes values between ‘0’ and ‘1’, where ‘1’ represents full compliance during one semester. By interacting this variable with the depression dummy variable, $\text{DEP}_s \times \text{TREAT}_i$, I can measure the effect of treatment on the GPA of depressed students given the extent of actual compliance with treatment.

The compliance measure used in my analysis is based on information obtained from the Health Center regarding acquisition dates, quantity dispensed and brand of medication for students with depression. Although this information is accurate, students may fail to take their medication as prescribed. This measurement error may induce noise into the treatment proxy and can bias the estimator of the impact of depression treatment toward zero. In the presence of this measurement error, the estimated effect of my treatment proxy constitutes a conservatively estimate of the real effect of compliance with drug therapy on student GPA.

In addition to depression, students can experience chronic diseases (allergy, diabetes, migraine and asthma) and/or acute diseases (a flu, pneumonia, broken arm/leg etc.). I generalize all these by constructing a dummy variable $\text{OTHER}_s$ that takes the value 1 if the student ‘i’ in semester ‘s’ experienced any health disorders other than depression.
and the value 0 otherwise. I expect that experiencing other health disorders$^6$ will reduce student school performance as well.

In the set of student specific characteristics, $W$, I include student age and dummy variables for student gender (female versus male), race (white versus non-white) and living status (living with roommate/parents/partner versus alone). Within the survey, for each month that students were working, they reported the degree to which work impaired their ability to complete school assignments. Based on this information, I construct a variable $\text{WORKIMP}_i$ that takes values from 0 to 100. SAT/ACT scores along with high school records have been used in the education literature to predict college student GPA (Stricker, Rock, & Burton, 1996). In my analysis, I use ACT$^7$ score as a measure of student ability$^8$ and I expect that students who entered the University with high ACT scores had more potential to have higher GPAs, ceteris paribus.

In the set of student school characteristics, $Z$, I include the number of attempted credit hours$^9$ that the student has taken per semester and a dummy variable for the student level (sophomore/junior/senior/freshmen- the omitted category) in each semester. In order to have an 'homogenous sample' I have excluded the graduate students from my sample based on the assumption that graduate students have different characteristics relative to undergraduate students. I do not include dummy variables for student

$^6$This will depend on the severity and duration of these disorders for which I do not have information.

$^7$ACT is the standard admission test at Western Michigan University.

$^8$A better measure for individual's ability is IQ score, but that is not available in the University records.

$^9$The attempted credit hours show all cumulative hours taken for a grade, while the earned credit hours show all credit hours taken for a grade or credit and successfully completed.
curriculum or major because the large number of categories would dramatically reduce the degrees of freedom. Also, a dummy variable for the college in which the student is enrolled is not considered because the information about this characteristic is not retrospective. It shows the current college enrollment and does not reflect the enrollment for each semester which is subject to changes due to student major changes. Instead, I consider a dummy variable MAJORCH\textsubscript{u} that indicates semesters in which students changed their major. This variable remains zero if students did not change their major over the academic year.

Then, I estimate the following empirical equation:

$$\text{GPA}_{i} = \alpha_{i} + \beta_{1} \text{DEP}_{i} + \beta_{2} \text{SELFDEP}_{i} + \beta_{3} (\text{DEP} * \text{TREAT})_{i} + \beta_{4} \text{OTHER}_{i} + \gamma' W_{i} + \delta' Z_{i} + \varepsilon_{i} \tag{3.1}$$

The coefficient $\beta_{1}$ of the $\text{DEP}_{i}$ dummy variable is the impact on student GPA due to untreated but diagnosed depression, while the coefficient $\beta_{2}$ of self-reported depression $\text{SELFDEP}_{i}$ dummy variable is the impact on student GPA due to potential depression. To measure the effect of treatment for depression on student GPA, I include in equation (3.1) an interaction term of the depression dummy variable with the treatment variable. The coefficient $\beta_{3}$ shows the impact of depressive disorders associated with treatment on student GPA. The interaction term can be combined with the depression dummy variable so that the effect of depression on student performance can be rewritten as: $(\beta_{1} + \beta_{3} \text{TREAT}_{i})\text{DEP}_{i}$. Because the treatment variable takes values between 0 and 1, the total effect of diagnosed depression on student GPA in the case of full compliance with
treatment is equal to \( \beta_1 + \beta_3 \). I expect that \( \beta_1 \) and \( \beta_2 \) to be negative and \( \beta_3 \) positive. Also, I expect that \( |\beta_2| < |\beta_1| \) and \( |\beta_3| < |\beta_1| \), which means that the impairment of the untreated diagnosed depression is larger than that of potential depression and is not completely offset by treatment.

The parameter \( \alpha \) represents individual effects that vary across students and impact their performance. It is assumed that these individual effects are time invariant and are not captured by any of the regressors in the GPA equation. In the context of my model, they may represent student ambition to study and work hard, their academic background, social events in their life etc., which are difficult to be accounted for by separate variables in the structural equation. These individual effects may be treated as either fixed or random. The nature of the data itself usually dictates the choice between a fixed or random effects estimator. My panel data consists of a large number of students and a relatively small number of semesters (maximum is 4). To use a fixed effects estimator, I need to estimate 368 dummy variables for each individual in my sample. Given such a large number of parameters to be estimated, the fixed effects estimator would have a very large sampling variability. Moreover, some of the regressors are time-invariant\(^{10}\) and the coefficients on these regressors are not identified with a fixed effects estimator. For these reasons, the appropriate estimator is the random effects estimator. However, before I compute the random effects estimator for equation (3.1), I will test for the existence of the error component in my model. I will apply the Lagrangian Multiplier test suggested by Baltagi and Li (1990) which is an extension of the Breusch and Pagan test (1980) for

\(^{10}\)Gender, race, age, and ACT score are time invariant variables.
the case of incomplete panel data. This LM statistic is constructed from the OLS residuals and is used to test the null hypothesis that the intercepts \( \alpha_i \) are equal.

An important feature of my panel data is that they are unbalanced, because some of the students may not be enrolled in all four academic terms for different reasons. Traditionally, students take the summer terms off to work outside school. However, I do not have information about why a student was not enrolled during the summer terms. It might be because students with depressive symptoms are more likely to take a summer break relative to their healthy peers. This is because students with depressive symptoms are less capable of dealing with the stress of school and work, thus a summer break from school can release some of the accumulated stress during the academic year. For this reason, I test for the existence of sample selection associated with the decision to attend the summer term using the procedure of Verbeek and Nijman (1992)\(^{11}\). Following their methodology, I construct a dummy variable \( r_{is} \) that denotes the availability of observations for the dependent variable. This variable takes the value 1 if \( \text{GPA}_{is} \) is observed for individual ‘i’ in semester ‘s’ and the value 0 otherwise. Then, the variable \( \text{SEMSTER}_i = \sum r_{is} \), which represents the number of semesters that student ‘i’ participated, is added to (3.1). Denoting the coefficient for the added variable \( \text{SEMSTER}_i \) by \( \beta_s \), the presence of sample selection can be checked by testing the null hypothesis \( H_0: \beta_5 = 0 \). If the null hypothesis is rejected, the test indicates that sample selection is present. In this case, the methodology suggested by Wooldridge (1995) will be utilized to correct the sample

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\(^{11}\)They propose different tests for selectivity bias such as the use of variable addition and (quasi-) Hausman tests that do not require any information of the response process.
Another econometric issue is the possibility of correlation of the depression proxies, \( \text{DEP}_a \) or \( \text{SELFDEP}_a \), with the unobservable individual effect \( \alpha_i \). The effect can be due to the medical stress incurred by sickness or death in the student’s family, financial stress incurred by the student or his/her parents in the case of losing jobs or social events in their lives that might have caused gloomy periods. In the presence of this correlation, the random effects estimator is no longer consistent. To test for the existence of this correlation, I apply the Hausman test (1978). If correlation is present, the fixed effects estimator will be estimated.

Empirical Results

Table 7 presents different estimates of the GPA equation. The OLS, random effects, and fixed effects estimates are listed in columns 2, 3 and 4 respectively. The OLS estimates serve as a benchmark to compare with random and fixed effects estimates. As shown by the OLS estimates, there is evidence of the negative effect imposed by depression on student GPA. The coefficient of \( \text{DEP}_a \) dummy variable shows that students who were diagnosed with depressive disorders experienced on average a 0.44 point drop in their GPAs. Treatment for depression saves 86% of this drop because it increases student GPA by 0.38 points. On the other hand, potentially depressed students did not have a significant impact on their school performance. Relative to students with depression, those who had experienced other health disorders (mental or physical disorders) had a decrease on their GPA by a smaller magnitude (0.15 points).
### Table 7
Estimated Coefficients of Equation 3.1 (GPA - Dependent Variable)

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. INTERCEPT</td>
<td>0.8894* (1.86)</td>
<td>0.9271 (1.48)</td>
<td>2.4276*** (6.29)</td>
</tr>
<tr>
<td>2. DEP</td>
<td>-0.4431*** (-3.83)</td>
<td>-0.4825*** (-4.52)</td>
<td>-0.4401** (-3.47)</td>
</tr>
<tr>
<td>3. SELFDEP</td>
<td>-0.0250 (-0.23)</td>
<td>0.0698 (0.60)</td>
<td>0.2811 (1.57)</td>
</tr>
<tr>
<td>4. DEP*TREAT</td>
<td>0.3814* (1.77)</td>
<td>0.4317** (2.21)</td>
<td>0.3759* (1.67)</td>
</tr>
<tr>
<td>5. OTHER</td>
<td>-0.1477** (-2.39)</td>
<td>-0.0884 (-1.53)</td>
<td>-0.0276 (-0.39)</td>
</tr>
<tr>
<td>6. AGE</td>
<td>0.0352* (1.89)</td>
<td>0.0331 (1.29)</td>
<td>- ( ^{a} )</td>
</tr>
<tr>
<td>7. GENDER</td>
<td>0.1877*** (2.62)</td>
<td>0.1617* (1.69)</td>
<td>- ( ^{a} )</td>
</tr>
<tr>
<td>8. RACE</td>
<td>0.0348 (0.38)</td>
<td>0.0307 (0.24)</td>
<td>- ( ^{a} )</td>
</tr>
<tr>
<td>9. LIVING</td>
<td>0.1506** (1.96)</td>
<td>0.1647** (1.97)</td>
<td>0.2358** (2.00)</td>
</tr>
<tr>
<td>10. WORKIMP</td>
<td>-0.0032*** (-2.78)</td>
<td>-0.0030*** (-2.43)</td>
<td>-0.0024 (-1.40)</td>
</tr>
<tr>
<td>11. ACT</td>
<td>0.0464*** (6.30)</td>
<td>0.0540*** (5.39)</td>
<td>- ( ^{a} )</td>
</tr>
</tbody>
</table>

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Table 7–Continued

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12. ATTHR</td>
<td>0.0026 (0.44)</td>
<td>-0.0052 (-0.97)</td>
<td>-0.0103* (-1.69)</td>
</tr>
<tr>
<td>13. SOPHOM</td>
<td>0.1666** (1.99)</td>
<td>0.1031 (1.36)</td>
<td>0.0248 (0.27)</td>
</tr>
<tr>
<td>14. JUNIOR</td>
<td>0.2541*** (2.90)</td>
<td>0.1895** (2.08)</td>
<td>0.0454 (0.33)</td>
</tr>
<tr>
<td>15. SENIOR</td>
<td>0.4332*** (4.38)</td>
<td>0.3608*** (3.27)</td>
<td>0.1130 (0.62)</td>
</tr>
<tr>
<td>16. MAJORCH</td>
<td>-0.0959 (-0.84)</td>
<td>-0.0821 (-0.82)</td>
<td>-0.0667 (-0.57)</td>
</tr>
<tr>
<td>17. SEMESTR</td>
<td></td>
<td>-0.0077 (-0.14)</td>
<td></td>
</tr>
</tbody>
</table>

R square 0.17 | 0.12 | 0.73 |
Number of observations 679 | 679 | 679 |
Error component test (LM) (ch-square(1)) 102.05 | | |
Hausman test (m-value) | 12.03 | |

Note: ***) Significant at 1% level; **) Significant at 5% level; *) Significant at 10% level; a) The dashes indicate that these variables are time invariant variables and their coefficients are not identified by the fixed effects estimator. The impact of these variables goes into the intercept.

The next step is to check for the presence of the error component by computing the LM statistic that has a chi-square distribution with one degree of freedom. The value of this statistic is 102.05 which indicates that ωₜs vary across the sample, and therefore,
individual effects are present. The absence of selectivity bias in my unbalanced panel data is confirmed by the insignificance of the coefficient of the SEMSTER variable. The Hausman test is not significant which suggests that unobservable individual effects and regressors are not correlated. With these results, I will rest my analysis on the random effects estimator since it is more efficient than the OLS or the fixed effects estimators. The majority of the random effects estimates listed in Table 7 are significant with the expected signs. Based on these coefficients, diagnosed depression seems to reduce student GPA by 0.48 points or almost half of a grade, but treatment makes up for most of this loss by increasing student GPA about 0.43 points. This result supports my hypothesis of the effectiveness of depression treatment when the individual effects are considered. As in the OLS results, the school performance of potentially depressed students is not significantly affected by their depressive disorders. Different from OLS results, the coefficient of other health disorders variable is not statistically significant but keeps the expected negative sign.

Female students seem to perform better in school relative to male students. Living status has a significant impact on student school outcomes which suggests that having people around (living with roommate/parents) help students better manage school work. The maximum amount that GPA can be impacted by the average number of hours of student work is 0.3 points (=0.003*100). If a student enters the University with an ACT score of one point more than another student, he/she is expected to have a GPA of 0.054 points higher. The coefficient of the attempted credit hours has a negative sign but not statistically significant. Finally, older students who are represented here by juniors and
seniors demonstrate higher performance at school relative to freshmen. While a junior has a GPA 0.19 points higher than a freshman, a senior has an even higher GPA (by 0.36 points). This result is consistent with conventional notion that older or more experienced students are already adjusted to the academic environment relative to those who just joint this environment. Another possible explanation is that students with poor academic performance are no longer in the University.

An Alternative Measurement of Student School Performance

Another issue concerns the measurement of school performance. So far, I have considered the objective measurement of school performance, student GPA. Although the objective measures of work performance are more preferable than subjective measures, researchers find them both valuable. When the sample to be analyzed is a mixture of different occupational groups, it is not feasible to have an objective measure of productivity. That might become possible if the study subjects are concentrated in one or few occupations. In some other studies, as Berndt et al. (1998) pointed out, subjective measures might be better than the objective ones in registering changes in interpersonal communication skills, ability to generate team enthusiasm and cognition. However, my data and subjects allow me to use both measures of school performance, GPA and self-reported performance, SPERF. The latter is represented by a continuous variable that takes values from 0 to 100. In the survey, I included two questions that asked students about their level of impairment due to depression, ImpDep, and other health disorders, ImpOther. Assuming that a healthy individual has a 100% performance level, I can find
the self-perceived level of school performance for those students who have experienced health disorders: SPERF = 100 - ImpDep - ImpOther. The information for this variable is monthly. In the survey, students report their level of school impairment due to depression or other health disorders for those months that they were enrolled in school. To be able to compare the estimated results using alternative measure with those of equation (3.1), I aggregate this information and obtain student self-reported school performance for each semester by taking the average. I ran a second regression using the self-reported performance proxy as the dependent variable and the components of vectors X, W, and Z as explanatory variables.

\[
\text{SPERF}_{is} = \mu_i + \mu_1 \text{DEP}_{is} + \mu_2 \text{SELFDEP}_{is} + \mu_3 (\text{DEP} \times \text{TREAT})_{is} + \mu_4 \text{OTHER}_{is} + \\
\lambda ' W_{is} + \sigma ' Z_{is} + \nu_{is} \tag{3.2}
\]

The coefficient \( \mu_1 \) of the \( \text{DEP}_{is} \) dummy variable is the effect of untreated depression on student self-reported performance, while the coefficient \( \mu_2 \) of the \( \text{SELFDEP}_{is} \) variable is the impairment of potential depression on \( \text{SPERF}_{is} \). The coefficient \( \mu_3 \) of the treatment interaction term measures the effect of depression associated with prescribed medication on student self-reported performance if the treatment has been followed during the whole semester. The parameter \( \mu_i \) represents the individual effects that are considered time invariant. To estimate equation (3.2), I apply the same estimators as I did in estimating equation (3.1). Issues of selectivity bias and correlation of the unobservable individual effects with regressors are treated in the same way as in the previous section.

In the second column of Table 8, I present the OLS estimated coefficients of
Table 8

Estimated Coefficients of Equation 3.2 (SPERF - Dependent Variable)

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. INTERCEPT</td>
<td>109.92*** (8.80)</td>
<td>116.47*** (6.98)</td>
<td>103.16*** (13.86)</td>
</tr>
<tr>
<td>2. DEP</td>
<td>-9.8796*** (-3.28)</td>
<td>-7.7802*** (-3.46)</td>
<td>-5.8588** (-2.39)</td>
</tr>
<tr>
<td>3. SELFDEP</td>
<td>-1.0639 (-0.38)</td>
<td>-3.4807 (-1.29)</td>
<td>-4.7649 (-1.38)</td>
</tr>
<tr>
<td>4. DEP*TREAT</td>
<td>14.6323*** (2.60)</td>
<td>8.4685** (2.09)</td>
<td>6.6275 (1.53)</td>
</tr>
<tr>
<td>5. OTHER</td>
<td>-8.5126*** (-5.28)</td>
<td>-4.2766*** (-3.49)</td>
<td>-2.4583* (-1.81)</td>
</tr>
<tr>
<td>6. AGE</td>
<td>-0.6712 (-1.38)</td>
<td>-1.0232 (-1.47)</td>
<td>-</td>
</tr>
<tr>
<td>7. GENDER</td>
<td>-1.4408 (-0.77)</td>
<td>-1.8794 (-0.72)</td>
<td>-</td>
</tr>
<tr>
<td>8. RACE</td>
<td>-1.3122 (-0.55)</td>
<td>0.1285 (0.04)</td>
<td>-</td>
</tr>
<tr>
<td>9. LIVING</td>
<td>3.6995* (1.85)</td>
<td>1.8413 (0.45)</td>
<td>-1.1565 (-0.51)</td>
</tr>
<tr>
<td>10. WORKIMP</td>
<td>-0.0211 (-0.71)</td>
<td>-0.0039 (-0.14)</td>
<td>0.0035 (0.11)</td>
</tr>
<tr>
<td>11. ACT</td>
<td>-0.2647 (-1.38)</td>
<td>-0.1495 (-0.54)</td>
<td>-</td>
</tr>
<tr>
<td>12. ATTHR</td>
<td>-0.0998 (-0.63)</td>
<td>-0.1333 (-1.20)</td>
<td>-0.1510 (-1.29)</td>
</tr>
</tbody>
</table>
Table 8–Continued

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>13. SOPHOM</td>
<td>7.9044*** (3.63)</td>
<td>2.0539 (1.28)</td>
<td>-0.7431 (-0.42)</td>
</tr>
<tr>
<td>14. JUNIOR</td>
<td>8.1222*** (3.56)</td>
<td>3.3070 (1.61)</td>
<td>0.1130 (0.04)</td>
</tr>
<tr>
<td>15. SENIOR</td>
<td>10.8186*** (4.20)</td>
<td>5.6502** (2.19)</td>
<td>2.5484 (0.72)</td>
</tr>
<tr>
<td>16. MAJORCH</td>
<td>1.2656 (0.43)</td>
<td>-1.1590 (-0.55)</td>
<td>-1.6650 (-0.73)</td>
</tr>
<tr>
<td>17. SEMESTR</td>
<td></td>
<td>1.5099 (1.03)</td>
<td></td>
</tr>
<tr>
<td>R square</td>
<td>0.09</td>
<td>0.05</td>
<td>0.84</td>
</tr>
<tr>
<td>Number of observations</td>
<td>676</td>
<td>676</td>
<td>676</td>
</tr>
<tr>
<td>Error component test (LM) (ch-square(1))</td>
<td>283.26***</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Hausman test (m-value)</td>
<td>—</td>
<td>26.98***</td>
<td>—</td>
</tr>
</tbody>
</table>

Note: ***) Significant at 1% level; **) Significant at 5% level; *) Significant at 10% level; a) The dashes indicate that these variables are time invariant variables and their coefficients are not identified by the fixed effects estimator. The impact of these variables goes into the intercept.

equation (3.2). The variables of interest \((DEP_a \text{ and } DEP_a \times TREAT_a)\) are statistically significant with the expected signs. The estimate of the DEP dummy variable shows a significant drop in student self-reported school performance of 9.88%, but treatment reduces this impairment to zero because the value of its estimated coefficient (14.63) exceeds that.
of depression coefficient and has the opposite sign. Other mental or physical disorders seem to significantly reduce student self-reported performance at school by 8.51% which is very close to the impairment caused by depressive disorders.

The computed LM test for the error component model has a chi-square value of 283.26 which confirms the presence of an error component in the data. Thus, the OLS does not provide an efficient estimator because it ignores the panel nature of the sample. For this reason, in the third and fourth columns of Table 8, I present the random and fixed effects estimates of equation (3.2). The insignificant coefficient of the SEMESTR\(_t\) variable in the second column shows the absence of selectivity bias in my sample, while the Hausman test shows the presence of correlation between hidden individual effects and the regressors in equation (3.2). This correlation induces inconsistency of the random effects estimator and the ordinary least square estimator. For this reason, I rest my analysis on the fixed effects estimates listed in column four of Table 8. The advantage of this estimator is that it remains consistent in the presence of correlation between unobservable individual effects and any of the regressors. However, the disadvantage of this estimator is that it cannot estimate the coefficient for the time invariant variables such as AGE, GENDER, RACE and ACT. Moreover, a substantial number of degrees of freedom are lost due to inclusion of individual dummy variables. Most of the fixed effects estimates are not significant. However, the coefficients of the variables of interest have the expected signs. According to these results, the level of school performance is significantly reduced by 5.86% due to diagnosed depression. The coefficients of SELFDEP and DEP*TREAT variable have the expected signs but they are not statistically significant
(their p-values are greater than 0.10). Other health disorders decrease school performance by a significant percentage (2.46%) which is less than that of diagnosed depression. In the next section, I summarize the results obtained from both equations and compare in detail the estimated coefficients of the health variables when different measures of school performance are employed.

Discussion and Conclusions

Depression is a prevalent and serious mental disorder among young people (children and adolescents). It is associated with an increase in family problems, school failure and particularly in adolescents, suicide, substance abuse and truancy (Emslie & Mayes, 1999). In this chapter, I analyzed only one aspect of depression impairment on student life: school performance. The random effects estimate shows that diagnosed depression decreases student GPA by 0.48 points (almost half of a grade), whereas potential depression does not cause a statistically significant drop in student GPA.

Since there is a strong negative impact of depression on student school performance, it is important to know how to decrease or even eliminate this impairment. One possible solution is drug treatment that aims to shorten the episode of depression, to prevent recurrence and to decrease the negative consequences of episodes (Emslie & Mayes, 1999). In this analysis, I investigated whether treatment helps to decrease the negative effect of depressive disorders on student school performance. Results supported the effectiveness of drug therapy which in most cases was applied in conjunction with psychotherapy. Full compliance with treatment prevented student GPA from falling by
0.43 points (referring to the coefficients of random effects estimate). Although this analysis demonstrated the effectiveness of treatment for depression, it could not answer the question of how long to continue treatment once it has been shown to be effective.

The fact that point estimates of the variables of interest (depression and treatment variables) are very similar across different estimators attests to the robustness of my results. However, the coefficients of the demographic indicators are rather sensitive to the estimation procedure and in most cases they do not show a significant impact on student school performance. This is to be expected since my data are constructed with the purpose of analyzing the impact of health variables on student performance and not the effect of demographic factors such as gender, race, age and etc., on performance. Representation of subgroups with these demographic characteristics is not large enough for adequate statistical evaluation. They are included in the model to account for the hypothesized variation and their impact on the variables of interest.

Next, I compare the estimated coefficients of the health variables obtained from the two models. Knowing that student GPA varies from 0 to 4.0 and student self-reported performance varies from 0 to 100, I transform the estimated coefficient of the health variables in equation (3.1) to a 0-100 scale to make them comparable with those in equation (3.2). As shown in Table 9, the negative effect of diagnosed depression is understated when the subjective measurement of student school performance is employed (assuming that the true effect is revealed in the case when the objective measurement is used). This is also the case for the coefficient of the treatment variable with the exception of OLS estimates. On the other hand, when subjective measurements of student
Table 9

The Estimates of Health Variables for Equations 3.1 and 3.2

<table>
<thead>
<tr>
<th>Variables</th>
<th>Equation 3.1</th>
<th></th>
<th></th>
<th>Equation 3.2</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>RE</td>
<td>FE</td>
<td>OLS</td>
<td>RE</td>
<td>FE</td>
</tr>
<tr>
<td>SELFDEP</td>
<td>-0.6250</td>
<td>1.7450</td>
<td>7.0275</td>
<td>-1.0639</td>
<td>-3.4807</td>
<td>-4.7649</td>
</tr>
<tr>
<td>OTHER</td>
<td>-3.6925**</td>
<td>-2.2100</td>
<td>-0.6900</td>
<td>-8.5126***</td>
<td>-4.2766***</td>
<td>-2.4583*</td>
</tr>
</tbody>
</table>

Note: ***) Significant at 1% level; **) Significant at 5% level; *) Significant at 10% level.

Productivity are used in equation (3.2), the negative impact of other health disorders on student school performance is overstated. For the coefficients of the other variables in the second model, I find some differences in terms of significance level, sign and magnitude what are to be expected based on the nature of the data itself. This finding is important as it reveals the possible discrepancy among health outcomes when subjective measurements of productivity are used as an alternative to objective measures of productivity.
CHAPTER IV

THE IMPACT OF DEPRESSION ON STUDENT LABOR MARKET OUTCOMES

In the past ten years, labor and health economists have analyzed the impact of mental disorders on labor market outcomes. It has been found that poor mental health status leads to a significant reduction in employment rate, work hours, personal income and work productivity. Mental disorders can influence labor force participation directly by causing involuntary unemployment or inability to seek or keep a job (Ettner, Frank, & Kessler, 1997). Moreover, workers with mental disorders are more likely to have lower on-job productivity due to less concentration, cognitive abilities or absenteeism. This poor on-job performance is associated with a lower offered wage which in turn may cause a lower labor force participation rate (Ettner et al., 1997).

Bartel and Taubman (1979) represents an earlier literature on the impact of mental disorders on labor market outcomes. They found a significant reduction in earnings, wage rate, weekly hours and probability of labor force participation due to psychiatric disorders among white males. Similar results were found by Benham and Benham (1982), Bartel and Taubman (1986), and Mullahy and Sindelar (1990) for the employment rate of white males who suffered from mental disorders or substance abuse. While Mitchell and Anderson (1989) showed empirically a positive relationship between mental health and employment for older men, they could not find evidence of this relationship.
for older women. Most of the above studies were focused on the male labor force participation rate and their health status. However, Ruhm (1992) showed that women who used antidepressants had a lower labor force participation rate.

A series of studies have examined the negative impact of mental distress or illness on the labor income of men and women. For example, Frank and Gertler (1991) showed that mentally distressed workers earned 21% less than their healthy peers. Miller and Kelman (1992) found that the impact of mental illness on income was higher among men than women.

The above findings underscore the necessity of good health in increasing employment, although this case is stronger for men than women (Mitchell & Anderson, 1989). The existing empirical evidence also establishes the negative impact of mental illness on labor income, but usually the degree of impairment is found to be low and in most cases it depends on the worker's age, gender, degree of disorder and measurement of health status (self-reported versus treatment-related). A possible explanation for the different results across groups is that these studies employ different econometric techniques. There is a concern about the potential simultaneity in the relationship between labor market outcomes and mental disorders. However, few studies have addressed this issue by using simultaneous equations technique to solve the biases arising from the endogeneity of health proxies (Ettner et al., 1997; Stern, 1989).

There is a core of literature on the impact of mental health disorders, particularly depressive disorders, on worker productivity. This literature can be divided into two subgroups. The first group of studies investigated the effect of depression on
absenteeism (number of hours missed due to depression). The main findings are that the length of short-term disability and the cost of treatment for long-term disability are higher among workers with depressive disorders relative to those with other health disorders (Birnbaum et al., 1999; Conti & Burton, 1994; Kessler et al., 1999; Simon et al., 2000). The second group of studies examined the effect of depression on presenteeism (on-job productivity). Researchers found a significant negative effect of depressive disorders on worker productivity when this was proxied by subjective instruments such as worker’s self-reports of performance (Berndt et al., 1998; Chilcott & Shapiro, 1996; Ferrari, 1998) or by an objective measure such as a worker productivity index.¹²

For policy purposes, it is important to ascertain the magnitude of the negative effects of mental disorders on labor market outcomes. Issues such as the possibility of providing minimum insurance coverage for mental disorder services or the employer’s decision of funding an employee assistance program are addressed by considering the degree of productivity impairment caused by mental disorders. These important issues are not only for wage earners who suffer from chronic or non-chronic mental disorders, but also for the university student population which engages in labor market activities during their academic careers. Although work is secondary to studying in student life, sometimes that gives a good experience or helps to determine or start a professional career for them. In the above literature, this population group has been ignored even when the data were available for analyzing the effect of mental disorders on student labor

¹²Worker productivity index measures the time absent from work and time lost because of not working in full capacity due to a disease (Burton et al., 1999).
market outcomes. For example, in analyzing the effect of psychiatric disorders on individual labor market outcomes, Ettner et al. (1997) excluded the student population in order to have a homogenous sample of working men and women. In the preliminary estimation of the likelihood of schooling versus employment for the student population, they found similar results as for the wage earner population. However, the effects of psychiatric disorders on employment status were a bit weaker among students. To add to this body of literature, I analyze the depression effects on student labor market outcomes such as the student employment decision, number of hours scheduled to work, number of hours missed due to poor health status and work performance at an employment site and at home. The estimated effects will be used to compute the indirect cost components of depression among University students.

The analysis uses a panel data that is obtained via survey from a sample of the student population of Western Michigan University. A description of the data and some statistics are provided in the next section. In the third section of this chapter, I address the following question: Does depression affect a student’s decision to participate in the labor force and the amount of work hours he/she perform? The fourth section address the following questions: How many work hours were missed due to depression relative to other health disorders? What degree of impairment is caused by depression on student performance at work and at home? Does the medical treatment for depression matter? Different econometric techniques are applied to estimate equations for student employment, work hours, absenteeism, work and household activities performance. Section five concludes with remarks for future research.
Descriptive Statistics

The data for this analysis were obtained from the Sindecuse Health Center and the Registrar’s Office of Western Michigan University. In addition, a survey was conducted and delivered to students of this University to provide information about their labor market status. To quantify the impact of depressive disorders and its treatment on student labor market outcomes, I construct a panel data from the same 367 students. This data differs from the academic performance panel used in Chapter III in that the frequency of this data is monthly instead of by semesters. In the survey, I asked students about their monthly employment status, number of hours worked, hourly wage, number of work hours lost due to depression or other health disorders and the impact of depression and other health disorders on work productivity and household activity performance (see sections 3, 6, and 7 of the questionnaire in Appendix A).

Table 10 presents the percentage of students who were not working, part-semester employed and full-semester employed during each semester. These percentages are provided for the group of students diagnosed with depression, potentially depressed students and controls. During the Fall and Winter semesters, the proportion of students who were full-semester employed was lower for the depressed group (46%-

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13 Detailed information about data collection and content was provided in Chapter II.

14 As mentioned in Chapter II, I have excluded 46 students who were diagnosed with depression off campus, and also, one student for whom the information on his employment status was missing.

15 Part-semester employed is defined as when the student worked one, two or three months during long semesters (Fall or Winter) and one month during short terms (Spring or Summer). Full-semester employed is defined as when the student worked four months during long semesters or two months during short terms.
Table 10

Employment Status by Semesters

<table>
<thead>
<tr>
<th>Number of months employed</th>
<th>Percentage</th>
<th>P-values of chi-square test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Depressed students (n=121)</td>
<td>Potentially depressed students (n=38)</td>
</tr>
<tr>
<td>---------------------------</td>
<td>--------------------------</td>
<td>----------------------------------</td>
</tr>
<tr>
<td><strong>Fall Semester</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No employment</td>
<td>33.06</td>
<td>18.92</td>
</tr>
<tr>
<td>Employed 1 month</td>
<td>4.96</td>
<td>5.41</td>
</tr>
<tr>
<td>Employed 2 months</td>
<td>4.96</td>
<td>2.70</td>
</tr>
<tr>
<td>Employed 3 months</td>
<td>10.74</td>
<td>2.70</td>
</tr>
<tr>
<td>Employed 4 months</td>
<td>46.28</td>
<td>70.27</td>
</tr>
<tr>
<td><strong>Winter Semester</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No employment</td>
<td>38.84</td>
<td>13.51</td>
</tr>
<tr>
<td>Employed 1 month</td>
<td>6.61</td>
<td>5.41</td>
</tr>
<tr>
<td>Employed 2 months</td>
<td>3.31</td>
<td>5.41</td>
</tr>
<tr>
<td>Employed 3 months</td>
<td>4.13</td>
<td>2.70</td>
</tr>
<tr>
<td>Employed 4 months</td>
<td>47.11</td>
<td>72.97</td>
</tr>
<tr>
<td><strong>Spring Semester</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No employment</td>
<td>28.10</td>
<td>21.62</td>
</tr>
<tr>
<td>Employed 1 month</td>
<td>6.61</td>
<td>5.41</td>
</tr>
<tr>
<td>Employed 2 months</td>
<td>65.29</td>
<td>72.97</td>
</tr>
<tr>
<td><strong>Summer Semester</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No employment</td>
<td>27.27</td>
<td>21.62</td>
</tr>
<tr>
<td>Employed 1 month</td>
<td>7.44</td>
<td>5.41</td>
</tr>
<tr>
<td>Employed 2 months</td>
<td>65.29</td>
<td>72.97</td>
</tr>
</tbody>
</table>

Note: Fall semester has four months; Winter semester has four months; Spring semester has two months; Summer semester has two months.
47%) compared to the control group (58%). However, only during the Fall semester the distribution of employment among depressed students was significantly different from that of the controls (p-value of chi-square test is 0.06). For the other semesters, the distribution of employment is not statistically different across the two groups of students: depressed and controls. Table 10 also shows that a considerable number of students worked part of the semester (one, two, or three months) and this part-semester employment was slightly higher proportionately for depressed students relative to controls (even though not statistically significant). Overall, the majority of students from all groups during the Spring and Summer terms had full-semester employment status (65%-73%) and only 22%-28% of them were not working.

Table 11 shows, by semesters, the percentage of working students in each group who were employed part-time, their mean work hours per week and mean hourly wage. Across semesters, the percentage of depressed students who worked part-time (less than 25 hours per week) is higher relative to controls, although this difference is not statistically significant. In each semester, there is no significant difference in the means of work hours per week and of hourly wage across the three groups of students. On average, students from each group make 8 dollars per hour and work 21-25 hours per week during long semesters and 34-38 hours per week during short terms.

The means of work impairment due to depression and other health disorders for working students are displayed in Table 12. The depressed students claim higher reduction of job productivity due to health disorders relative to controls and also to potentially depressed students. The impairment was greater during the winter semester (38%) than
Table 11

Employment, Work Hours, and Wage by Semesters

<table>
<thead>
<tr>
<th>Variables</th>
<th>Means</th>
<th>P-values of t-tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Depressed students (n=121)</td>
<td>Potentially depressed students (n=38)</td>
</tr>
<tr>
<td>Fall Semester</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed students</td>
<td>81</td>
<td>30</td>
</tr>
<tr>
<td>Part time (%)</td>
<td>76.5</td>
<td>63.3</td>
</tr>
<tr>
<td>Hours per week</td>
<td>22.04</td>
<td>25.10</td>
</tr>
<tr>
<td>Dollars per hour</td>
<td>8.24</td>
<td>7.97</td>
</tr>
<tr>
<td>Winter Semester</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed students</td>
<td>74</td>
<td>32</td>
</tr>
<tr>
<td>Part time (%)</td>
<td>75.7</td>
<td>65.6</td>
</tr>
<tr>
<td>Hours per week</td>
<td>21.15</td>
<td>23.42</td>
</tr>
<tr>
<td>Dollars per hour</td>
<td>8.38</td>
<td>7.53</td>
</tr>
<tr>
<td>Spring Semester</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed students</td>
<td>87</td>
<td>29</td>
</tr>
<tr>
<td>Part time (%)</td>
<td>31.0</td>
<td>34.5</td>
</tr>
<tr>
<td>Hours per week</td>
<td>33.87</td>
<td>33.64</td>
</tr>
<tr>
<td>Dollars per hour</td>
<td>8.11</td>
<td>8.02</td>
</tr>
<tr>
<td>Summer Semester</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed students</td>
<td>88</td>
<td>29</td>
</tr>
<tr>
<td>Part time (%)</td>
<td>27.3</td>
<td>17.2</td>
</tr>
<tr>
<td>Hours per week</td>
<td>34.34</td>
<td>37.86</td>
</tr>
<tr>
<td>Dollars per hour</td>
<td>8.13</td>
<td>8.14</td>
</tr>
</tbody>
</table>

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Table 12

Impairment Caused by Depression and Other Health Disorders on Work Productivity, Absenteeism, and Household Performance by Semesters

<table>
<thead>
<tr>
<th>Variables</th>
<th>Means</th>
<th>P-values of t-tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Depressed students (n=121)</td>
<td>Potentially depressed students (n=38)</td>
</tr>
<tr>
<td><strong>Fall Semester</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work impairment due to health disorders (%)</td>
<td>27.90</td>
<td>20.54</td>
</tr>
<tr>
<td>Number of lost hours due to health disorders (hr)</td>
<td>8.29</td>
<td>2.27</td>
</tr>
<tr>
<td>Impairment on hs. perf. due to health disorders (%)</td>
<td>28.82</td>
<td>20.38</td>
</tr>
<tr>
<td><strong>Winter Semester</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work impairment due to health disorders (%)</td>
<td>38.49</td>
<td>17.85</td>
</tr>
<tr>
<td>Number of lost hours due to health disorders (hr)</td>
<td>2.78</td>
<td>2.34</td>
</tr>
<tr>
<td>Impairment of hs. perf. due to health disorders (%)</td>
<td>31.94</td>
<td>21.18</td>
</tr>
<tr>
<td><strong>Spring Semester</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work impairment due to health disorders (%)</td>
<td>30.39</td>
<td>9.66</td>
</tr>
<tr>
<td>Number of lost hours due to health disorders (hr)</td>
<td>4.03</td>
<td>1.81</td>
</tr>
<tr>
<td>Impairment of hs. perf. due to health disorders (%)</td>
<td>9.98</td>
<td>4.28</td>
</tr>
<tr>
<td><strong>Summer Semester</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work impairment due to health disorders (%)</td>
<td>18.48</td>
<td>17.67</td>
</tr>
<tr>
<td>Number of lost hours due to health disorders (hr)</td>
<td>4.65</td>
<td>3.33</td>
</tr>
<tr>
<td>Impairment of hs. perf. due to health disorders (%)</td>
<td>11.31</td>
<td>4.66</td>
</tr>
</tbody>
</table>
during Fall or shorter terms. This may be explained by the fact that during the Spring and Summer terms students take fewer classes resulting in less stress which allows them to better cope in the working environment.

Table 12 shows that on average, depressed students reported 3-8 work hours lost per month due to depression during the long semesters and 4-5 hours lost per month during the short semesters. Absenteeism is significantly higher for the group of depressed students relative to controls. Additionally, Table 12 presents the mean impairment caused by health disorders on the student's performance at home. This impairment is higher for the group of depressed students particularly during the Fall and Winter semesters (28-32%), and it seems to be reduced during the Spring and Summer terms (10-11%). Although, it is significantly higher for both groups of depressed students relative to controls.

Table 13 reports the mean impairments caused by depressive disorders on student performance at work and at home during the month when they were diagnosed with depression and also six months before and after. These means follow an inverted U-shaped pattern that takes the maximum value (33.56% and 31.76% respectively) during the month when students were diagnosed with depression. These means are also high one month prior to their first visit (29.62% and 28.26% respectively) and one month after their diagnosis date (30.35% and 27.68% respectively). After two months, the impairment caused by depression on student productivity at work and at home is significantly reduced.

The third column of Table 14 shows a U-shaped pattern that supports the
Table 13
Impairment Caused by Depression on Student Work Productivity and Performance of Household Activities

<table>
<thead>
<tr>
<th>Months</th>
<th>Work Impairment (%)</th>
<th>Household Activities Impairment (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Mean</td>
</tr>
<tr>
<td>M-6</td>
<td>53</td>
<td>16.23</td>
</tr>
<tr>
<td>M-5</td>
<td>51</td>
<td>15.29</td>
</tr>
<tr>
<td>M-4</td>
<td>51</td>
<td>14.90</td>
</tr>
<tr>
<td>M-3</td>
<td>56</td>
<td>18.57</td>
</tr>
<tr>
<td>M-2</td>
<td>66</td>
<td>20.15</td>
</tr>
<tr>
<td>M-1</td>
<td>74</td>
<td>29.62</td>
</tr>
<tr>
<td>Mb</td>
<td>73</td>
<td>33.56</td>
</tr>
<tr>
<td>M+1</td>
<td>71</td>
<td>30.35</td>
</tr>
<tr>
<td>M+2</td>
<td>58</td>
<td>25.43</td>
</tr>
<tr>
<td>M+3</td>
<td>46</td>
<td>18.46</td>
</tr>
<tr>
<td>M+4</td>
<td>33</td>
<td>15.61</td>
</tr>
<tr>
<td>M+5</td>
<td>27</td>
<td>20.74</td>
</tr>
<tr>
<td>M+6</td>
<td>26</td>
<td>17.12</td>
</tr>
</tbody>
</table>

Note: a) These are p-values of the t-tests for the mean differences in work impairment or household activities impairment between months M and M+i or M and M-i; b) M represents the month when the student was diagnosed with depression.

hypothesis that students reduced the number of scheduled work hours per week during the months when they experienced depressive symptoms. Their work schedule was reduced to 21.26 hours per week during the month when they were diagnosed with depression. The number of work hours lost due to depression is clearly higher during those months and this is reflected in the inverted U-shaped pattern of those means in the fifth column. The maximum of the number of hours that students lost due to depression is 2.61 which is reached on the month when they were diagnosed with depression.
Table 14

Work Absenteeism

<table>
<thead>
<tr>
<th>Months</th>
<th>Depressed students</th>
<th>Number of work hours scheduled per week</th>
<th>Number of work hours missed due to depression in one month</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>P-values(^{b})</td>
</tr>
<tr>
<td>M-6</td>
<td>53</td>
<td>30.24</td>
<td>0.0037</td>
</tr>
<tr>
<td>M-5</td>
<td>51</td>
<td>31.35</td>
<td>0.0025</td>
</tr>
<tr>
<td>M-4</td>
<td>51</td>
<td>30.57</td>
<td>0.0043</td>
</tr>
<tr>
<td>M-3</td>
<td>56</td>
<td>30.39</td>
<td>0.0088</td>
</tr>
<tr>
<td>M-2</td>
<td>66</td>
<td>24.83</td>
<td>0.1368</td>
</tr>
<tr>
<td>M-1</td>
<td>74</td>
<td>22.54</td>
<td>0.3399</td>
</tr>
<tr>
<td>M+1</td>
<td>73</td>
<td>21.26</td>
<td>—</td>
</tr>
<tr>
<td>M+2</td>
<td>71</td>
<td>21.01</td>
<td>0.2790</td>
</tr>
<tr>
<td>M+3</td>
<td>58</td>
<td>23.95</td>
<td>0.1731</td>
</tr>
<tr>
<td>M+4</td>
<td>46</td>
<td>27.91</td>
<td>0.0284</td>
</tr>
<tr>
<td>M+5</td>
<td>33</td>
<td>30.97</td>
<td>0.0217</td>
</tr>
<tr>
<td>M+6</td>
<td>27</td>
<td>30.04</td>
<td>0.0434</td>
</tr>
<tr>
<td></td>
<td>26</td>
<td>25.35</td>
<td>0.0421</td>
</tr>
</tbody>
</table>

Note: a) These are p-values of the t-tests for the mean differences in scheduled work hours per week or absenteeism between months M and M+1 or M and M-1; b) M represents the month when the student was diagnosed with depression.

Overall, Tables 11-14 show that students are poorly attached to the labor market during their academic career. Few of them have a stable full-time job, while the majority keep spring/summer jobs (1-4 months) or part-time jobs that are less than 25 hours/week. It is interesting to observe that within a semester, often students work during the first three months and quit the job in the last month of the semester perhaps due to preparation for final exams or leaving town. The above statistics also support the expectation that students with depressive disorders work fewer hours and fewer months relative to their...
healthy peers. In addition, they report higher impairment on job and home activities and absenteeism due to depression. This descriptive analysis have already shown the significant negative influence of depression on student labor market outcomes. In the upcoming sections, I further explore this impact within the context of a labor supply framework.

Student Labor Supply

Depression disorders induce penalties to working students as manifested in the following: less hours of work supplied, absenteeism at work, which in most cases is not compensated by employers\textsuperscript{16} and possibly lower wage rates. In fact, the third consequence is more prevalent among individuals who suffer from chronic illnesses rather than those who experience acute cases. They will choose jobs that are lower paying and more tolerant toward absenteeism due to their poor health conditions. Moreover, when individuals are involved in other activities such as schooling, they will take jobs that are flexible regarding work time which will affect their offered wage.

Let me assume that the University student as a decision making agent chooses to go to school and work outside the academic environment simultaneously. Then the student allocates his time between school (this includes the time attending classes and studying), work (time spent at work) and leisure (this includes the time for different social activities). The optimum number of work hours that the student supplies can be obtained by maximizing student utility subject to his budget and time constraints. The number of

\textsuperscript{16}Also work absenteeism can induce delays of promotion and raises.
hours that the student supplies in the labor market or the probability of student labor participation will depend on the student individual characteristics, health status, financial status and school status.

In order to investigate empirically the impact of these factors and particularly the effect of student health status on his labor force participation decision, I use panel data that consists of 367 undergraduate students. The employment information obtained from the survey allows me to compile a monthly data set from which I create a panel of 4404 observations. I construct a ranked trichotomous dependent variable for the employment equation. It takes the value 0 if the student 'i' was not working in month 'm', the value 1 if the student 'i' was working less than 25 hours per week in month 'm' and the value 2 if the student 'i' was working more than 25 hours per week in month 'm'.

The sets of regressors include: (a) X - a vector of factors that represents student health status, (b) Z - a vector of student specific characteristics, and (c) S - a vector of student school characteristics. Most of the variables used in this chapter are the same as in Chapter III but the frequency of these variables are now monthly instead of by semesters. The depression dummy variable DEP\_im takes the value 1 if the student 'i' was diagnosed with depression in month 'm' or if this month fell within a 180 day interval from the diagnosis date. It takes the value zero for months before the diagnosis date and after a period of 180 days from the diagnosis date. The health guidelines state that generally the period that an individual may experience depressive symptoms can last 4-6 months.

\[17\] Usually, in the labor supply literature, a part-time employee is considered an individual who supplies less than 35 hours per week. Considering the fact that work is secondary to studying in a student's life, a part-time worker is considered one who supplies less than 25 work hours per week.
Therefore, in this analysis I have constructed a conservative proxy for depression by assuming these students to have depressive symptoms for 6 months (180 days). The second dummy variable SELFDEPₘₙ takes the value 1 if the student 'i' from the control group met the DSM-IV criteria for depression in month 'm', and takes the value 0 otherwise\textsuperscript{18}. Thus these dummy variables distinguish three groups of students: the first group consisting of diagnosed students for whom a treatment was recommended (121 students), the second group consisting of potentially depressed students (37 students), and the third group representing the pure controls (209 students).

The information about depression treatment comes from two sources: the study instrument in which students self-report depression and treatment, and the Sindecuse Health Center where students followed drug therapy or/and counseling. Given that information from the Health Center is objective and more accurate, I use that to construct the treatment dummy variable. Depression treatment consists of drug therapy taken at the Health Center and sometimes interacted with psychotherapy offered at this Center or at the Counseling Center. Because the information on student counseling therapy is not sufficient, the treatment variable used in this analysis mostly reflects drug therapy. Thus, TREATₘₙ takes the value '1' if student 'i' was under treatment for depression during month 'm' and takes the value '0' otherwise. To better measure the effect of depression treatment on a student's decision to participate in the labor force, I regard the starting date for treatment in my analysis as six weeks after the reported starting point. This shift

\textsuperscript{18}In the survey, I included a question that asks students about the months when they experienced the depressive symptoms.
in treatment starting date is justified by the literature regarding depression treatment that states that treatment becomes effective after six weeks. Also it is reasonable to assume that it takes longer (more than a month) for students under treatment of depression to get back to their normal life and make rational decisions on working or studying activities.

To control for the impact of other health disorders on student labor force participation, I construct a dummy variable OTHER\textsubscript{im} that takes the value '1' if the student 'i' in month 'm' reported any other health disorders and the value '0' otherwise. I expect that experiencing other health disorders may decrease students' probability of labor force participation or the number of hours that they supply per week. This is true for chronic disorders rather than acute cases. If within my student population there are more students who had suffered acute disorders rather than chronic disorders, then one can expect insignificant effect of other health disorders on student employment status. This is because a full-time worker who experiences a short-time physical disorder will not change his/her employment status within a month. On the contrary, an individual who is diagnosed with depressive disorder or other chronic disorders usually is expected to change the labor force participation status, because these are long lasting disorders.

As for the set of student specific characteristics, Z, I include student age and dummy variables for student gender (female versus male), race (white versus non-white), living status (living with roommate/parents/partner versus alone). These demographics are commonly used in the labor supply literature. Often, it is found that middle aged white males supply more work hours per week relative to other population groups. In my analysis, I expect that older students, male and white students to have higher probability
of participating in the labor force and also working more hours per week.

In the set of student school characteristics, S, I include the number of attempted credit hours\(^{19}\) that a student has taken per semester\(^{20}\). Students who attempt to earn a large number of credit hours in school are less likely to participate in the labor force or supply a large number of work hours per week. Another proxy that accounts for the time students spend in school within a month is \(\text{TIME}_{im}\) that takes values from 0 to 100%. For example, there is no school break in February, thus students take classes all month long, while in April the semester ends by the third week so students spend only 75% of their time at school during this month. I expect that during those months that students spend 100% of their time at school, they will supply less hours of work relative to those months with school breaks (spring break, winter break, summer break, etc.).

Since EMPL is an ordered categorical variable taking the value not working, working part-time and working full-time, I estimate equation (4.1) as an ordered logit model:

\[
\text{EMPL}_{im} = \alpha_i + \beta_1 \text{DEP}_{im} + \beta_2 \text{SELFDEP}_{im} + \beta_3 (\text{DEP}^\ast \text{TREAT})_{im} + \beta_4 \text{OTHER}_{im} + \\
+ \gamma' Z_{im} + \delta' S_{im} + \epsilon_{im} \tag{4.1}
\]

I expect that students who were clinically diagnosed with depression or those who met the criteria for depression are less likely to engage in work activities. This is reflected in

\(^{19}\)The attempted credit hours show all cumulative hours taken for a grade, while the earned credit hours show all credit hours taken for a grade or credit and successfully completed.

\(^{20}\)This variable remains the same across the months of one semester.
the coefficients of the depression proxies. Moreover, it is hypothesized that being treated for depression increases the probability of depressed students participating in the labor force (supported by the positive sign of the coefficient of the treatment interaction term). Further, I estimate the following equation to examine the effect of depression and its treatment on the number of hours scheduled to work, $HOURS_{im}$, for the sample of 367 students:

$$HOURS_{im} = \alpha_i + \beta_1 DEP_{im} + \beta_2 SELFDEP_{im} + \beta_3 (DEP*TREAT)_{im} + \beta_4 OTHER_{im} + \gamma' Z_{im} + \delta' S_{im} + \epsilon_{im} \quad (4.2)$$

The coefficient $\beta_1$ of the depression dummy variable ($DEP_{im}$) in equation (4.2) is the effect on students' scheduled work hours per week due to untreated but diagnosed depression, while the coefficient $\beta_2$ of the (SELFDEP)$_{im}$ dummy variable is the effect on students' scheduled work hours due to potential depression. The effect of treatment for depression on student work hours is represented by the coefficient of the treatment interaction term $\beta_3$. The interaction term can be combined with depression dummy variable so that the effect of depression on student work hours per week can be rewritten as:$(\beta_1 + \beta_3 TREAT_{im})DEP_{im}$. Because the treatment variable takes values 0 or 1, the total effect of diagnosed depression on student work hours per week in the case of treatment is equal to $\beta_1 + \beta_3$. I expect $\beta_1$ and $\beta_2$ to be negative and $\beta_3$ positive. Also, I expect that $|\beta_2| < |\beta_1|$ and $|\beta_3| < |\beta_1|$, which means that the impairment of the diagnosed depression is larger than that of potential depression and that treatment does not fully counteract this impairment.
The parameter \( \alpha_i \) in both equations represents individual effects that vary across students and impact their employment status. It is assumed that these individual effects are time invariant and are not captured by any of the regressors in either equation. In the context of my model, they may represent student ambition to work and make money, their financial status, etc., which are difficult to be accounted for by separate variables in the structural equation. Unfortunately, the survey did not ask questions regarding student financial status, which therefore is embodied in the parameter \( \alpha_i \). These individual effects may be treated as either fixed or random. The nature of the data renders itself to the choice of a random effects over a fixed effects estimator. This panel data consists of a large number of students and a relatively small number of months (12). To use a fixed effects estimator, I need to estimate 367 dummy variables for each individual in the sample. Given such a large number of parameters to be estimated, the fixed effects estimator would have a very large sampling variability. Moreover, some of the regressors are time-invariant\(^{21}\) and the coefficients of these regressors are not identified with a fixed effects estimator. For these reasons, the appropriate estimator is the random effects estimator. However, before computing the random effects estimator for equation (4.1) and (4.2), I test for the existence of error component in the model. In the context of an ordered logit model, the likelihood ratio test is conducted to identify the presence of error components in equation (4.1). The Lagrangian Multiplier test suggested by Breusch and Pagan (1980) is used to test the null hypothesis that the intercepts \( \alpha_i \) are equal in equation (4.2).

\(^{21}\)Gender, race, and age are time invariant variables.
There are some econometric issues regarding the estimation of the above equations. It is suggested that employment, income and health are endogenous variables determined simultaneously (see Grossman, 1972). It is known that mental health disorders such as depression may affect the individual decision to work, the number of hours worked and his wage rate. On the other hand, mental health can be affected positively or negatively by being employed which entails social networks, enhanced self-esteem and stress (Ettner et al., 1997). The lines of causality are often open to debate. Economists usually deal with the issue of endogeneity of health status by using the simultaneous equations technique (Ettner et al., 1997; Lee, 1982; Ruhm, 1992; Sickles & Taubman, 1986) where employment and health status are jointly determined. Within the student population, the non-working students might be in a poor financial situation and may suffer depressive symptoms from it or on the contrary, they might not need extra money and do not want to bear extra stress. To tell one possibility from the other causal direction, depressed students were asked in the survey about the causes of their depressive symptoms. Among 131 students diagnosed with depression, 59 students claimed poor financial conditions as a cause of their depressive symptoms, but no one reported that as the only cause. On average, students cited on average more than two other reasons along with poor financial situation as causes of their depressive symptoms. Considering these, I assume that causation runs from health disorders to employment status.

---

22However, some studies do not find evidence that work hours or employment status affect individual’s health status (Haveman, Stone, & Wolf, 1989).
Empirical Results

Table 15 displays the estimated coefficients of the employment equation (4.1) where the dependent variable EMPL takes three values 0, 1, and 2 as described in the previous section. The panel is balanced and consists of 4404 observations. The OLS estimates are listed in the second column, while the estimated coefficients of the ordered logit model for the pooled data are listed in the third column. The health variables (DEP, and DEP*TREAT) perform well in either model (OLS and Ordered Logit) as they appear significant with hypothesized signs. Thus, the ordered logit coefficient of depression dummy variable clearly shows the expected negative effect that this mental disorder has on the student labor supply decision, while treatment increases student’s likelihood to participate in the labor force. However, the other two health variables (SELFDEP and OTHER) do not perform well (they appear with opposite signs) and this can be due to the fact that the panel feature of the data is not yet exploited.

An indication of the presence of error component in the data is the significant likelihood ratio statistic reported at the bottom of column four (chi-square value equals to 2416.958). Thus, I estimate the employment equation using a random effects ordered logit model. As can be seen in the last column, the estimated coefficients of the depression and treatment dummy variables are still statistically significant with the expected signs. Diagnosed depression is typically associated with reduced labor supply. Even the group of potentially depressed students seem to have a lower employment probability relative to their healthy peers. The estimation results also show that the effect of
### Table 15

Estimated Coefficients of Equation 4.1 (EMPL - Dependent Variable)

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS</th>
<th>Ordered Logit</th>
<th>Random Effects Ordered Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. INTERCEPT</td>
<td>0.7488*** (8.54)</td>
<td>1.4207*** (7.83)</td>
<td>1.8910*** (5.77)</td>
</tr>
<tr>
<td>2. DEP</td>
<td>-0.1034** (-2.20)</td>
<td>-0.4849*** (-4.46)</td>
<td>-0.4919*** (-4.23)</td>
</tr>
<tr>
<td>3. SELFDEP</td>
<td>0.1321*** (2.15)</td>
<td>-0.2547 (-1.37)</td>
<td>-0.4731*** (-2.97)</td>
</tr>
<tr>
<td>4. DEP*TREAT</td>
<td>0.1329* (1.67)</td>
<td>0.3891* (2.04)</td>
<td>0.5362* (2.36)</td>
</tr>
<tr>
<td>5. OTHER</td>
<td>0.1661*** (3.57)</td>
<td>0.3946*** (3.17)</td>
<td>0.2281*** (2.61)</td>
</tr>
<tr>
<td>6. AGE</td>
<td>-0.0015 (-0.54)</td>
<td>0.0053 (0.96)</td>
<td>-0.0030 (-0.27)</td>
</tr>
<tr>
<td>7. GENDER</td>
<td>0.0894*** (2.73)</td>
<td>0.1904*** (2.60)</td>
<td>0.4226*** (3.44)</td>
</tr>
<tr>
<td>8. RACE</td>
<td>0.0144 (0.00)</td>
<td>0.1115 (1.13)</td>
<td>0.5603*** (3.54)</td>
</tr>
<tr>
<td>9. LIVING</td>
<td>-0.0752* (-1.82)</td>
<td>-0.2437** (-2.44)</td>
<td>-0.1241 (-1.30)</td>
</tr>
<tr>
<td>10. TIME</td>
<td>0.0011** (2.27)</td>
<td>0.0023** (2.04)</td>
<td>-0.1117 (-0.99)</td>
</tr>
<tr>
<td>11. ATTHR</td>
<td>-0.0178*** (-5.37)</td>
<td>-0.1119*** (-14.24)</td>
<td>-0.1665*** (-22.14)</td>
</tr>
<tr>
<td>12. HOUR (-1)</td>
<td>0.0001** (2.43)</td>
<td>0.0005*** (5.03)</td>
<td>0.0006*** (4.28)</td>
</tr>
</tbody>
</table>

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Table 15—Continued

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS</th>
<th>Ordered Logit</th>
<th>Random Effects Ordered Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log likelihood function</td>
<td>–</td>
<td>-4531.698</td>
<td>-3323.219</td>
</tr>
<tr>
<td>Restricted log likelihood</td>
<td>–</td>
<td>-4808.464</td>
<td>-4531.698</td>
</tr>
<tr>
<td>Chi-squared</td>
<td>–</td>
<td>553.532***</td>
<td>2416.958***</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>4404</td>
<td>4404</td>
<td>4404</td>
</tr>
<tr>
<td>Number of observation</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: ***) Significant at 1% level; **) Significant at 5% level; *) Significant at 10% level.

depression treatment on labor supply is consistent with the hypothesis. The estimated coefficient of the treatment interaction term (0.5362) offsets the impairment caused by diagnosed depression (-0.4919), which demonstrates the strong efficacy of depression treatment on the student labor participation decision. The effect of other health disorders appears to be consistently positive in all three estimation results displayed in Table 15. This is an unexplained finding.

Regarding the other control variables included in equation (4.1), the findings are quite standard and only need brief comments. Employment probabilities are higher for female and white students. In the labor supply literature a common finding is that men are more likely to participate in the labor force and supply longer work hours relative to
women. This is not the case for my student population sample here for several reasons. First, my sample is not truly representative of the general male/female population. Recall from Table 1 (Chapter II), 85% of students in my sample are female. Second, the majority of female students in my sample are not married and do not have children. Thus, their employment decision is not affected by those factors commonly discussed in the female labor supply literature. The negative coefficient of the ATTHR variable shows that if students are enrolled in a large number of classes, they are less likely to participate in the labor force or to work full-time. Also, those students who worked in the previous month, they are expected to work during the current month as well.

The estimated coefficients of the work hours equation (4.2) are displayed in Table 16. The second column lists the OLS estimates, while the third and fourth columns report the random effects and fixed effects estimates respectively. The OLS estimates show that the scheduled work hours per week is significantly reduced by 3.02 hours due to depressive disorders. There is no significant effect of potential depression and depression treatment on student hours of work per week. However, the OLS estimator is not efficient because it does not account for the panel feature of the data. The Lagrangian Multiplier statistics reported at the bottom of the second column indicates the presence of an error component in the data. For this reason, the random effects and fixed effects estimators are applied to estimate equation (4.2). The Hausman test is not significant suggesting that unobservable individual effects are uncorrelated with regressors in the hours equation. Due to the inclusion of time invariant variables in the structural equation and the large number of individuals (367), the random effects estimator is preferred over
Table 16

Estimated Coefficients of Equation 4.2 (HOURS - Dependent Variable)

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. INTERCEPT</td>
<td>23.5523*** (14.47)</td>
<td>22.3083*** (5.79)</td>
<td>8.1437** (2.56)</td>
</tr>
<tr>
<td>2. DEP</td>
<td>-3.0176*** (-3.47)</td>
<td>-1.6556** (-2.39)</td>
<td>-1.5166** (-2.17)</td>
</tr>
<tr>
<td>3. SELFDEP</td>
<td>0.3756 (0.33)</td>
<td>-0.5571 (-0.45)</td>
<td>-0.7768 (-0.59)</td>
</tr>
<tr>
<td>4. DEP*TREAT</td>
<td>1.9843 (1.35)</td>
<td>2.1339* (1.92)</td>
<td>2.1346* (1.91)</td>
</tr>
<tr>
<td>5. OTHER</td>
<td>3.8693*** (4.48)</td>
<td>2.5400*** (3.33)</td>
<td>2.3523*** (3.01)</td>
</tr>
<tr>
<td>6. AGE</td>
<td>0.0556 (1.06)</td>
<td>0.0880 (0.65)</td>
<td>-a</td>
</tr>
<tr>
<td>7. GENDER</td>
<td>-0.1665 (-0.27)</td>
<td>-0.1421 (-0.09)</td>
<td>-a</td>
</tr>
<tr>
<td>8. RACE</td>
<td>1.2323 (1.57)</td>
<td>0.9217 (0.45)</td>
<td>-a</td>
</tr>
<tr>
<td>9. LIVING</td>
<td>-0.8290 (-1.08)</td>
<td>0.3570 (0.40)</td>
<td>0.6565 (0.68)</td>
</tr>
<tr>
<td>10. TIME</td>
<td>0.0064 (0.70)</td>
<td>-0.0234*** (-3.25)</td>
<td>-0.0263*** (-3.61)</td>
</tr>
<tr>
<td>11. ATTHR</td>
<td>-0.9841*** (-16.02)</td>
<td>-0.7961*** (-16.27)</td>
<td>-0.7762*** (-15.66)</td>
</tr>
</tbody>
</table>
Table 16–Continued

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>R square</td>
<td>0.14</td>
<td>0.22</td>
<td>0.63</td>
</tr>
<tr>
<td>Number of observations</td>
<td>4404</td>
<td>4404</td>
<td>4404</td>
</tr>
<tr>
<td>Error component test (LM) (ch-square(1))</td>
<td>6632.02***</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Hausman test (m-value)</td>
<td>–</td>
<td>12.20</td>
<td>–</td>
</tr>
</tbody>
</table>

Note: ***) Significant at 1% level; **) Significant at 5% level; *) Significant at 10% level; a) The dashes indicate that these variables are time invariant variables and their coefficients are not identified by the fixed effects estimator. The impact of these variables goes into the intercept.

The random effects estimates listed in the third column of Table 16 affirm the negative impact of depressive disorders on the hours that students were scheduled to work per week. Those students who were diagnosed with depression at the Health Center reduced their work load per week by 1.66 hours on average. This small effect has plausible explanations. The majority of students work less than 25 hours per week and their work usually does not involve mental activities. Thus, it is not necessary for them to reduce the scheduled work hours per week by a large number due to their depressive disorders. The coefficient of SELDEP variable has the expected negative sign but is not significant. Depression treatment demonstrates a statistically significant positive effect on student scheduled work hours per week. It seems that treatment offset the negative
impact of diagnosed depressive disorders on student work hours supply. Similar to the findings of the employment equation (4.1), the scheduled work hours per week are increased for those students who suffered other health disorders. This contradicts my prior expectation and can not be explained.

The demographic variables (AGE, GENDER, and RACE) do not have any significant impact on student scheduled work hours per week. This might be related to the nature of the student population itself. They are mostly part-time workers, belonging to similar age group and are mostly female and white. It is interesting to note that during those months that students spent 100% of their time in school (no semester breaks), they reduced their work schedule by 2.34 hours per week. In addition, a high load of classes seems to reduce their weekly work as well. For example, if students attempt to earn three more credit hours (equivalent to a class) per semester they reduce their weekly work by 2.39 hours on average.

So far, I have analyzed the possible correlation between student health status and their employment status. In the next section, I turn to investigate the negative impact of health disorders on student work productivity, focusing on those students who participated in the labor force during the academic year.

Student Work Productivity

The impairment of depressive disorders on both absenteeism and on-job performance is widely investigated by health economists. The prevalence of depression among wage earners is estimated to be around 10%, although in most cases this illness is under
diagnosed. Depression usually impact worker performance by decreasing their level of concentration, inducing fatigue and physical weakness, insomnia or oversleep and also other health disorders. All these will lead to higher absenteeism rates and lower productivity among depressed workers. When depressed individuals undergo any form of medical treatment for depression such as drug therapy or counseling, it is expected that this impairment will be reduced and in most cases will approach zero. Several studies have found that treatment for depression is cost saving for employers from lowered worker absenteeism (Rizzo et al., 1996) and increased on-job performance (Berndt et al., 1998).

The impact of depression and its treatment on work productivity is also an important issue and needs to be discussed for University students who engage in labor market activities. A significant part of the student population participates in the labor force during their academic career. As to be expected their health conditions will be a crucial factor on their job performance. The work hours that students have lost due to depression are part of the indirect cost of this illness and the work hours saved due to medical treatment are another important component in the cost benefit analysis of depression. The reduction on student job performance due to depression is another indirect cost component that needs to be transformed into a dollar value. What follows is a comprehensive study because it considers both aspects of depression impairment: absenteeism and presenteeism. Let me explain in detail how I approached these two problems in a University student population where the majority participate in the labor force.
**Absenteeism**

Work absenteeism is constructed based on information obtained from the survey. Students are asked how many work hours per month they have missed due to depressive symptoms and due to other health disorders. The sum of work hours missed due to these health conditions gives the work hours lost due to disability per month (\( \text{ABSENT}_{im} \)). This is a self-reported absenteeism and naturally potential measurement errors may exist due to the following reasons. First, students may have difficulty recalling their past disability work hours. This is particularly true of short-term illnesses such as flue, minor injury, etc. Second, there is a possibility of double counting of disability hours of work when they were lost due to a portfolio of health conditions such as depression and anxiety.

I run the following regression by using \( \text{ABSENT}_{im} \) as the dependent variable and the components of vector \( X, Z, \) and \( S \) (described in the earlier labor supply section) as explanatory variables. Also, hourly wage, \( \text{WAGE}_{im} \), is considered as an important factor in the absenteeism equation.

\[
\text{ABSENT}_{im} = \alpha_i + \beta_1 \text{DEP}_{im} + \beta_2 \text{SELFDEP}_{im} + \beta_3 (\text{DEP}^*\text{TREAT})_{im} + \beta_4 \text{OTHER}_{im} + \\
+ \gamma' Z_{im} + \delta' S_{im} + \varphi \text{WAGE}_{im} + \epsilon_{im}
\]  

(4.3)

The coefficient \( \beta_1 \) of the depression dummy variable (\( \text{DEP}_{im} \)) is the effect of untreated depression on student disability work hours, while the coefficient \( \beta_2 \) of the \( \text{SELFDEP}_{im} \) variable is the impairment caused by potential depression on absenteeism. The total effect...
of treatment for depression on student disability work hours is given by the coefficient of treatment interaction term $\beta_3$. The interaction term can be combined with depression dummy variable so that the effect of depression on student absenteeism rate can be rewritten as: $(\beta_1 + \beta_3 \text{TREAT}_{in}) \times \text{DEP}_{in}$. Because the treatment variable takes values 0 or 1, the total effect of diagnosed depression on student disability hours in the case of treatment is equal to $\beta_1 + \beta_3$. Again $\beta_1$ and $\beta_2$ are expected to be positive and $\beta_3$ negative implying that students who were depressed will have a significant number of disability work hours due to depression, but those absenteeism hours will be reduced if they follow an appropriate treatment. Also, I expect that $|\beta_2| < |\beta_1|$ and $|\beta_3| < |\beta_1|$, which means that the impairment of the diagnosed depression is larger than that of potential depression and that treatment does not fully countervail this impairment. The parameter $\alpha_q$ represents the individual effects that are considered time invariant.

In estimating equation (4.3), I apply the same estimators used in estimating equation (4.2). However, the data used for this estimation differs from that used in the previous section in the following ways. It is a subsample of 239 working students over a 12-month period. Since not every student had participated in the labor force all year long the data sample used here is an unbalanced panel data. Typically, students work outside school during summer, spring, or winter breaks, but it is not uncommon that students also work during the academic year as well. The information about why a student was engaged in labor market activities during the school or break periods is not provided in the data. It is possible that students with depressive symptoms are more likely not to work during school because it is harder for them to handle the extra stress that might
result from a combination of schooling and labor market activities. For this reason, I test for the existence of sample selection associated with the decision to work during school or break months using the procedure of Verbeek and Nijman (1992). Following their methodology, I construct a dummy variable $r_{im}$ that denotes the availability of observations for the dependent variable. This variable takes the value 1 if student ‘i’ was working in month ‘m’ and the value 0 otherwise. Then, the variable $\text{MONTH}_i = \sum r_{im}$, which represents the number of months that student ‘i’ participated in labor force, is added to equation (4.3). Denoting the coefficient for the added variable $\text{MONTH}_i$ by $\lambda$, the presence of sample selection can be checked by testing the null hypothesis $H_0: \lambda = 0$. If the null hypothesis is rejected, then it can be concluded that sample selection is present.

Table 17 presents the estimated coefficients of equation (4.3). The OLS estimated coefficients of the health variables listed in the second column reveal that depressive disorders have marked effects on disability work hours per month. The adverse effects of depression on disability hours is higher for students who have been diagnosed with depression (2.89) than for those who are potentially depressed (1.32). Treatment saves more than half of the loss caused by diagnosed depression. Other health disorders have a positive significant effect on disability hours raising absenteeism by 6.82 hours on average.

The LM test for the presence of an error component in the unbalanced panel (see Baltagi & Li, 1990) indicates the importance of employing a random effects or fixed effects estimator to increase efficiency of estimation. The random effects estimates are given in the third column of Table 17, while the fixed effects estimates are listed in the
Table 17

Estimated Coefficients of Equation 4.3 (ABSENT - Dependent Variable)

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. INTERCEPT</td>
<td>-3.3296*** (-3.38)</td>
<td>-3.7693** (-2.08)</td>
<td>-3.3421* (-1.79)</td>
</tr>
<tr>
<td>2. DEP</td>
<td>2.8898*** (5.76)</td>
<td>1.7925*** (3.60)</td>
<td>1.2136** (2.32)</td>
</tr>
<tr>
<td>3. SELFDEP</td>
<td>1.3162** (2.33)</td>
<td>1.8405** (2.57)</td>
<td>2.3394*** (2.79)</td>
</tr>
<tr>
<td>4. DEP*TREAT</td>
<td>-1.5827** (-1.99)</td>
<td>-1.4930** (-1.98)</td>
<td>-1.5693** (-2.02)</td>
</tr>
<tr>
<td>5. OTHER</td>
<td>6.8202*** (16.22)</td>
<td>7.7017*** (17.06)</td>
<td>8.0620*** (16.32)</td>
</tr>
<tr>
<td>6. AGE</td>
<td>0.1964*** (5.45)</td>
<td>0.1745** (2.58)</td>
<td>-</td>
</tr>
<tr>
<td>7. GENDER</td>
<td>0.0198 (0.06)</td>
<td>0.3984 (0.62)</td>
<td>-</td>
</tr>
<tr>
<td>8. RACE</td>
<td>-0.1735 (-0.41)</td>
<td>-0.4972 (-0.63)</td>
<td>-</td>
</tr>
<tr>
<td>9. LIVING</td>
<td>0.7558* (1.91)</td>
<td>1.6421*** (3.08)</td>
<td>2.5014*** (3.71)</td>
</tr>
<tr>
<td>10. TIME</td>
<td>0.0045 (0.96)</td>
<td>0.0035 (0.76)</td>
<td>0.0024 (0.50)</td>
</tr>
<tr>
<td>11. ATTHR</td>
<td>-0.0711** (-2.15)</td>
<td>-0.0368 (-1.13)</td>
<td>-0.0218 (-0.64)</td>
</tr>
<tr>
<td>12. WAGE</td>
<td>-0.0730** (-2.14)</td>
<td>0.0053 (0.10)</td>
<td>-0.1267* (-1.75)</td>
</tr>
</tbody>
</table>
Table 17--Continued

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>13. MONTH</td>
<td>-</td>
<td>-0.0696 (-0.88)</td>
<td>-</td>
</tr>
<tr>
<td>R square</td>
<td>0.11</td>
<td>0.10</td>
<td>0.40</td>
</tr>
<tr>
<td>Number of observations</td>
<td>2868</td>
<td>2868</td>
<td>2868</td>
</tr>
<tr>
<td>Error component test (LM) (ch-square(1))</td>
<td>591.82***</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Hausman test (m-value)</td>
<td>-</td>
<td>30.06**</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: *** Significant at 1% level; ** Significant at 5% level; *) Significant at 10% level; a) The dashes indicate that these variables are time invariant variables and their coefficients are not identified by the fixed effects estimator. The impact of these variables goes into the intercept.

fourth column. The coefficient of the MONTH variable is not significant, which suggests that there is no selectivity bias in my sample. However, the significance of the Hausman test statistic shows that the unobservable individual effects are correlated with some of the regressors in equation (4.3). Therefore, the OLS and random effects estimators are inconsistent, and my analysis is based on the fixed effects estimating results. The results indicate that diagnosed depression increases the disability hours by 1.21 hours per month on average, while potential depression increases the disability hours by 2.34 hours. Other health disorders raised absenteeism by a higher magnitude relative to depression, which is expected given job nature that the majority of students are performing. Indeed, it can be seen from the last column of Table 17 that 8.06 hours per month are lost due to other
mental or physical disorders. According to the fixed effects estimated coefficient in Table 17, I find that treatment for depression significantly decreases the absenteeism rate by saving 1.57 hours per month.

Turning to individual characteristics, I find that living with parents, partners or roommates increases disability by 2.50 hours on average. These students who share the cost of living with others are more likely to be absent from work perhaps they face less financial pressure from their lost work. There is no significant correlation between the time spent at school or attempted credit hours and disability hours. A high hourly wage rate is associated with a significant decrease in absenteeism, but the magnitude is small which can be due to the fact that this group typically gets paid a minimum wage, so using sick days or hours of work will not incur considerable monetary losses to them.

**Presenteeism**

To measure the impairment of student job performance associated with depression, I construct a continuous variable (WPERF_{im}) that takes values from 0 to 100. This proxy is to capture the level of student self-reported work performance in month ‘m’, where 100 points represent full performance. In the survey, I included two questions that ask students about their level of work impairment due to depression, ImpDep_{im}, and other health disorders, ImpOther_{im}. Assuming that a healthy individual has a 100% work performance level, I can find the actual level of on-job productivity for those students who have experienced health disorders: WPERF_{im} = 100 - ImpDep_{im} - ImpOther_{im}. This proxy is constructed based on student self-reported information about
their on-job productivity and for the same reasons mentioned in the previous section, it may have some errors. Basing on the subsample of working students (239 students), I estimate the following equation:

$$WPERF_{im} = \alpha + \beta_1 \text{DEP}_{im} + \beta_2 \text{SELFDEP}_{im} + \beta_3 (\text{DEP}\ast\text{TREAT})_{im} + \beta_4 \text{OTHER}_{im} +$$

$$+ \gamma' Z_{im} + \delta' S_{im} + \phi WAGE_{im} + \varepsilon_{im}$$ (4.4)

I expect that depression will have a negative effect on student work performance, but treatment of depression will affect positively their performance. The issue of selectivity bias is treated in the same way as in the previous section.

First, I pool the data and estimate equation (4.4) using an OLS estimator. The OLS estimated coefficients are presented in the second column of Table 18. The health variables are strongly significant with the expected signs. Students with diagnosed depressive disorders suffered a drop in their work productivity of 23.12% while those who were potentially depressed experienced less impairment on their performance at work, 13.02% on average. Treatment for depression seems to be effective because it improves the work performance of depressed students by 9.66%. An even stronger impairment on student performance at work is caused by other health disorders, almost doubling that caused by diagnosed depression (42.16% versus 23.12%).

Next, I compute the LM statistic which is statistically significant indicating the presence of an error component in the data. Because the panel is unbalanced, I check for selectivity bias by considering the estimated coefficient of the MONTH variable. There is no evidence of selectivity.
Table 18

Estimated Coefficients of Equation 4.4 (WPERF - Dependent Variable)

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. INTERCEPT</td>
<td>91.9925*** (30.23)</td>
<td>98.3899*** (13.83)</td>
<td>101.12*** (21.54)</td>
</tr>
<tr>
<td>2. DEP</td>
<td>-23.1232*** (-14.92)</td>
<td>-10.9171*** (-8.53)</td>
<td>-9.2872*** (-7.07)</td>
</tr>
<tr>
<td>3. SELFDEP</td>
<td>-13.0233*** (-7.45)</td>
<td>-5.5192*** (-2.81)</td>
<td>-6.5876*** (-3.13)</td>
</tr>
<tr>
<td>4. DEP*TREAT</td>
<td>9.6596*** (3.94)</td>
<td>8.3633*** (4.37)</td>
<td>8.4678*** (4.34)</td>
</tr>
<tr>
<td>5. OTHER</td>
<td>-42.1642*** (-32.48)</td>
<td>-42.5163*** (-35.79)</td>
<td>-42.5363*** (-34.33)</td>
</tr>
<tr>
<td>6. AGE</td>
<td>0.0315 (0.28)</td>
<td>-0.0965 (-0.36)</td>
<td>-</td>
</tr>
<tr>
<td>7. GENDER</td>
<td>-2.0094* (-1.86)</td>
<td>-1.9280 (-0.75)</td>
<td>-</td>
</tr>
<tr>
<td>8. RACE</td>
<td>4.3090*** (3.30)</td>
<td>4.7446 (1.51)</td>
<td>-</td>
</tr>
<tr>
<td>9. LIVING</td>
<td>5.7074*** (4.67)</td>
<td>1.2907 (0.85)</td>
<td>-0.2855 (-0.17)</td>
</tr>
<tr>
<td>10. TIME</td>
<td>-0.0313** (-2.14)</td>
<td>-0.0234** (-1.96)</td>
<td>-0.0233* (-1.91)</td>
</tr>
<tr>
<td>11. ATTHR</td>
<td>0.0339 (0.33)</td>
<td>-0.0670 (-0.80)</td>
<td>-0.0751 (-0.88)</td>
</tr>
<tr>
<td>12. WAGE</td>
<td>-0.4483*** (-4.25)</td>
<td>0.0063 (0.04)</td>
<td>0.1664 (0.92)</td>
</tr>
</tbody>
</table>

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Table 18—Continued

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>13. MONTH</td>
<td>-</td>
<td>-0.4398 (-1.44)</td>
<td>-</td>
</tr>
<tr>
<td>R square</td>
<td>0.36</td>
<td>0.34</td>
<td>0.71</td>
</tr>
<tr>
<td>Number of observations</td>
<td>2868</td>
<td>2868</td>
<td>2868</td>
</tr>
<tr>
<td>Error component test</td>
<td>3150.58***</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>(LM) (ch-square(1))</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hausman test (m-value)</td>
<td>-</td>
<td>49.54***</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: ***) Significant at 1% level; **) Significant at 5% level; *) Significant at 10% level; a) The dashes indicate that these variables are time invariant variables and their coefficients are not identified by the fixed effects estimator. The impact of these variables is relegated to the intercept.

bias in the panel, but there is correlation between hidden individual effects and regressors since the Hausman test statistic is significant. This becomes fixed effects estimator as the remaining consistent estimator. Thus, fixed effects estimated coefficients listed in the fourth column of Table 18 are used to examine the impact of health status on student work performance. Diagnosed depression reduces student productivity at work by 9.29%, while the group of students who were potentially depressed have a 6.59% reduction of productivity caused by their depressive symptoms. The effectiveness of treatment is clearly revealed by its significant positive coefficient. Since treatment significantly reduces the impairment caused by depression on student work performance, treatment is cost saving from employer’s perspective. Other health disorders reduce student...
productivity by a high magnitude of 42.54% which is 4.58 times higher than the reduction induced by the diagnosed depression. While wage rate, living status and attempted credit hours do not demonstrate any association with student productivity, the time spent at school reduces student productivity at work. This is expected because more time spent at school may make students tired which will negatively impact their performance at work.

Work Performance at Home

In the survey, students are asked similar questions regarding their work performance at an employment site and at home. I believe that health conditions have also affected their performance of household activities. To validate my conjecture, in this section, I further explore student work performance in the non-market sector, i.e. the level of productivity at home. This is done by constructing a similar subjective measure of performance in household activities, \( \text{HPERF}_{\text{im}} \), that takes values from 0 to 100 where 100 points represent full performance. The questionnaire included two questions that ask students about their level of household activities impairment due to depression, \( \text{ImpDep}_{\text{im}}^H \), and other health disorders, \( \text{ImpOther}_{\text{im}}^H \). Assuming that a healthy individual has a 100% performance level in household production, I can measure the level of work productivity at home for those students who have experienced health disorders: \( \text{HPERF}_{\text{im}} = 100 - \text{ImpDep}_{\text{im}}^H - \text{ImpOther}_{\text{im}}^H \). This proxy serves as the dependent variable in the following equation:
HPERF_{im} = \alpha + \beta_1 \text{DEP}_{im} + \beta_2 \text{SELFDEP}_{im} + \beta_3 (\text{DEP}^* \text{TREAT})_{im} + \beta_4 \text{OTHER}_{im} + \\
\quad + \gamma' Z_{im} + \delta' S_{im} + \varepsilon_{im} \quad (4.5)

To estimate equation (4.5) I use balanced panel data that consists of 367 undergraduate students over a 12-month period. As in the labor supply section, I employ a similar set of regressors and econometric techniques to quantify the effect of depression and its treatment on student performance at home. Table 19 presents the estimation results of equation (4.5). The OLS estimated coefficients of the depression variables show that for both groups of students with diagnosed and potential depression, there is a decrease in their performance of household activities by 19.35%-19.44%. As expected, the impairment caused by other health disorders is higher. According to the OLS estimates, treatment for depression significantly reduced the impairment caused by diagnosed depression.

Computing the LM test statistics suggested by Breusch and Pagan (1980), I find evidence of an error component in the model. Also a significant Hausman test statistic shows that both OLS and random effects estimators are inconsistent. Thus, the fixed effects estimated coefficients of equation (4.5) are displayed in the fourth column of Table 19 and are used for a more detailed interpretation of estimation results. Similar to the results in the previous section, diagnosed depression and potential depression reduce student household productivity by a magnitude of 6.94%-8.45% on average, but treatment saves 5.46% of this reduction in household production almost offsetting the negative effect of the illness. Still the other health disorders played a negative role on student...
### Table 19

Estimated Coefficients of Equation 4.5 (HPERF - Dependent Variable)

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. INTERCEPT</td>
<td>85.9014*** (33.51)</td>
<td>89.1603*** (15.28)</td>
<td>98.4614*** (18.62)</td>
</tr>
<tr>
<td>2. DEP</td>
<td>-19.3519*** (-14.11)</td>
<td>-8.4587*** (-7.36)</td>
<td>-6.9353*** (-5.95)</td>
</tr>
<tr>
<td>3. SELFDEP</td>
<td>-19.4434*** (-10.80)</td>
<td>-7.3866*** (-3.61)</td>
<td>-8.4488*** (-3.86)</td>
</tr>
<tr>
<td>4. DEP*TREAT</td>
<td>4.2036* (1.81)</td>
<td>5.2850*** (2.86)</td>
<td>5.4609*** (2.94)</td>
</tr>
<tr>
<td>6. AGE</td>
<td>0.0176 (0.21)</td>
<td>-0.0577 (-0.28)</td>
<td>-</td>
</tr>
<tr>
<td>7. GENDER</td>
<td>-1.1869 (-1.24)</td>
<td>-1.4261 (-0.59)</td>
<td>-</td>
</tr>
<tr>
<td>8. RACE</td>
<td>2.6984** (2.18)</td>
<td>2.9719 (0.97)</td>
<td>-</td>
</tr>
<tr>
<td>9. LIVING</td>
<td>6.6142*** (5.46)</td>
<td>4.5960*** (3.12)</td>
<td>3.5893*** (2.23)</td>
</tr>
<tr>
<td>10. TIME</td>
<td>-0.0571*** (-3.96)</td>
<td>-0.0240** (-2.00)</td>
<td>-0.0189 (-1.56)</td>
</tr>
<tr>
<td>11. ATTHR</td>
<td>0.3440*** (3.55)</td>
<td>-0.0458 (-0.56)</td>
<td>-0.0997 (-1.21)</td>
</tr>
</tbody>
</table>

R square 0.17 0.11 0.59

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### Table 19--Continued

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS coefficients (t-statistics)</th>
<th>RE coefficients (t-statistics)</th>
<th>FE coefficients (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>4404</td>
<td>4404</td>
<td>4404</td>
</tr>
<tr>
<td>Error component test (LM) (ch-square(1))</td>
<td>4830.53***</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Hausman test (m-value)</td>
<td>–</td>
<td>93.77***</td>
<td>–</td>
</tr>
</tbody>
</table>

Note: *** Significant at 1% level; **) Significant at 5% level; *) Significant at 10% level; a) The dashes indicate that these variables are time invariant variables and their coefficients are not identified by the fixed effects estimator. The impact of these variables is relegated to the intercept.

household activities. That this impairment is higher relative to that caused by depression and can be explained by the nature of the household duties that an individual performs at home. These usually involve physical activities which will be more impaired by physical disorders than mental disorders. Living with parents, partners or roommates increases student performance at home, while more involvement at school (high number of enrolled classes) does not significantly affect their household productivity.

**Discussion and Conclusions**

This chapter provides empirical evidence that depressive disorders significantly reduce employment probabilities by 0.49 and work hour supplied per week by 1.66 hours
among University students. This impairment associated with depressive disorders on employment status is alleviated by the positive effect of treatment for depression. These findings are consistent with earlier studies that investigated the correlation between psychiatric disorders and employment status (Ettner et al., 1997; Mullahy & Sindelar, 1990; Ruhm, 1992). I also find evidence of a small increase in the absenteeism rate for depressed working students. The slightly larger reduction in scheduled work hours than in disability hours can be explained by the nature of jobs this population group perform which are mostly part-time work (less than 25 per week) and involve physical activities with a very flexible week schedule. It is also interesting to find that student productivity at home or work is significantly reduced by the depressive disorders and is robust to alternative specifications. Treatment for depression reduces severity of impairment which is reflected in the improvement of student productivity caused by treatment. Similar evidence is found in studies by Berndt et al., 1998; Broadhead et al. 1990; and Rizzo et al., 1996.

This study adds to the literature by addressing the negative impact of depressive disorders on labor market outcomes in the student population which so far has been ignored by researchers. Also, it reveals the effectiveness of drug therapy which in most cases is conducted in conjunction with psychotherapy provided at the Health Center or at the Counseling and Testing Center in the University. This is an important finding as it underscores the necessity of mandating minimum insurance coverage for mental health services among students, or of implementing different assistance programs supported by student employers.
One limitation of this study is that it uses a subjective measurement of student work performance. Usually, objective measures of work productivity are difficult to attain and particularly in the case where the subjects are working in a wide variety of occupations and have different employers. By using a self-reported performance scale, it is possible that as student depressive disorders become less severe, students feel more efficient or productive at work or at home regardless of whether that was true objectively. Another limitation of this study is the usage of self-reported disability hours which in some cases can be reported with errors or double counted. The third limitation is related to the construction of the treatment variable. In this analysis, I assume that students who were under drug therapy took the medication regularly as was prescribed by the doctor. However, it is possible that some students did not follow the treatment as prescribed and that may cause downward biases in the analysis of treatment effect.

The results obtained from this analysis will be used in the next chapter to estimate the indirect cost of depression and the benefits of treatment among University students.
CHAPTER V

COST-BENEFIT ANALYSIS OF DEPRESSION TREATMENT

Depression is a very common and expensive disease. It is estimated that depression has a high lifetime prevalence of 10 percent and according to the Angst’s study (1995), the prevalence is even higher (14.4%) among young people up to 30 years old. Also, on average depression is responsible for 60% of suicides (Barraclough, Bunch, & Nelson, 1974; Brent, Kupfer, & Bromet, 1988). Relative to healthy people, depressed individuals have limitations in their daily activities. Their productivity at work or home is reduced and their disability work days are increased. In addition, depressed individuals may have lower labor participation rate and also lower labor income.

This evidence indicates the severity of this disorder and the importance of seeking treatment. The impairment caused by depression in the individual’s quality of life can be translated into dollar terms and are considered in the literature an indirect cost of disease. Along with the direct cost of treatment, they impose a considerable burden on society. There are several studies that have estimated the cost of depression as either a total cost to a specific population and/or country or as average cost per patient. Berto, D’llario, Ruffo, Di Virgilio, and Rizzo’s study (2000) provides a detailed literature review of the international cost-of-illness studies for depression. Among 46 articles that supply cost data, seven studies were selected by them and their results were summarized. Three
studies (Greenberg et al., 1993b; Rice & Miller, 1993; Stoudemire, Frank, Hedemark, Kamlet, & Blazer, 1986) have estimated the total cost of depression for the U.S. population in 1980 and 1990. The study by Stoudemire et al. (1986) was the first one in this area and its methodology and part of the results has been used by other researchers. This study considered only major depression and ignored the indirect cost incurred through lower on-job productivity of depressed workers. The other two studies have extended Stoudemire et al.’s (1986) analysis by considering all affective disorders and all possible indirect cost components. They estimated the total cost of depression for the USA population in 1990. They used similar methodology and found that hospitalization is the main driver of depression cost. However, differing from Greenberg et al. (1993b), Rice and Miller (1993) did not include in their estimation the indirect cost component caused by the reduction of worker productivity, thus, their cost estimate is lower than at in the Greenberg et al.’s (1993b) study.

Similar to the US studies, three studies for the United Kingdom population (Jonsson & Bebbington, 1994; Kind & Sorensen, 1993; West, 1992) found that the burden of depression to the society is substantial. They also found hospitalization cost to be a major component of depression’s total cost, varying from 43 to 52% and the pharmaceutical cost to be only 11% (Kind & Sorensen, 1993). To this group of studies, Bertol et al. (2000) added another study by Tarricone (1997) which computed the direct cost of depression in Italy using a different methodology. While the US and UK studies employed the top-down approach that used national data and statistics to estimate the average cost of a single patient, the Italian study considered a bottom-up technique that
uses data at the patient level to obtain the average depression cost per patient within the sample and then projected the cost for the national population.

Besides the studies at the national level, there are other studies that estimate the indirect cost of depression and the savings attributed to its treatments for a specific population (Birnbaum et al., 1999; Claxton et al., 1999; Kessler et al., 1999; Rizzo et al., 1996). Usually, researchers focused their attention on the employer costs of providing pharmaceutical treatment to their employees. Due to high drug costs, employers often hesitate to provide their employees with pharmaceutical benefits. This is because they underestimate the indirect cost to be caused by untreated depression and they have concerns about the effectiveness of treatments. Epidemiological evidence has shown that depressed workers incur between $182 and $395 more in salary-equivalent work loss than their non-depressed colleagues in a 30-day period. Birnbaum et al. (1999) analyzed the extent of disability before and after depression treatment and found that the cost of treatment is less than the employer’s disability cost savings in the first 30 days. This savings consists of $93 per depressed patient. Others found that the net benefits of depression treatments in a one-year period is $822 and in the case of full compliance23, this is increased further by another $277 (Rizzo et al., 1996). Furthermore, depression is associated with a high rate of short-term disability, and early medical intervention in this respect will reduce the high depression cost of inpatient care and long-term disability.

Usually, the cost-benefit analysis is conducted from the employer’s perspective,

23If the patient has been under medical treatment all year long, this is considered a case of full compliance.
where the main portion of the cost is pharmaceutical expenses and the benefit is the productivity gains resulting from reduction of absenteeism (disability days) and increases in on-job productivity. In this dissertation, I consider the cost and benefits of depression treatments for a specific population group, University students. Hence, it is different from the usual employer-perspective type of analyses. This analysis estimates the direct and indirect cost components of diagnosed depression from the societal point of view. Within the University environment, students pay 100% for their treatments if they do not have a health insurance plan, which is not mandatory. Unlike large self-insured employers that provide their employees with pharmaceutical benefits, the University does not provide the pharmaceutical benefits to the students. However, the University provides health facilities such as the Health Center where the fees for doctor visits are reduced for the enrolled students who have paid the semester fees. In addition, students can obtain free counseling sessions at the Counseling and Testing Center. These services constitute costs to society and are estimated in the following analysis. The next section briefly describes the methodology used in this cost-benefit analysis and compares it to other methods usually used in the literature. Section three provides an estimation of each direct and indirect cost component and section four provides my conclusions.

Methodology

To evaluate the indirect cost of illness, researchers have used different approaches. The most commonly used is ‘human capital approach’ (Hodgson, 1983; Hodgson & Meiners, 1979, 1982; Koopmanschap & Rutten, 1993; Weisbrod, 1961). It
evaluates the benefits in terms of economic productivity of individuals gained through eliminating the impairment caused by health disorders. This method considers an individual as a human investment with an objective of producing output. Thus, the indirect cost of illness is born from the impairment of an individual’s production output while the benefits of health care are reflected in the savings attributed to this output. To estimate the cost, researchers aggregate the time units of work loss through disability, morbidity, and premature mortality in the absence of any health care program. In general, work loss incurred through missed or reduced hours of work, reduced in on-job productivity or being paid below the market wage. In addition, among a young population, a considerable loss in human capital is incurred through reduced school performance reflected by their low GPA, high dropout rates and delayed graduation. These losses can be translated into work productivity losses when the individual enters the labor market and earns less than desired wage.

The human capital approach has been criticized by analysts because it considers market wage as an evaluator of productive contributions. However, the existing discrimination could cause individuals of different gender, race or age groups to receive differential payments for identical contributions to output. In addition, this approach ignores contributions of non-labor market participants toward society. This causes the cost to society due to productivity reduction to be underestimated.

The second methodology developed to estimate the cost of illness to society is the ‘willingness-to-pay’ approach (Mishan, 1971; Schelling, 1968). While the human capital method measures the market value of livelihood, the willingness-to-pay method measures
the value of human life by evaluating the amount of dollars an individual would pay to reduce the risk of illness or death. In their book "Cost-Benefit and Cost-Effectiveness Analysis in Health Care", Warner and Luce defines this approach as follows: "...Conceptually the approach has much appeal: within the determined values rest individuals' valuation of the physical and emotional costs of illness, for themselves and others. That is, one can value a reduction in risk for its benefit to someone, even if that someone is not oneself..." (1982, page 89). However, there are difficulties in applying this method, primarily because the concepts need to be translated into monetary terms. A common way used in health economics to value a reduction in the risk of death or illness is by asking people directly. But this can produce different values because the answer depends on the structure of questions asked. Another weakness of this method is that it does not consider different levels of risk across individuals and can not be applied to other population group such as young children and elderly.

A new methodology employed to calculate the indirect cost of disease is the 'friction cost' method. Koopmanschap and Rutten (1996) provided a practical guide to this methodology. They argue that production losses to society caused by health disorders will be smaller if sick workers during their absence are replaced by other temporary workers. The time period that is needed to replace a sick worker with someone from the ranks of the unemployed is called the 'friction period'. In the case of short-term leaves, the work loss can be picked up by the existing employees or by the sick workers after they return to work. Koopmanschap and Rutten described this new approach as follows: "...The basic idea of the friction cost method is that the amount of production lost as a
result of disease depends on the time-span that organizations need in order to restore the initial production level...” (1996, page 461). Thus, when the friction method is applied instead of the human capital approach, the cost of lost production due to absenteeism is less. It is clear that the friction period will depend on the unemployment rate. If unemployment is lower than the level of frictional unemployment then it is impossible to replace a sick worker with a new employee.

In the literature, the human capital method is used more often than the new approach. This is because information about the friction period is usually hard to obtain. The methodology used in the following cost-benefit analysis is dictated by the availability of data. That is, the human capital approach is employed to estimate the indirect costs of diagnosed depression among University students.

Results

This section describes how I calculate the total cost of diagnosed depression per student. This cost refers to the first year following the diagnosis date for depression. To estimate this cost, I use the results from the analyses of student school performance and labor market outcomes in Chapters III and IV. The components of total cost are the direct cost (the cost of treatment and medical care) and the indirect cost (the cost due to less performance at school, work and home). All costs are converted into 2000 dollars. Throughout the analysis, I assume that each depressed student experiences only one episode of depression in one year. This way, I do not consider the possibility of a recurrent episode of depression within the year following the date of diagnosis. Thus, the estimated
cost estimated per depressed student will be overstated to the extent that additional episodes occurred within this time period since all utilization is attributed to the first diagnosis.

Direct Cost of Diagnosed Depression

The cost of treatment consists of the costs of outpatient services, inpatient care and medicines. Information obtained from the Sindecuse Health Center includes the total expenditures for depression drugs and the number of visits for each of the 314 students diagnosed with depression at the Center from January 1, 1998 to April 30, 2000. However, this analysis uses only the 121 undergraduate students, a sub-sample of depressed students, who responded to the survey and for whom the impairment caused by depression on school performance and labor market outcomes is estimated in Chapters III and IV. The total cost of diagnosed depression per student is expressed as the sum of the following components:

\[ C_{\text{DIR}} = C_{\text{RX}} + C_{\text{OV}} + C_{\text{COUN}} + C_{\text{HOSP}} + C_{\text{OFF}} \]  

where:

1. \( C_{\text{RX}} \) represents the pharmaceutical cost per diagnosed depressed student. Out of 121 students diagnosed with depression, 92 students purchased at least one prescription to treat depression. The maximum number of prescriptions for students in this sample is seven. On average, students purchased prescriptions supply enough medication to last 5.6 months. The pharmaceutical charges are reported in 1998, 1999 or 2000 dollars.
depending when the student purchased the medication. The information released from the Center indicates only the date the first prescription was purchased. Thus, to express the total charges in 2000 dollars, I first find the midpoint date between the date of the first prescription and the date of the last one. For those students whose midpoint date is in 1998 or 1999, I convert their pharmaceutical expenditures into 2000 dollars by adjusting for the inflation rate of prescription drugs and medical supplies\(^2\). For those students with midpoint date in 2000, the pharmacy charges are assumed to be reported in 2000 dollars. Summing the pharmaceutical charges for each student gives a total cost of drug therapy equaling $37,489.67. Thus, \(C_{\text{RX}} = \frac{TC_{\text{RX}}}{121} = \$309.83\) per depressed student. This is very close to the estimated prescription drug component ($383 per depressed patient) in the Birnbaum et al. study (1998).

2. \(C_{\text{OV}}\) represents the cost of office visits per diagnosed depressed student at the Sindecuse Health Center. Information obtained from this Center reports the total number of office visits a student had made for depressive disorders, but does not identify whether the visits were with a regular clinician (medical doctor or physician assistant) or with a specialist (psychiatrist). Information provided by the administrators of the Health Center indicated that one in every four or five students had visits with the psychiatrist. Additionally, a typical case of depression will involve four visits: the first visit at the diagnosis day, the second one after a month, the third three months after diagnosis and the fourth after six months after diagnosis. However, in severe cases, the number of visits can be

\(^2\)The CPI for the prescription drugs and medical supplies are obtained from the Bureau of Labor Statistics.
doubled and are performed by the psychiatrist. I find that 75% of the students in the sample had one to five visits for depression and 25% of them had more than five visits for depression (up to a maximum of 11 visits). Based on the information provided by the Center's administrators, I assume that the office visits for the first sub-sample of students were with a regular clinician at the Health Center, and the office visits for the second sub-sample of students were with a psychiatrist. The reason for separating the visits by the clinician specialty is because of the different costs these visits incur. On average, during the academic year 1999-2000, the average cost per appointment regardless of specialist was $69.15, while the cost per appointment with the psychiatrist was $80-85 and with a regular clinician, $50-54. Then, on average, the cost of the total office visits for 121 students diagnosed with depression is:

$$TC_{OV} = (\# \text{ office visits with clinician}) \times \text{(cost of office visits with a regular clinician)} + (\# \text{ office visits with psychiatrist}) \times \text{(cost of office visits with psychiatrist)} = 244 \times \$52.5 + 225 \times \$82.5 = $31,372.50.$$  

Thus, $C_{OV} = \frac{TC_{OV}}{121} = $259.28 per depressed student. This estimate is a proxy for the total cost of outpatient care because it takes into account the out-of-pocket charges for office visits and the semester base fees to the Health Center.

3. $C_{COUN}$ represents the cost of counseling per diagnosed depressed student. In the survey, students were asked to report where they obtained treatment for depression. Every student in the sample claimed the Health Center as a provider of their depression treatment. Also, 60 out of 121 students claimed they had also obtained psychotherapy
at the Counseling and Testing Center. Unfortunately, there is no information on the number of sessions they had at this Center, thus, the following estimate of the cost of counseling is developed. Statistics for the number of sessions for students treated at the Counseling and Testing Center were obtained. However, the information released from the Center regarding the number of sessions per patient is difficult to interpret because it does not distinguish the sessions for depressive disorders from those for other disorders. Also, the estimated cost per session was calculated as a ratio of the Center’s estimated annual budget that goes toward sessions ($750,000) with the total number of sessions the Center delivered during the academic year 2000-2001 (3887 sessions\(^2\)). The cost of $194 per session is high due to the high revenues this Center receives from other services such as scanning, and also due to the higher fringe benefits the staff members of this Center receive relative to private counseling centers. Because of these unique circumstances, I estimate the cost of counseling based on information obtained from clinics off campus. It is believed that these data will be more reflective of counseling costs across University settings. In Appendix B, I have listed the clinics and information obtained from them regarding the average cost per session and the average number of sessions a typical case with depression might have. On average, I find that a patient with depression will have 10 sessions and the charge per session is $100 which is equivalent to $97.53 in 2000 dollars. Thus, the total cost of counseling for 60 students in the sample is:

\[
TC_{\text{COUN}} = (\text{number of students with counseling}) \times (\text{number of counseling sessions per})
\]

\(^2\)3537 sessions were delivered from July 1, 2000 to April 30, 2001 at the Counseling and Testing Center. The Center projected 350 more sessions to be delivered from May 1, 2001 to June 30, 2001.
student) * (charge per counseling session) = 
= 60*10*$97.53 = 
= $58,519.46.

Thus, $C_{COUN} = \frac{TC_{COUN}}{121} = $483.63 per depressed student.

4. $C_{HOSP}$ represents the cost of hospitalization per diagnosed depressed student. Ideally, estimates of the hospitalization cost will be based on information of the hospitalized cases within the sample of depressed students and the cost of hospitalization for each case. The administrators of the Health Center reported three cases of hospitalization for depression from January 1, 1998 to April 30, 2000 which is the period covered this analysis. This Center did not have data on the cost of each hospitalization. Thus, to calculate the cost of hospitalization per depressed student, I use the Health Cost Utilization Project (HCUP) data for the year 1996. This data is released by the Agency for Healthcare Research and Quality and each year the Nationwide Inpatient Sample (NIS) provides information on approximately 5 million to 7.1 million inpatient stays from over 900 hospitals. The 1996 data contains this information for 19 states in the US. HCUP data from all NIS hospitals are randomly divided into two 10% subsamples of discharges. From each of these sub-samples, I selected the individuals for whom the principal diagnosis of hospitalization was depression, which corresponds to 396.2x and 396.3x codes based on the ICD-9 code book. In Table 20, I report the statistics of the total hospitalization charges for these two groups of depressed patients. Thus, the average cost of hospitalization per patient is $8,028.49, which is equivalent to $9,136.42 in the year 2000\textsuperscript{26}. The

\textsuperscript{26}This cost is adjusted by considering the inflation rate for inpatient hospital services obtained from the Bureau of Labor Statistics.
Table 20
Total Charges of Hospitalization (HCUP Data)

<table>
<thead>
<tr>
<th>Total charges</th>
<th>N</th>
<th>Mean</th>
<th>Sum</th>
<th>Std. Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>First Group</td>
<td>76</td>
<td>9,418.08</td>
<td>715,774</td>
<td>15,415.15</td>
<td>615</td>
<td>126,652</td>
</tr>
<tr>
<td>Second Group</td>
<td>70</td>
<td>6,519.80</td>
<td>456,386</td>
<td>4,919.63</td>
<td>976</td>
<td>24,300</td>
</tr>
<tr>
<td>Both Groups</td>
<td>146</td>
<td>8,028.49</td>
<td>1,172,160</td>
<td>11,684.97</td>
<td>615</td>
<td>126,652</td>
</tr>
</tbody>
</table>

The total cost of hospitalization within the sample of 121 students is:

$$TC_{HOSP} = (\text{hospitalization cost per patient}) \times (\text{number of hospitalized cases for depression}) =$$

$$= ($9136.42) \times 3 \times (121/314) =$$

$$= $10,562.17.$$

Because the sample for this analysis is a sub-sample of the total sample of depressed students, this number is weighted to reflect the total cost of hospitalization for the 121 depressed students for whom all data are available. The cost of hospitalization per depressed student is:

$$C_{HOSP} = TC_{HOSP} / 121 = $87.29.$$

5. $C_{OFF}$ represents the cost of depression treatment per diagnosed depressed student obtained from clinics off-campus. The survey shows that 40 out of 121 students have reported some form of treatment for depression off campus. The treatment received
from centers outside the University will add an additional cost component to the total cost of depression treatment. Information about the kinds of treatments students received off campus, the duration of this treatment and its cost is not available. For this reason, I calculate the total direct cost of depression treatment obtained on campus for two groups of depressed students: the 40 students who received treatment at the Health Center and off campus clinics and the 81 students who received treatment for depression only on campus. I assume that if the cost of depression treatment per student is greater for the second group of students relative to the first one, then the cost difference is due to the missing information about the treatment that the first group of students received off campus. Table 21 reports the direct cost components of depression treatment for each group of students in 2000 dollars. I find that those students who were not treated off-campus have an estimated cost of depression $50.97 higher than those students who did receive treatment from clinics off-campus. The additional cost of depression

Table 21

Cost Components of Depression Treatment for Two Groups of Students²⁷

<table>
<thead>
<tr>
<th>Cost components</th>
<th>First Group (n=40 students)</th>
<th>Second Group (n=81 students)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total pharmaceutical cost (dollars)</td>
<td>13,918.72</td>
<td>23,569.44</td>
</tr>
<tr>
<td>Total office visits cost (dollars)</td>
<td>10,245.00</td>
<td>21,127.50</td>
</tr>
<tr>
<td>Total counseling cost (dollars)</td>
<td>16,580.10</td>
<td>41,937.90</td>
</tr>
<tr>
<td>Direct cost per student (dollars)</td>
<td>1,018.60</td>
<td>1,069.57</td>
</tr>
</tbody>
</table>

²⁷Hospitalization cost contributes to both groups equally, thus it is excluded from the calculations.
treatment that the first group received off campus is equal to: $\text{TC}_{\text{OFF}} = (40 \text{ students}) \times ($50.97) = $2,038.80. Therefore, the cost of depression incurred at the off-campus clinics per depressed student is equal to $\text{C}_{\text{OFF}} = \text{TC}_{\text{OFF}} / 121 = $16.85.$

**Indirect Cost of Diagnosed Depression and Benefits of Its Treatment**

The indirect cost of depression to the individual student is less observable. It includes the dollar losses due to lower performance in school, work and home. Using the human capital method, I calculate each indirect cost component incorporating the results obtained from Chapters III and IV. The total indirect cost of depression per student is given as:

$$\text{C}_{\text{INDIR}} = \text{C}_{\text{SCH}} + \text{C}_{\text{DRP}} + \text{C}_{\text{GRAD}} + \text{C}_{\text{HRWK}} + \text{C}_{\text{ABS}} + \text{C}_{\text{PRES}} + \text{C}_{\text{HOME}}$$

(5.2)

while the total benefits of depression treatment per student is given as:

$$\text{B}_{\text{INDIR}} = \text{B}_{\text{SCH}} + \text{B}_{\text{HRWK}} + \text{B}_{\text{ABS}} + \text{B}_{\text{PRES}} + \text{B}_{\text{HOME}}$$

(5.3)

1. $\text{C}_{\text{SCH}}$ and $\text{B}_{\text{SCH}}$ represent the cost of depression and benefits of its treatment per diagnosed depressed student due to poor performance at school. Before I estimate these factors, I have to define the cost of education per student from a societal point of view. The cost of education has two components: the amount paid by students through tuition, fees and expenses for school supplies, ($\text{C}_{\text{STUD}}$) and the amount funded through other sources ($\text{C}_{\text{OTHER}}$). The data used in estimating $\text{C}_{\text{STUD}}$ is based on the demographics of the 121 undergraduate students who were diagnosed with depression at the Health Center.
Based on the University fact sheet, 6.27% of the 1999-2000 enrollment were from other states, while 6.29% were from other countries. Applying these proportions to the sample of 121 students, I estimate that 106 students were from Michigan and 15 students from other states or countries. The semesters on which students were not enrolled are dropped from the panel which leaves a total of 286 semesters. To calculate the total cost of enrollment per semester for depressed students, I use the information obtained from the Registrar’s Office regarding student enrollment status, attempted credit hours per semester, and class level\textsuperscript{28} for each semester. On average, I find that a student attempts to earn 10.97 credit hours per semester. The tuition charges differ across student level and also students can change their level within the same academic year. Based on earned credit hours, I find that during 50.7\% of 286 semesters the students in the sample are freshmen or sophomore and during 49.3\% of 286 semesters they are juniors or seniors. Since available information does not allow me to separate the students who pay in-state tuition from those who pay out-of-state tuition, I assume the proportions of freshmen/sophomore and juniors/seniors are the same for two groups of students. The cost of tuition per student in one semester is calculated as follows:

\[
\text{Tuition} = (\text{proportion of resident students}) \times [(\text{proportion of freshmen & sophomore}) \times (\text{credit hours per semester}) \times (\text{cost of a freshmen/sophomore credit hour}) + (\text{proportion of junior & senior}) \times (\text{credit hours per semester}) \times (\text{cost of a junior/senior credit hour})] + (\text{proportion of non-resident students}) \times [(\text{proportion of freshmen & sophomore}) \times (\text{credit hours per semester}) \times (\text{cost of a freshmen/sophomore credit hour}) + (\text{proportion of junior & senior}) \times (\text{credit hours per semester}) \times (\text{cost of a junior/senior credit hour})]
\]

\textsuperscript{28}The Registrar's Office provided the current class level of the student, but with information about student total credit hours earned and credit hours earned for each semester, I can determine student class level for each semester.
& senior)*(credit hours per semester)*(cost of a junior/senior credit hour) =
= 0.8744 * [(0.507*10.97*$116.4) + (0.493*10.97*$130.42)] + + 0.1256 *
[(0.507*10.97*$290.99) + (0.493*10.97*$326.73)] =
= $1,608.04.

In addition to tuition students also pay an enrollment fee per semester which
varies from part-time to full-time students
29. The average enrollment fee charged per
semester is given as follows:

\[
\text{Fee} = [(\text{proportion of full-time Fall & Winter terms}) + (\text{proportion of full-time Spring & Summer terms})] \times \text{(enrollment fee for full-time students)} + [(\text{proportion of part-time Fall & Winter terms}) + (\text{proportion of part-time Spring & Summer terms})] \times \text{(enrollment fee for part-time students)} =
\]

= $(0.59 + 0.09)\times $289 + (0.21 + 0.11)\times $120 =

= $234.92.

According to the statement of finances released by the WMU Office of International
Students Services, the cost of books and supplies per semester is 250 dollars. Thus, the
total cost of school to the student per semester is:

\[
\text{C}_{\text{STUD}} = \text{Tuition} + \text{Fee} + \text{Books} & \text{Supplies} =
\]

= $1,608.04 + $234.92 + $250 =

= $2,092.96.

The other component of education cost is born by funding sources other than tu­
tion. To estimate this, I refer to the total University budget for the academic year 1999-2000. The General Fund revenue estimate for that academic year was $211,731,965

---

29Based on the WMU fact sheet, the student enrollment fee is $120 for part-time semesters and $289 for full-time semesters. If the undergraduate student enrolls in 12 or more credit hours during Fall and Winter or 6 or more credit hours during Spring and Summer, he is considered a full-time student.

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where $90,840,474 was tuition revenue and $120,891,491 was other revenues\textsuperscript{30}. The whole academic year consists of 48 weeks where the break weeks are excluded. Table 22 shows, by semester, the number of school weeks, total student enrollment, the total funds the University spent above tuition and the amount spent per student. Knowing the funds spent above tuition per student for each semester and also the terms that each depressed student within my sample enrolled, I can calculate the average dollar amount the University spent per semester above tuition for each student as follows:

\begin{equation}
C_{\text{OTHER}} = (\text{proportion of Fall semesters}) \times (\text{funds above tuition spent per student in Fall}) + (\text{proportion of Winter semesters}) \times (\text{funds above tuition spent per student in Winter}) + (\text{proportion of Spring terms}) \times (\text{funds above tuition spent per student in Spring}) + (\text{proportion of Summer terms}) \times (\text{funds above tuition spent per student in Summer}) = \\
= 0.39 \times \$1452.32 + 0.41 \times \$1567.16 + 0.13 \times \$1986.07 + 0.07 \times \$2909.70 = \\
= \$1,670.81\textsuperscript{31}.
\end{equation}

This amount consists of funds not covered by tuition that go toward covering instructor compensation and the cost of school facilities. Thus, the total cost of education per semester including both the student tuition and the cost above tuition, amounting to $3,763.77 per student.

The estimated coefficient of the depression dummy variable in equation (3.1) gives the average GPA point reduction in a semester due to an untreated depression per student. Since students take classes with the intention of obtaining human capital, a

\textsuperscript{30}It includes: state appropriation - base, investment income, application fees, graduation fees, transcript fees, international students service fee, indirect cost recovery, forfeited deposits, financial aid administration reimbursement, accounts receivable service charge, departmental revenue, and all others. Source: Western Michigan University, 1999/2000 Budget Summary.

\textsuperscript{31}This is the net amount after deducting the student's tuition and fees.
Table 22

University Funds by Semesters

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td># of school weeks</td>
<td>16</td>
<td>16</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>% of academic year</td>
<td>33.33</td>
<td>33.33</td>
<td>16.67</td>
<td>16.67</td>
</tr>
<tr>
<td>Total of enrolled students</td>
<td>27,744</td>
<td>25,711</td>
<td>10,147</td>
<td>6,926</td>
</tr>
<tr>
<td>Total funds spent above tuition</td>
<td>40,293,134</td>
<td>40,293,134</td>
<td>20,152,612</td>
<td>20,152,612</td>
</tr>
<tr>
<td>Funds spent above tuition per</td>
<td>1452.32</td>
<td>1567.16</td>
<td>1986.07</td>
<td>2909.70</td>
</tr>
<tr>
<td>student ($)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


decrease in their GPA will be translated into a 12.06 percent reduction in the amount of human capital that they would have obtained. In this analysis, I assumed that an episode of depression lasts for 180 days which is equivalent to 1.62 semesters in the sample. Given the estimated total cost of education per semester, I can express in dollar terms the cost of human capital loss due to depression per student:

\[
C_{SCH} = 0.1206 \times 3,763.77 \times 1.62 \text{ semesters} = 735.34.
\]

The next step in this analysis is to estimate the benefit of depression treatment to education. For this, I use the estimated coefficient of the treatment interaction term in the empirical equation (3.1). This coefficient in the GPA equation provides the marginal benefit of treatment in terms of GPA points improved by taking prescribed medication.
versus not taking any. The benefit of treatment on student school performance is transformed into dollars in the same way as the cost of depression per student. The amount of dollars saved by treating a depressed student in the process of obtaining human capital is given as: $B_{\text{SCH}} = 0.1079 \times $3763.77 \times 1.51 \text{ semesters} \times (92/121) = $466.26$. This amount is weighted because only 92 out of 121 students have taken prescribed medication.

2. $C_{\text{DRP}}$ represents the cost of depression per diagnosed depressed student associated with student's dropping out of school. Before I include this cost into the analysis, I compare the rate of dropping out of school or transferring to another school among controls with that of depressed students. I assume that a student may have dropped out of school or transferred if he/she has not enrolled for a period of one year (equivalent to four semesters) and is not identified as having graduated. Based on this algorithm, I find that the proportion of students who dropped out of school or transferred within the depressed group (0.066) is not statistically different from that within the control group (0.0622). The z-score is 1.07 and the p-value of the two tailed test is equal to 0.2846. Since there is no statistical difference in the rate of dropout or transfer between the two groups, I do not include in the analysis the cost associated with dropping out of school.

3. $C_{\text{GRAD}}$ represents the cost of depression per diagnosed depressed student due to delayed graduation. It is possible that students with depressive disorders took less classes per semester or completed fewer credit hours than their healthy peers. Thus, I compare the credit hours attempted and earned per semester between depressed students
and controls. If students with depression have enrolled and completed less credit hours per semester they might graduate later than their healthy peers. Delayed graduation induces an indirect cost to depressed students, which is equal to the indirect cost of schooling for those extra semesters needed for graduation forgone incremental wages. I find that there is no statistical difference in the attempted and earned credit hours between the two groups of students during the semester before the diagnosis date and the semester when students were diagnosed with depression (see Table 4 in Chapter III). Thus, I conclude that there is no additional cost associated with delayed graduation among the depressed students.

4. $C_{HRWK}$ and $B_{HRWK}$ represent the cost of depression and the benefit of its treatment per diagnosed depressed student due to less scheduled work hours per week. In Chapter IV, I explored the impact of student health status on their labor supply. The results from the empirical equation (4.2) showed that if students suffer from depression disorders they reduce the scheduled work hours per week by 1.66 hours which is equivalent to 7.19 work hours per month ($=1.66 \text{ work hours/week} \times 4.33 \text{ weeks/month}$). However, this negative effect of depression is compensated by the positive effect of depression treatment reflected in the significant positive coefficient of treatment interaction term in equation (4.2). Treatment for depression saves 9.22 work hours per month ($=2.13 \text{ work hours/week} \times 4.33 \text{ weeks/month}$). By multiplying these numbers of lost and saved work hours per month by the average wage of all students in the sample (depressed and non-depressed), I obtain the amount of money lost due to untreated depression and money saved due to treatment for the group of depressed students in one month. Since
early estimation of the wage equation did not show any significant impact of student health status on their hourly wage, the average wage of the total sample of students (depressed and non-depressed) is an appropriate measure of student hourly compensation. This wage rate was converted to 2000 dollars in the following way: first, I estimated the mean wage rate for each group of students who reported having been working on 1998, 1999 and 2000. Then, I convert the mean wage rates for the years 1998 and 1999 in 2000 dollars and the final wage rate was computed as a weighted average of the means.

As assumed in Chapters III and IV, a student experiences depressive disorders for a six month period. The total cost of depression per depressed student due to a reduction of scheduled work hours is given as: \( C_{\text{HRWK}} = 7.19 \text{ work hours/month} \times 8.16 \$\text{/hour} \times 6 \text{ months} = \$352.02 \). Statistics show that 92 students out of 121 students diagnosed with depression received treatment for a period of 5.6 months on average. Thus, the benefits of depression treatment per depressed student can be written as: \( B_{\text{HRWK}} = 9.22 \text{ work hours/month} \times 8.16 \$\text{/hour} \times 5.6 \text{ months} \times (92/121) = \$320.34 \).

5. \( C_{\text{ABS}} \) and \( B_{\text{ABS}} \) represent the cost of depression and benefits of its treatment per diagnosed depressed student due to absenteeism. In Chapter IV, I discussed the possible negative effect of depression on student disability work hours. The coefficient of the depression dummy variable in equation (4.3) shows the average hours of work missed due to untreated depression per month. By multiplying this coefficient of lost work hours with the average hourly wage of students in the sample, I obtain the monthly loss of income due to absenteeism. The total income lost due to missed work hours per
depressed student is equal to: \( C_{ABS} = 1.21 \) work hours/month \(* 8.16 \$\)/hour \(* 6 \) months = $59.24. This cost incurred by student's work absenteeism is smaller than the one found for a typical wage earner in Birnbaum et al.'s study (1999). According to the results of empirical equation (4.3), there is a significant positive effect of treatment on disability work hours. Therefore, the total benefits of depression treatment for absenteeism is: \( B_{ABS} = 1.57 \) work hours/month \(* 8.16 \$\)/hour \(* 5.6 \) months \(* (77/99) = \$55.80. \)

6. \( C_{PRES} \) and \( B_{PRES} \) represent the cost of depression and benefits of its treatment per diagnosed depressed student due to the reduction on-job productivity. This is a very important cost component and is usually ignored by analysts. It reflects the cost to society associated with the loss of production of depressed workers while at work. To estimate this cost, first, I estimate the value of output at risk, the hours scheduled to work during the depression episode. From the average number of work hours per month that a depressed student spent at work, I subtract the disability work hours missed due to depression and I obtain the so called 'remaining episode hours of work' per month (111.69 hours). Multiplying this number with the average wage rate (8.16\$/hour) I find the value of output that can be produced if the student works at his full capacity per month, which is equal to $911.39. The estimated coefficient of depression dummy variable in equation (4.4) shows that 9.29% of production was reduced due to depression per month. The total loss of output due to depression per student is equal to: \( C_{PRES} = 0.0929 \) \(*$911.39 \) \(* 6 \) months = $508.01. However, this cost is compensated by the benefit of its treatment. The coefficient of treatment variable in equation (4.4) shows a 8.47% increase of work productivity of depressed students if they have taken treatment for the
whole month. The total benefit of depression treatment per student is calculated as: \[ B_{\text{PRES}} = 0.0847 \times 911.39 \times 5.6 \text{ months} \times (77/99) = 336.23. \]

7. \( C_{\text{HOME}} \) and \( B_{\text{HOME}} \) represent the cost of depression and benefit of its treatment per diagnosed depressed student due to less performance at home. In the survey, students are asked about the number of hours per week they spent on average on household activities. The depressed students in the sample spent on average 9.17 hours per week in household production or 39.71 hours per month (=9.17 hours/week * 4.33 weeks). The value of the output they may produce in a month is equal to $244.22 assuming that the hourly rate for household activities is equivalent to the minimum wage of 6.15 $/hour\(^{32}\). The coefficient of the depression dummy variable in equation (4.5) reflects a 6.94 percent decrease in the productivity at home while the treatment increases productivity by 5.46 percent. The cost of depression due to less performance at home is equal to: \[ C_{\text{HOME}} = 0.0694 \times 244.22 \times 6 \text{ months} = 101.69, \] while the benefit of treatment is equal to: \[ B_{\text{HOME}} = 0.0546 \times 244.22 \times 5.6 \text{ months} \times (92/121) = 74.67. \]

Conclusions

In Table 23, I have listed the direct and indirect cost components of depression and the benefits of its treatment for the group of students diagnosed with depression. Using equation (5.1), I add all the direct cost components to arrive at the total direct cost of depression expressed in 2000 dollars being $139,982.60, while the average direct cost

\(^{32}\)The minimum wage rate reflects the new minimum wage set by the Congress on March 2000.
### Table 23
Total Cost of Depression and Benefits of Its Treatment

<table>
<thead>
<tr>
<th>Description</th>
<th>Total cost/benefit ($)</th>
<th>Percentage of total cost (%)</th>
<th>Cost/benefit per student ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Direct cost</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1) Pharmaceutical</td>
<td>37,489.67</td>
<td>26.78</td>
<td>309.83</td>
</tr>
<tr>
<td>2) Office visits</td>
<td>31,372.50</td>
<td>22.41</td>
<td>259.28</td>
</tr>
<tr>
<td>3) Counseling</td>
<td>58,519.46</td>
<td>41.80</td>
<td>483.63</td>
</tr>
<tr>
<td>4) Hospitalization</td>
<td>10,562.17</td>
<td>7.55</td>
<td>87.29</td>
</tr>
<tr>
<td>5) Off campus</td>
<td>2038.80</td>
<td>1.46</td>
<td>16.85</td>
</tr>
<tr>
<td><strong>Indirect cost of diagnosed depression</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1) School performance</td>
<td>88,976.14</td>
<td>44.04</td>
<td>735.34</td>
</tr>
<tr>
<td>2) Drop outs</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>3) Scheduled work hours/ week</td>
<td>42,594.42</td>
<td>21.08</td>
<td>352.02</td>
</tr>
<tr>
<td>4) Absenteeism</td>
<td>5,864.76</td>
<td>2.90</td>
<td>59.24</td>
</tr>
<tr>
<td>5) Presenteeism</td>
<td>52,292.99</td>
<td>25.88</td>
<td>508.01</td>
</tr>
<tr>
<td>6) Household productivity</td>
<td>12,304.49</td>
<td>6.09</td>
<td>101.69</td>
</tr>
<tr>
<td><strong>Benefits of treatment</strong></td>
<td>109,423.15</td>
<td>100.00</td>
<td>1,253.30</td>
</tr>
<tr>
<td>1) School performance</td>
<td>42,895.92</td>
<td>39.20</td>
<td>466.26</td>
</tr>
<tr>
<td>2) Drop outs</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>3) Scheduled work hours/ week</td>
<td>29,471.28</td>
<td>26.93</td>
<td>320.34</td>
</tr>
<tr>
<td>4) Absenteeism</td>
<td>4,296.60</td>
<td>3.93</td>
<td>55.80</td>
</tr>
<tr>
<td>5) Presenteeism</td>
<td>25,889.71</td>
<td>23.66</td>
<td>336.23</td>
</tr>
<tr>
<td>6) Household productivity</td>
<td>6,869.64</td>
<td>6.28</td>
<td>74.67</td>
</tr>
</tbody>
</table>

direct cost of depression per diagnosed depressed student being $1,156.88. Counseling has the highest cost share and accounts for 41.80% of the total direct cost, while hospitalization accounts for 7.55% due to the low number of hospitalized cases within the sample. This analysis also accounts for the cost of treatment obtained off campus by looking at the cost difference between two groups of students, those who received treatment on
campus exclusively and those who received on and off-campus treatment.

The total indirect cost of depression associated with student low performance at school, work and home is equal to $202,032.80, while the average indirect cost of depression per diagnosed depressed student is equal to $1,756.30. The cost categories for student school performance and presenteeism claim the largest proportions of the indirect cost of depression, 44.04% and 25.88% respectively. While in other studies absenteeism usually accounts for a large proportion of indirect cost [such as in Greenberg et al.'s (1993b) and Stoudemire et al.'s (1986) studies], it shows a low burden to society in this analysis. This could be because students usually perform jobs that have a flexible schedule and thus, the burden of depression can be reflected by the reduction of work hours per week rather than by the missed work hours.

In the sample of depressed students, there are 92 students who received drug therapy and the total benefits of this treatment is $109,423.15 or $1,253.30 per diagnosed depressed student. The highest savings are obtained in increasing student school performance (39.20%), schedule work hours per week (26.93%) and student work performance (23.66). Comparing the total cost of depression and the total benefit of its treatment per diagnosed depressed student, I find that treatment saves $96.42 per treated student on average.

To summarize, this analysis shows that total cost of depression amounts to $342,015.40 among students who were diagnosed with depression or $2,826.57 per diagnosed depressed student. This total can be broken down as follows: direct cost categories (41%) and indirect cost categories (59%). Because treatment can reduce the
productivity losses caused by depression, the total net cost of depression is reduced to $232,592.25 or $1,659.88 per diagnosed depressed student.
 CHAPTER VI

SUMMARY AND CONCLUSIONS

In past decades, enormous studies have analyzed the impairment that depression causes on an individual's life. Usually, this impairment is expressed in monetary terms and compared with impairments imposed by other health disorders. Statistics have confirmed the significance of this disease, ranking it as third by prevalence and sixth in terms of economic cost (Berto et al., 2000). The Consensus Conference of the National Institute of Mental Health noted the following:

depression imposes an enormous burden on society - resulting from its high prevalence, under-diagnosis and under-treatment. Depression has many costs and consequences, including decreased quality of life for patients and their families, high morbidity and mortality, and substantial economic losses. (Berto et al., 2000)

Another characteristic of this disorder is that it affects young individuals causing significant burden on their school, work and home activities. However, this population group is often ignored by analysts. So far, there is no research that investigates the burden of depression among this population by considering all the possible impairments caused by this disorder. While there is some work done on the relationship between mental disorders and high school dropouts (Farahati, Marcotte, & Wilcox-Gok, 2001), the impact of depression on student school performance has not been investigated. This is very important not only because the prevalence of mental illness is higher during school
years, but because indirect cost associated with the loss of human capital will last for an individual’s lifetime. Due to the strong correlation between years of schooling and labor market outcomes (Becker, 1993; Blackmore & Low, 1984; Card, 1999; Nerdrum, 1999), the negative impact of depression on student performance will have a long term negative effect on labor force participation, employment status and income. While there is a core of literature that investigates the relationship between health and human capital investment, there is no study that focuses on the impact of depression. This study is the first one that estimates the economic burden of depressive disorders among University students. It is comprehensive because it investigates the impairment caused by depressive disorders on student performance at school and outside the academic environment. Also, the costs associated with this impairment are estimated together with the direct cost of treatment.

The first hypothesis tested in this analysis is that depressive disorders negatively affect student school performance. A sample of Western Michigan University students was selected to achieve the above objective. From the total sample of 1209 students, only 368 undergraduate students who responded to the questionnaire were included in the final sample. This sample breaks into three groups: 121 students diagnosed with depression from a health professional, 38 potentially depressed students based on DSM-IV criteria and 209 students (controls) without symptoms of depression. The analysis in Chapter III revealed a significant negative impact of depression disorders on student school performance measured by their grade point average (GPA). Among students who were diagnosed with depression by a health professional there was a decrease in their
school performance by 0.48 GPA points (or 12%). However, the analysis showed that
treatment increased depressed student GPA by 0.43 points, assuming that students took
their medication regularly during the whole semester.

Another important issue discussed in Chapter III is the alternative measurement
of school productivity. Objective measures of productivity are hard to collect and they
depend on workers’ occupations. Most of the studies that have analyzed the impact of
mental disorders, particularly depression, on worker productivity have relied on subjective
measures of productivity. In this study, I chose a student population to investigate
the relationship between health disorders and school performance because students be-
long to a group for which the quality and quantity of work is objectively and subjectively
evaluated routinely. The undergraduate GPA was used as an objective measure of stu-
dent performance while self-reported performance was a subjective one. I found that the
negative effect of depression and the effectiveness of treatment are underestimated, while
the negative effect of other health disorders are overestimated when the self-reported per-
formance of students were employed. These evidence indicated a discrepancy among
health outcomes when the subjective measure of student school performance is employed
versus the objective one.

In Chapter IV of this dissertation, I further investigated the impact of depression
and its treatment on student performance outside the academic environment. Usually stu-
dents are viewed as a population that primarily works in human capital formation. How-
ever, a significant number of them work outside the academic environment. Some of
them use the work for meeting their financial needs and some others to gain professional
experience. Taking advantage of the detailed information regarding employment status provided by students through the survey, I explored the relationship between student health status and labor market outcomes. It is interesting to note that students are a very good representative of a part-time or part-year employed group. Descriptive statistics provided in this chapter showed that during the Spring and Summer terms a majority of students worked full-time, while during the Fall and Winter semesters they worked part-time supplying less than 25 work hours per week. On average, their wage rate was $8/hour but was not significantly affected by their health conditions. However, their employment was impaired during the months when they experienced depressive disorders. The probability of employment was reduced by 0.49 and the scheduled work hours per week were reduced by 1.66 hours due to diagnosed depression. Additionally, this analysis revealed a negative impact of depression on student work productivity measured by work absenteeism and presenteeism. The measures of student work productivity employed in this analysis were subjective because they were constructed based on student self-reports on the number of work hours missed due to health disorders and also on the percentage reduction of their on-job performance. While the estimation showed that on average students missed a very small number of hours due to depression, the impairment of on-job productivity was significant (6.59-9.29%) which results in a significant cost to employers. Relative to depression, other health disorders, including all acute or chronic diseases experienced by the respondents seemed to demonstrate higher impairment on student job performance at work and home.

A new finding from this chapter is that students were more likely to reduce their
work hours per week rather than to miss hours of scheduled work per week due to their depression. This is an important contribution to the labor supply literature because it reveals a possible characteristic for a population that works part-time and have jobs involving physical activities with a flexible schedule. Another interesting finding is that all impairments caused by depression were reduced by treatment. The treatment variable was constructed to represent drug therapy, but for 65% of students drug treatment was also associated with psychotherapy.

This study aimed to calculate the total cost of diagnosed depressive disorders among University students and also the benefits of its treatment. The cost-benefit analysis provided in Chapter V showed that the average cost of diagnosed depression per student was $2,826.57 which consists of 41% treatment cost and 59% morbidity cost. I found that the main driver of treatment cost was counseling cost while the main drivers of indirect cost were school performance and presenteeism. The analysis indicated the effectiveness of treatment in preventing student GPA from falling, saving hours of work scheduled to work and increasing student performance at work and home. Thus, the total net cost of depression was reduced to $232,592.25 or $1,659.88 per diagnosed depressed student.

Among my student population there were 38 students who met DSM-IV criteria for having depressive disorders but they never sought medical help for their depression symptoms. The information and experience about the Sindecuse Health Center and Counseling and Testing Center, two main providers of medical care for depression, can be a very important factor in a student’s choice for professional help. If students had
been in these centers and were satisfied with the care given to them, they were more likely to go back and seek treatment when they experienced depressive symptoms. If they had never been at the centers, it can be assumed that students had little information about the services provided there. This is a possible reason why some students who experienced depressive symptoms did not consult a health professional. Another potential explanation is access to treatment. When students are enrolled in school, they have easy physical access to the school health facilities. Access is even easier if they live on campus. With regard to financial access, the University offers free counseling to students for any mental disorders or other social problems and the office fees at the Sindecuse Health Center are discounted. Students can benefit by solving some of their emotional problems through talking to the professionals in the Counseling and Testing Center or obtaining drug therapy through the Health Center.

Another phenomenon observed within my data set is that among 121 students diagnosed with depression at the Sindecuse Health Center, there were 29 students who failed to purchase medication for their disorders. A possible reason for the above fact is the lack of insurance. Drug therapy is provided at the University Health Center, yet it induces high cost to those students who do not have any health insurance. Insurance coverage is a strong predictor for seeking treatment (Berndt, Frank, & McGuire, 1997; Frank & McGuire, 1986; Keeler, Manning, & Wells, 1988; Manning, Wells, & Duan, 1986; Wells, Manning, & Duan, 1982). Since drug therapy is costly to students who usually have other financial obligations (tuition and school supplies) during their academic career, I believe that having health insurance would increase the likelihood of them
following the recommended treatment for depressive disorders.

The results of this study needs to be taken into consider because they have important policy implications:

1. Knowing the impact of depression on student's academic, work and home performance and the importance of treatments for depression, the University needs to increase students' awareness of the disease state and reduce barriers to care seeking such as concern about the stigma, lack of information of the care providers and lack of confidence about the efficacy of care.

2. Assuming that lack of health insurance decreases the students' likelihood to seek medical help for their health disorders, the University needs to impose policies that make insurance mandatory among students.

It is also important to mention the limitations of this study. The first limitation comes from the sample used in these analyses. The student population was drawn from one university, Western Michigan University, thus, the results can not be generalized for the national student population. Originally, this study attempted to answer the main questions by using a matched pair analysis. The initial sample of 314 students diagnosed with depression were matched to 892 students based on gender, class, curriculum, graduate versus undergraduate and GPA of semester prior to the date of first visit. However, there were only 414 undergraduate students who responded to the survey and from them I could developed only 75 pairs. Due to the small number of matched pairs, this analyses has used a non-matched pair sample which reduces the efficiency of the estimated effects of depression and its treatment on student performance. Additionally, the small number
of potentially depressed students (38) and number of untreated depressed students (29) did not allow me to estimate variables affecting the students' choice for medical care. Earlier estimation found that dropout rates were higher for potentially depressed students relative to controls or diagnosed depressed students. This phenomenon increased the indirect cost of depression for potentially depressed students. However, due to small size of this group (38), I could not draw some major conclusion for potentially depressed students.

A second limitation comes from the information obtained through the questionnaire. Students may have answered the questions in the survey with errors due to the need to recall information. Thus, possible error can be induced in measuring the effect of depression disorders on student work productivity. The proxies for absenteeism and presenteeism were obtained by considering student self-reports on the number of work hours missed due to depression and other health disorders and on the impairment caused by these disorders on student work performance. These are subjective measures of productivity and usually are not very preferable relative to objective ones (Berndt et al., 1998).

Third, the treatment variable was constructed based on information provided by the Health Center regarding acquisition dates, quantity dispensed and name of medications. The daily dosage required to compute the duration of treatment was defined based on information taken by Physicians' Reference Desk (1999). However, the actual daily dosage may be different from that assumed in this analysis, thus the duration of treatment may have been in error. Another limitation related to the treatment variable is that along
the analysis, treatment was considered to be taken regularly by students. If true compliance was less than was assumed, the effect of treatment on student productivity at school, work or home will be understated. In this analysis, the treatment variable mostly reflected drug therapy. Due to insufficient information regarding counseling therapy, I could not separate the effect of counseling from that of drug therapy.

The results of this study suggest that depression has a significant negative impact on student life that needs to be taken seriously by society. Treatment benefits exceeded the direct cost of depression by $96.42. This is because treatment reduced the impairment caused by depression on student performance at school, work and home. However, there are some issues remaining to be addressed in future research: first, one would need to investigate how long to continue treatment; second, to investigate the impact of student insurance health status on a student’s decision to seek medical help for their disorders. These issues would be of interest to University, health providers, health insurance companies and to society overall.
Appendix A

The Second Form of Questionnaire
Today's Date: _____________
Code: _____________

1. School Status

a. Are you an international student?
   Yes (Specify the country _____________) No

b. Did you change your major during the calendar year 1999? (circle one)
   Yes No (Go to section 2)

c. Please follow each of the following three steps:
   1. In the table below please circle the months in the calendar year 1999 when you changed your major.
   2. For each month circled, write on the first line below it, what your major was before that change was made.
   3. For each month circled, write on the second line below it, what your major was after that change was made.

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2. Demographic Characteristics

a. Race: (circle one)

   African-American Alaskan Native American Indian Asian-American
   Caucasian Hispanic Multiracial Pacific Islander

b. Indicate your living status during each academic term. (check one in each column)

<table>
<thead>
<tr>
<th></th>
<th>Winter '99</th>
<th>Spring '99</th>
<th>Summer '99</th>
<th>Fall '99</th>
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</thead>
<tbody>
<tr>
<td>Only adult in household</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Roommate(s) (how many__)</td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>With parents</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>With spouse/partner</td>
<td></td>
<td></td>
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</table>
c. How many children did you have in the year 1999: (circle one)
   None (go to question e)  One  Two or more

d. If any, did they live with you? (circle one)
   Yes  No

e. On average, how many hours per week do you spend doing household activities (cooking, cleaning, laundry, etc.)? ________ hours.

f. On average, how many hours per week do you spend doing school activities (attending classes, studying, preparing assignments, etc.)? ________ hours.

3. Employment Status

a. Were you employed (full time or part time) at any time during the calendar year 1999? (circle one)
   Yes  No (Go to section 4)

b. Please follow each of the four following steps:
   1. In the table below please circle the months in which you were employed.
   2. For each month circled, write on the first line below it the number of hours/week you were scheduled to work during that month:
   3. For each month circled, write on the second line below it the average wage ($/hour) you were paid:
   4. For each month circled, write a number from 0 to 100 on the third line below it that indicates how much your employment impaired your ability to complete your school assignments:

   Base your answer on the following rating scale:
   0% .............................................................. 100%

   No impairment due to employment  Total impairment due to employment

   |                           |                           |
   __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __
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4. Health Care Evaluation

a. Have you ever received medical care from the Sindecuse Health Center? (circle one)

Yes No (Go to question c)

b. Please draw a **vertical line** through the scale below that indicates your **level of satisfaction** with
the care you received from the **Sindecuse Health Center**:

```
0 1 2 3 4 5 6 7 8 9 10
| | | | | | | | | | |
Totally unsatisfied   Totally satisfied
```

c. Have you ever received counseling for any psychological problem(s) from the WMU Counseling
and Testing Center? (circle one)

Yes No (Go to section 5)

d. Please draw a **vertical line** through the scale below that indicates your **level of satisfaction** with
the care you received from the **WMU Counseling and Testing Center**:

```
0 1 2 3 4 5 6 7 8 9 10
| | | | | | | | | | |
Totally unsatisfied   Totally satisfied
```

5. Health Status

a. During the calendar year **1999**, which of the following symptoms did you experience?
(Check all that apply)

__1. Depressed mood most of the day, nearly every day (feel sad or empty).
__2. Loss of interest or pleasure in all, or almost all, activities most of the day, nearly every day.
__3. Significant weight loss (when not dieting) or weight gain; or decrease or increase in appetite
   nearly every day.
__4. Insomnia or excessive sleep nearly every day.
__5. An increase or decrease of activity noticeable by others nearly every day.
__6. Fatigue or loss of energy nearly every day.
__7. Feeling of worthlessness or guilt nearly every day.
__8. Diminished ability to think or concentrate, or indecisiveness, nearly every day.
__9. None of the above. (go to section 7)
b. Please circle the months when you experienced five or more of the above symptoms:

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c. Did you experience any of these symptoms at any time before age 18? (circle one)

Yes  No

d. Which of the following do you think might be the cause(s) of these symptoms? (circle all that apply)

- School performance/achievement
- Relationships
- Family problems
- Financial problems
- Others (specify) __________________________________________

e. Have you consulted any of the following health professionals regarding these symptoms? (circle all that apply)

- Psychiatrist
- Psychologist
- Therapist
- School counselor
- Clinician (Medical Doctor / Physician Assistant / Doctor of Osteopathy / Nursing Practitioner)
- Others (specify) ______________

None (give the reason why, then go to question h): __________________________________________

f. Did the health professional(s) diagnose you as suffering from depression? (circle one)

Yes  No (go to question h)

 g. Which of the following treatments did the health professional recommend for your depression? (circle all that apply)

- Drug therapy
- Counseling/Psychotherapy
- Herbal Remedies
- Other (specify) ______________________

h. Did you obtain any treatment for depression during the calendar year 1999?

Yes  No (go to question q)
i. If yes, please circle those months within the calendar year 1999 that you have been under any treatment for depression:

Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec

j. Where did you obtain treatment? (circle all that apply)

Sindecuse Health Center Counseling and Testing Center Off Campus

k. Which of the following treatments did/do you undertake for your depression? (circle all that apply)

Drug therapy Counseling/Psychotherapy Herbal Remedies Other (specify)

l. If you have taken prescription drug therapies, on average how effective have they been for your depression? (Please draw a vertical line through the scale below that indicates this level of efficacy; if you have not taken prescription drug therapies please go to next question):

Ineffective Fully effective

m. If you have had counseling and/or psychotherapy, on average how effective have they been for your depression? (Please draw a vertical line through the scale below that indicates this level of efficacy; if you have not had counseling and/or psychotherapy please go to next question):

Ineffective Fully effective

n. If you have used herbal remedies, on average how effective have they been for your depression? (Please draw a vertical line through the scale below that indicates this level of efficacy; if you have not used herbal remedies please go to next question):

Ineffective Fully effective
o. Are you currently under treatment? (circle one)
   Yes (go to question q) I've never had treatment (go to question q)
   I've been under treatment, but it has been discontinued

p. Whose decision was it to discontinue treatment? (circle one)
   Clinician's Mine Others (specify__________)

q. Have your parents experienced any of the following disorders sometime during their lives? (Circle all that apply)
   Depression Anxiety disorder Substance dependence
   None Don't know

6. Productivity impairment related to depression

   If you were not employed during the calendar year 1999 go to question c.

   a. Please follow each of the following two steps:
      1. Please circle the months when depression impaired your on job performance during the calendar year. (circle all that apply)
      2. For each month circled, write a number from 1 to 100 on the line below that indicates your level of job performance:
         Base your answer on the following rating scale:
   0% ........................................ 100%
   | No impairment Total impairment
   due to depression due to depression

   Jan    Feb    Mar    Apr    May    Jun    Jul    Aug    Sep    Oct    Nov    Dec

   b. How many hours of work did you miss during the calendar year 1999 due to depression?
      (indicate the number of hours missed for each month on the lines below)

   Jan    Feb    Mar    Apr    May    Jun    Jul    Aug    Sep    Oct    Nov    Dec

   # hours.
c. During the calendar year 1999, how many months were you unemployed due to depression?
   _____ # months.

d. Please follow each of the following two steps:
   1. Please circle the months that depression impaired your household activities (cooking, cleaning, laundry, etc.) during the calendar year 1999. (circle all that apply)
   2. For each month circled, write a number from 1 to 100 on the line below that indicates your level of performance at these activities:
      Base your answer on the following rating scale:
      0% ........................................100%
      |  
      No impairment  Total impairment  
      due to depression  due to depression

      |  
      Jan  Feb  Mar  Apr  May  Jun  Jul  Aug  Sep  Oct  Nov  Dec  

      %.

e. Please follow each of the following two steps:
   1. Please circle the months that depression impaired your school activities (attending classes, studying, preparing assignments, etc.) during the calendar year 1999. (circle all that apply)
   2. For each month circled, write a number from 1 to 100 on the line below that indicates your level of performance at school:
      Base your answer on the following rating scale:
      0% ........................................100%
      |  
      No impairment  Total impairment  
      due to depression  due to depression

      |  
      Jan  Feb  Mar  Apr  May  Jun  Jul  Aug  Sep  Oct  Nov  Dec  

      %.

f. Is your answer above regarding impairment based on: (circle all that apply)

   your own expectations  your parents’ expectation
   your peers’ performance  your instructor’s expectation  Others (specify)
g. Is your impairment of school activities from depression due to: (circle all that apply)

1. decreased concentration
2. decreased motivation
3. insomnia or excessive sleep
4. fatigue or loss of energy
5. others (specify) ________________

f. During the calendar year 1999, how many classes did you miss due to depression? ______# classes.

i. During the calendar year 1999, did you drop any class due to depression? ______# classes.

j. During the calendar year 1999, how many exams did you miss due to depression? ______# exams.

k. During the calendar year 1999, how many assignments did you miss due to depression? ______# assignments.

l. During the calendar year 1999, how many school/sport/club activities did you miss due to depression? ______# activities.

7. Productivity impairment related to other health disorders

If during the calendar year 1999 you had any health disorders (mental or physical) OTHER THAN DEPRESSION that impacted your ability to perform work or school activities (attending classes, studying, preparing assignments, etc.), please answer this section.

If you were not employed in the calendar year 1999 go to question c.

a. Please follow each of the following two steps:

1. Please circle the months that other health disorders impaired your job performance during the calendar year 1999? (circle all that apply)

2. For each month circled, write a number from 1 to 100 on the line below that indicates your level of job performance:

   Base your answer on the following rating scale:
   
   0% ............................................. 100%

   No impairment Total impairment
due to other due to other
health disorders health disorders
b. How many hours of work did you miss during the calendar year 1999 due to other health disorders? (indicate the number of hours missed for each month on the lines below)

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# hours.

c. During the calendar year 1999, how many months were you unemployed due to other health disorders? _____ # months.

d. Please follow each of the following two steps:

1. Please circle the months that other health disorders impaired your household activities (cooking, cleaning, laundry, etc.) during the calendar year 1999. (circle all that apply)

2. For each month circled, write a number from 1 to 100 on the line below that indicates your level of performance at household activities:

   Base your answer on the following rating scale:

   0% .......................................................... 100%

   No impairment Total impairment
   due to other health disorders

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e. Please follow each of the following two steps:

1. Please circle the months that other health disorders impaired your school activities (attending classes, studying, preparing assignments, etc.) during the calendar year 1999. (circle all that apply)

2. For each month circled, write a number from 1 to 100 on the line below that indicates your level of performance at school:

   Base your answer on the following rating scale:

   0% .......................................................... 100%

   No impairment Total impairment
   due to other health disorders

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%.
f. Is your answer above regarding impairment based on: (circle all that apply)

your own expectations your parents' expectation
your peers' performance your instructor's expectation Others (specify)

[g. Is your impairment of your school activities from other health disorders due to: (circle all that apply)

1. decreased concentration
2. decreased motivation
3. insomnia or excessive sleep
4. fatigue or loss of energy
5. others (specify) __________

f. During the calendar year 1999, how many classes did you miss due to other health disorders?

# classes.

i. During the calendar year 1999, did you drop any class due to other health disorders?

# classes.

j. During the calendar year 1999, how many exams did you miss due to other health disorders?

# exams.

k. During the calendar year 1999, how many assignments did you miss due to other health disorders?

# assignments.

l. During the calendar year 1999, how many school/sport/club activities did you miss due to other health disorders?

# activities.

Thank you for your participation in this survey. Please mail or return the survey to Mr. Scott Musial, Sindecuse Health Center, Western Michigan University, Kalamazoo, MI 49008, by using the addressed envelope provided. Your compensation of $20 will be mailed to you within a month of the date we receive the survey. If you have any questions, you may contact Prof. Donald Alexander at 616 387-5526, Alketa Hysenbegasi at 616 833-1989, the Human Subjects Institutional Review Board at 616 387-8293 or the vice president for research at 616 387-8298.
Appendix B

Information Obtained From the Counseling Clinics in the Kalamazoo Area
Number of Sessions and the Cost per Session for a Typical Case with Depression

<table>
<thead>
<tr>
<th>Counseling clinics in Kalamazoo area</th>
<th>Number of sessions per depressed patient</th>
<th>First visit charge (dollars)</th>
<th>Charge for follow-up visits (dollars)</th>
<th>Total charge (dollars)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dr. Karen Casebeer</td>
<td>10</td>
<td>85-100</td>
<td>85-100</td>
<td>925</td>
</tr>
<tr>
<td>West Side Family Mental Health Clinic</td>
<td>10&lt;=</td>
<td>135</td>
<td>95</td>
<td>990</td>
</tr>
<tr>
<td>Delano Outpatient</td>
<td>10</td>
<td>181</td>
<td>75-140</td>
<td>1148.5</td>
</tr>
<tr>
<td>Behavioral Health Resources</td>
<td>10</td>
<td>125</td>
<td>95</td>
<td>980</td>
</tr>
<tr>
<td>Dr. Patricia Lyman</td>
<td>10-15</td>
<td>125</td>
<td>95</td>
<td>980</td>
</tr>
</tbody>
</table>
Appendix C

Protocol Clearance From the Human Subjects
Institutional Review Board
Date: 7 March 2000

To: Donald Alexander, Principal Investigator
   Alketa Hysenbegasi, Student Investigator

From: Sylvia Culp, Chair

Re: HSIRB Project Number 00-02-06

This letter will serve as confirmation that your research project entitled "The relationship between chronic health disorders and the performance of University students" has been approved under the expedited category of review by the Human Subjects Institutional Review Board. The conditions and duration of this approval are specified in the Policies of Western Michigan University. You may now begin to implement the research as described in the application.

Please note that you may only conduct this research exactly in the form it was approved. You must seek specific board approval for any changes in this project. You must also seek reapproval if the project extends beyond the termination date noted below. In addition if there are any unanticipated adverse reactions or unanticipated events associated with the conduct of this research, you should immediately suspend the project and contact the Chair of the HSIRB for consultation.

The Board wishes you success in the pursuit of your research goals.

Approval Termination: 7 March 2001
You are invited to participate in a research project entitled "The relationship between chronic health disorders and the performance of university students." The project will analyze the effectiveness of treatment on students' performance and validate different measurements of students' school productivity. The objectives of this project will be achieved through analysis of anonymous data from this survey and from the Sindecuse Health Center and the Registrar's Office.

Mental and physical health disorders can have a significant impact upon a patient's social and work performance. Depression is an example where the linkage between a chronic disorder and its impact on productivity has been well established. Because of this, a number of items in this questionnaire will deal with symptoms of depression and how it may have affected your performance. Your name has been obtained from among those receiving any type of care from Sindecuse Health Center. The fact that you have received this questionnaire should NOT be taken as an indication that you have been identified as a student treated for depression.

This project is a cooperative effort of Prof. Donald L. Alexander and Alketa Hysenbegasi of the Department of Economics, and Scott Musial of the Sindecuse Health Center. This research is part of the internship requirements for Alketa Hysenbegasi. Funding is being provided by Pharmacia & Upjohn.

This survey is comprised of 68 questions, and will take a maximum of approximately 30 minutes to complete. Your replies will be completely anonymous, so do not put your name or social security number anywhere on the form. You may choose not to answer any question by simply leaving it blank. If you choose not to participate in this survey, you may discard it. Returning the survey indicates your consent for use of the answers you supply. The information obtained from your answers will be confidential to the staff members of the Health Center and anonymous to the investigators. All answers will be reported in aggregate. Those students who return the questionnaire by April 21, 2000 will receive a monetary compensation of $20 sent to them by a staff member of the Sindecuse Health Center.

Please mail or return the survey to Mr. Scott Musial, Sindecuse Health Center, Western Michigan University, Kalamazoo, MI 49008, by using the self addressed envelope. Your compensation will be mailed to you within a month of the date we receive the survey. If you have any questions, you may contact Prof. Donald Alexander at 616 387-5526 or Alketa Hysenbegasi at 616 833-1989. You may also contact the Chair of the Human Subjects Institutional Review Board (616 387-8293) or the Vice President for Research (616 387-8298) if questions or problems arise during the course of the project.

The Human Subjects Institutional Review Board has approved the use of this document for a period of one year. The Board's approval is indicated by the stamped date and signature of the board chair in the upper right corner. You should not participate in this project if the corner does not have a stamped date and signature.
Western Michigan University's policy states that "the HSIRB's review of research on a continuing basis will be conducted at appropriate intervals but not less than once per year." In compliance with that policy, the HSIRB requests the following information:

**PROJECT TITLE:** "The relationship between chronic health disorders and the performance of University students."

**HSIRB Project Number:** 00-02-06

**Date of Review Request:** 02/06/01  **Date of Last Approval:** 03/07/00

**PRINCIPAL INVESTIGATOR OR ADVISOR**

Name: Donald Alexander  
Department: Econ  
Electronic Mail Address: donald.alexander@wmich.edu

**(1) CO-PRINCIPAL OR STUDENT INVESTIGATOR**

Name: Alketa Hysenbegasi  
Department: Econ  
Electronic Mail Address: alketa.hysenbegasi@wmich.edu

**(2) CO-PRINCIPAL OR STUDENT INVESTIGATOR**

Name:  
Department:  
Electronic Mail Address:  

1. The research, as approved by the HSIRB, is completed.  
   [ ] Yes (Continue with items 5-7 below.)  
   [X] No (Continue with items 2-5 below.)

2. Have there been changes in Principal or Co-Principal Investigators?  
   [ ] Yes  
   [X] No

3. Is the approved protocol still accurate and being followed with respect to:  
   (If no to any item below, provide details on an attached sheet.)
   a. Procedures  
      [X] Yes  
      [ ] No
   b. Subjects  
      [X] Yes  
      [ ] No
   c. Design  
      [X] Yes  
      [ ] No
   d. Data collection  
      [X] Yes  
      [ ] No

4. Has any instrumentation been modified or added to the protocol?  
   (If yes, attach new instrumentation or indicate the modifications made.)
   [ ] Yes  
   [X] No

5. Have there been any adverse events which need to be reported to the HSIRB?  
   (If yes, provide details on an attached sheet.)
   [X] Yes  
   [ ] No

6. Current total number of subjects enrolled: 1206  
   Current number of subjects in the control group: 892

7. Provide copies of the consent documents signed by the last two subjects enrolled in the project. Cover the signature in such a way that the name is not clear but there is evidence of signature. If subjects are not required to sign the consent document, provide a copy of the most current consent document being used.  
   (Remember to include a clean original of the consent documents to receive a renewed approval stamp.)

---

**Principal Investigator/Faculty Advisor Signature**  
Date: 8 Feb. 2001

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**Co-Principal or Student Investigator Signature**  
Date: 02/07/01

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**Approved by the HSIRB:**  
Date: 2/12/01

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Revised 5/98  WMU HSIRB

All other copies obsolete.


