Chapter III. Data and Methodology

3.1 Introduction

This chapter discusses the data and methodology used to test the dissertation hypotheses. First, a conceptual model is presented to provide the rationale for the following hypotheses and analyses. Second, specific aims and hypotheses are discussed. Finally, datasets and analytical models for hypothesis testing are described.

3.2 Conceptual Model

In this section, I first describe the conceptual framework for race and mental health (see Figure 3.1), and then describe the conceptual framework for the effect of access to care on depression prevalence (see Figure 3.2).

3.2.1 Conceptual Model for Race and Mental Health

In this dissertation, I apply LaVeist's model of race and health (LaVeist et al., 1994) and Andersen's model of health care access and use (Andersen 1983, 1995) to explore disparities in depression prevalence, access and quality of healthcare across racial/ethnic groups among Medicare beneficiaries (see Figure 3.1).

As shown in Figure 3.1, LaVeist’s model includes four steps along the pathway through which racial and ethnic disparities may exist. First, people’s health is determined by individual characteristics (e.g. demographic and socioeconomic characteristics) and community environmental characteristics (e.g. availability of healthcare services and convenience to care). Second, when disease symptoms emerge, patients recognize those symptoms and are willing to go to a doctor for help. Third, after barriers to access
healthcare are overcome, patients enter the healthcare delivery system and interact with medical providers to receive treatment.

In the first step, minorities are more likely to have lower socioeconomic status and live in neighborhoods with higher levels of risk factors for depression (such as a higher crime rate, higher unemployment rate and lack of health professionals). In the second step, there are differences in types of symptom due to cultural background, differences in help-seeking behaviors due to beliefs in health and healthcare, and differences in barriers to care (such as health insurance, availability of healthcare services, and convenience to care) across racial and ethnic groups. It is more feasible to observe and estimate disparities in access to care compared with differences in symptom presence and help-seeking behaviors in large-scale national surveys. In the third step, there may be racial and ethnic disparities in quality of care due to factors such as physician bias and/or discrimination, patient-physician interaction and communication, and demand competition. Also, minorities may go to providers who are under-resourced and thus less able to provide high quality care (Bach et al., 2004). In the fourth step, patients’ depression status is determined by the previous three steps mentioned in the previous paragraph involving factors at the individual, community, and healthcare delivery system levels (See Figure 3.1 for L1-L4).

### 3.2.2 Conceptual Framework for Access to Care and Depression

I extend Andersen’s Behavioral Model of Health Care Access and Use (Andersen, 1983; 1995) to examine the effect of access to care and healthcare utilization on depression status (see Figure 3.2). Andersen’s Model stipulates that healthcare access and
use are influenced by a combination of predisposing, enabling, and need factors. In the present study, predisposing factors include age, gender, race and ethnicity, and marital status. Enabling factors are categorized into personal resources and external resources. Personal resources include education, income, health insurance, and number of children, while external resources include rural/urban status, availability of health professionals, and convenience. Need factors include self-rated health status, comorbidity, and disability. The combination of these three groups of factors determines people’s behavior and preferences for healthcare access and use. These three groups of factors plus healthcare access and use affect people’s mental health status (in the present study, depression).
Figure 3.1 Conceptual Framework of Racial/Ethnic Disparities in Depression Prevalence, Access and Quality of Health Care among the Elderly

**Individual characteristics**
- **Demography** (age, gender, marital status, living arrangement, family structure)
- **Socioeconomic status** (Education, annual household income, health insurance)
- **Physical health status** (Self-report health, ADLs, IADLs, chronic conditions)

**Community characteristics**
- Rural/urban
- Median annual household income
- Employment rate
- Proportion of older adults
- Local health resources (e.g., health professional shortage)

**Question 1**
- Depressive disorders

**Question 2**
- **Access to care**
  - Usual source of care; Health insurance
  - Convenience (average length of time traveling to work for people age 16+ age country level)

**Question 3**
- **Quantity of mental health care**
  - a. Detection of mental health problems
  - b. Communication about mental health problems once detected

**Question 4**
- **Depression status**
  - Screened depression (yes/no) in past 12 months
3.3 Specific Aims and Hypotheses

In this dissertation, there are four Specific Aims to answer research questions relating to disparities in depression prevalence, access to care, and quality of care for depression among the community-dwelling Medicare beneficiaries in the traditional Medicare fee-for-service system.

**Research Question 1:** Are there racial/ethnic disparities in the prevalence of depression among the elderly at the national level? Are findings consistent for different measures of depression?

**Hypothesis 1.1:** Among the elderly, minorities are more likely to have depression compared with non-Hispanic whites.
Hypothesis 1.2: The two-item screen is a good general measure for studying disparities in depression prevalence across racial/ethnic groups compared with the SCID for the DSM-IV criteria.

**Research Question 2:** Are there disparities in having a usual source of care among community-dwelling Medicare beneficiaries?

Hypothesis 2: Minorities are less likely to have a usual source of care compared with whites.

**Research Question 3:** What is the effect of having a usual source of care on depression prevalence among Medicare beneficiaries?

Hypothesis 3.1: Among the community-dwelling elderly, people who have a usual source of care are more likely to have ambulatory care visits.

Hypothesis 3.2: People with barriers to access to care are more likely to screen positive for depression among the elderly living in the community.

**Research Question 4:** Are there racial/ethnic disparities in quality of mental healthcare among people who screened positive for depression, in terms of physician recognition and communication?

Hypothesis 4.1: Minorities are less likely to be recognized by physicians as having depression compared with whites among people who screened positive for depression using the two-item screen.
Hypothesis 4.2: Physicians are less likely to communicate with minorities about their mental health disorders compared to non-Hispanic whites, among people who were recognized by physicians as having depression.

3.4 Data and Methods

3.4.1 Data and Study Population

3.4.1.1 Data

In this dissertation, three data sources are used to test the hypotheses: the Medicare Current Beneficiaries Survey (MCBS) and associated claims (2001-2003), the National Epidemiology Survey of Alcoholism and Related Conditions (NESARC) (2001-2002), and the Area Resource File (ARF) (2002). The MCBS provides information on the primary outcomes of interest (mental health status [screened depression], access to care [having a usual source of care], and quality of mental healthcare [physician recognition and communication]) and covariates at the individual level (demographic and socioeconomic characteristics and physical health status). NESARC data provide measures of depression including the SCID diagnosis for the DSM-IV criteria in a nationally representative household sample of adults age 18+. The ARF data provides covariates at the community and system levels. The MCBS and ARF data are used to test the hypotheses for Questions 1-4. NESARC data are employed to test the hypotheses for Question 1.

Medicare Current Beneficiaries Survey
The MCBS is a continuous survey of a representative national sample of the Medicare population, conducted by the Office of Strategic Planning of the Centers for Medicare & Medicaid Services (CMS). The sample for the MCBS is drawn from CMS’s Medicare enrollment file. The first stage of sampling was the selection of 107 geographic primary sampling units (PSUs), consisting of groups of counties representing the nation. Within each PSU the sample was restricted to addresses within certain geographic subareas corresponding to postal zipcodes. Interviews were conducted every four months using computer-assisted personal interviewing to yield longitudinal series of data on the use of health services, medical care expenditures, health insurance coverage, sources of payment, health status and functioning, and a variety of demographic and behavioral information such as income, assets, living arrangements, family supports, and access to medical care. Efforts were made to interview each sampled person directly, but if the person was unable to answer the survey questions, he or she was asked to designate a proxy respondent. Most beneficiaries in the MCBS sample received the Community Interview rather than the Institution Interview.

_Inclusion criteria:_

In this dissertation, participants who were under 65 years old, resided in long-term care (facilities or other institutions such as prisons), enrolled in Medicare HMOs, or died during the survey were excluded. Thus, only elderly (65 years old or over) community-dwelling beneficiaries enrolled in the traditional Medicare fee-for-service (FFS) system who participated in the MCBS survey for the entire year were included in the analysis. In
2001-2003, there were 21,550 person-years (56.64% of 38,047 person-years) in the MCBS data that met the inclusion criteria.

**National Epidemiology Survey of Alcoholism and Related Conditions**

The National Epidemiology Survey of Alcoholism and Related Conditions (NESARC) is used to test Hypothesis 1.1 & 1.2. It was conducted from August 2001 to May 2002 among 43,093 respondents 18 years of age or older via face-to-face personal household interviews administered by professional lay interviewers from the U.S. Census Bureau. The interviewers used a computer-assisted interview that allowed for skip patterns and response-contingent rewording of questions. The interview gathered information on subject background, substance abuse and mental health disorders, associated disabilities, and family substance abuse and mental health history. The survey response rate was 81%. The NESARC data include sample weights to account for oversampling of certain populations (for example, non-Hispanic blacks). The weighted data represent the civilian, non-institutionalized United States population based on the 2000 Decennial Census. Detailed information on the design of the survey is provided elsewhere (Grant et al., 2003).

**Inclusion criteria:**

I extracted all participants aged 65+ who were identified as Medicare beneficiaries. There were 8,205 elderly out of the 43,093 participants in this cross-sectional survey, of which 7,629 responded that they were enrolled in Medicare.
**Area Resource File**

The Area Resource File (ARF) (2002) provides information on the nation’s healthcare delivery system and factors that may affect health status and healthcare at the county level, including information on healthcare facilities, healthcare professions, measures of resource scarcity, health status, economic activity, healthcare professions training programs, and socioeconomic and environmental characteristics. It has been widely reported that environmental context (for example, socioeconomic status at the county level, convenience to care, and local health professionals’ availability) has significant effects on people’s mental health and quality of life (e.g. Schootman et al., 2007). The ARF basic file contains geographic codes, which enable its linkage with other national survey files such as the MCBS. In this dissertation, a cross tabulation between the 5-digit zipcode and the Federal Information Processing Standards (FIPS) county code is used to link the MCBS data and the ARF data. For example, if a participant lived in an area with zipcode 35004, which matched the FIPS county code 1115, then participants living in zipcode 35004 in the MCBS data are linked with county code 1115 for community variables in the ARF file.

**3.4.1.2 Study Population**

**3.4.1.2a Targeted Study Population**

This dissertation focuses on community-dwelling Medicare beneficiaries age 65 years and older in the traditional Medicare fee-for-service system in the years 2001-2003.

For the MCBS data, the inclusion criteria are as follows:

- Participated in Medicare and the MCBS survey for the full calendar year;
• Age 65 or older;
• No End Stage Renal Disease (ESRD);
• Covered by both Medicare Part A & Part B;
• No participation in a Medicare risk HMO;
• Community-dwelling.

For the NESARC data, the inclusion criteria are as follows:
• Medicare beneficiary;
• Age 65+.

### 3.4.1.2b Inclusion Criteria for Specific Aim 1

Specific Aim 1 is to compare depression prevalence based on different measures of depression for different racial/ethnic groups using two different measures of depression. The study samples analyzed differ somewhat between the MCBS data and the NESARC data. The inclusion criteria are listed directly above for both datasets. There is no information provided in the NESARC data about whether the participants were enrolled in a Medicare HMO or not, whether they enrolled in both Part A and Part B or Part A only, or whether the participants had ESRD. The prevalence of ESRD is 0.05% among Medicare beneficiaries in 2001 (NIH, 2001). Patients with ESRD are highly likely to have comorbidities (such as diabetes, obesity, hypertension, and cardiovascular diseases) and to be institutionalized (e.g. Bakris et al., 2000). The NESARC survey is a household survey, the proportion of participants with ESRD should be very small. Key population characteristics (demographic and socioeconomic characteristics, and health status) are compared between those two study samples to see whether they are
statistically significantly different from each other (see Appendices B & C). The results indicate that the MCBS and NESARC study samples are comparable in terms of the distribution of key population characteristics. It is assumed that they are two independent representative samples of community-dwelling Medicare beneficiaries in the U.S. A total of 21,550 out of 38,047 person-years meet the study criteria in the MCBS data for 2001-2003, 5.1% of which reported dementia (n = 1,095), and 1.6% were residing in Puerto Rico (n = 343). Among the person-years for those residing in Puerto Rico during 2001-2003, 96.2% are Hispanic. There are 8,205 persons aged 65+ identified in the NESARC data. Of these, 576 (6.71%) reported no Medicare coverage.

3.4.1.2c Inclusion Criteria for Specific Aims 2 & 3

The sample analyzed for Specific Aims 2 & 3 included all the MCBS community-dwelling participants for any full calendar year from 2001 through 2003, excluding those under 65 years of age, those eligible for Medicare Part A or Part B only, and Medicare HMO enrollees. The reason to exclude those younger than 65 years is that they have substantial disability or are enrolled in the ESRD program, and are therefore rather different from the general elderly population (Freedman, 2005). Beneficiaries who enrolled in Medicare HMOs for any length of time in a given year, beneficiaries with only Medicare Part A or Part B, and those who participated in the MCBS for part of a calendar year were excluded because there was incomplete information about their health care use. People who reported diagnosis of dementia were excluded for Specific Aim 3 since cognitive functioning is associated with depression and self-reported depressive symptoms (Bassuk et al., 1998).
For Specific Aim 2, 21,550 person-years met the inclusion criteria, representing 6.76 million community-dwelling Medicare beneficiaries (population size = 67,584,060).

For Specific Aim 3, the inclusion criteria were met by 20,455 person-years. Only person-years without missing values for variables of interest were included in the analysis (n = 18,889, 92.3% of 20,455). Of those excluded (n = 1,566, 7.7% of 20,455), 30.9% had a missing value for screened depression, 3.2% had a missing value for race and ethnicity, and 3.3% had a missing value for having a usual source of care. A total of 7.7% missing is small and is not expected to appreciably bias the results. Sample statistics were compared between the final sample and a list-wise sample (see Appendix D). A list-wise sample includes only observations without missing values for variables of interest.

3.4.1.2d Inclusion Criteria for Specific Aim 4

In addition to the inclusion criteria for Specific Aims 2 & 3, person-years screened positive as having depression and had at least one ambulatory care visit in the past year in the MCBS data (N = 2,312) were included in the analysis for Specific Aim 4.1 and the seemingly unrelated bivariate model for Specific Aim 4.2 (see the Method section).

In addition to the inclusion criteria for Specific Aims 4.1, only community-dwelling person-years recognized as having depression by physicians in the past year in the MCBS data were included in the non-adjusted analysis and the logistic model for Specific Aim 4.2 (N = 2,693).

Figure 3.3 provides a summary of the study sample analyzed for Specific Aims 1-4. This figure details how the sample frame eroded for each hypothesis.
3.4.1.2e Sensitivity Analyses Using Different Subsamples

Sensitivity analyses were done for each hypothesis using different subsamples. Puerto Rico was not included in the analysis sample in the NESARC data. No questions about dementia were included in NESARC. For Hypothesis 1.2, to compare the depression prevalence of different racial/ethnic groups based on different measures of depression using the MCBS and NESEARC data, sensitivity analyses were carried out using three subsamples: (1) excluding people who reported dementia; (2) excluding people residing in Puerto Rico; and (3) excluding people who reported dementia and/or were residing in Puerto Rico. For Hypothesis 2, sensitivity analysis was done to exclude people reporting dementia. For Hypothesis 4.1, physician recognition of depression was defined as: (1) people with a diagnosis of depression and/or antidepressant use; (2) people with a depression diagnosis only; and (3) people with antidepressant use only.
Figure 3.3 Sample Size for Each Hypothesis in the MCBS

Raw MCBS data 2001-2003 (N = 38,047)

2001 sample (N = 12,864)

- Remove institutionalized (N = 11,893)

- Remove Medicare A only (N = 10,583)

- Remove HMO participants (N = 8,726)

- Remove under age 65 (N = 7,215)

- Remove part-year participants (N = 7,092)

Hypothesis 1: (N = 21,550)

- Remove people with dementia (N = 20,455)

List-wise sample for Specific Aims 2 & 3 (N = 18,889)

List-wise sample for Hypothesis 4.1 (N = 2,479)

List-wise sample for Hypothesis 4.2 (N = 2,693)
3.4.1.3 Quality of Data

To examine the quality of the data used to test the dissertation hypotheses, missing data were examined for the variables that were either used directly in the analyses, or used to construct variables included in the analyses. In the NESEARC data, missing data have been imputed for background variables deemed critical for analysis, e.g., age, sex, race, education, and income. A hot deck procedure and logical checks were used in the imputation of data. Detailed information about imputation on missing data in the NESEARC data is provided by the NIAAA (Grant et al., 2003). In this dissertation, I used data with imputation.

In the MCBS data, there were no missing data for the variables that were the inclusion criteria. In the study sample that met the inclusion criteria (N = 21,550), 5.7% of the observations had missing data for clinical diagnosis and/or self-reported antidepressant use, 3.7% had missing data for screened depression, 3.4% for ADLs, 1.7% for self-rated health, 1.7% for BMI, 1.6% for race and/or ethnicity, 1.5% for IADLs, 1.5% for smoking, 1.4% for having a usual source of care, 1.4% for comorbidities, 0.4% for education, 0.1% for marital status, and 0.01% for living arrangement. There were 8.9% person-years with missing data for one or more variables. In sum, a reasonably small proportion of the observations had missing data for one or more of the critical variables mentioned above.

Thus, both the NESARC and MCBS data were of sufficient quality to test the hypotheses in this dissertation.
3.4.2 Operational Definition of Measurement

3.4.2.1 Dependent Variables:

In this section, the dependent variables for each hypothesis are listed (see Table 3.1). First, for Specific Aim 1, depression prevalence is identified by five measures (the two-item screen, the ICD-9 diagnosis, the single-item screen, the PHQ-2 and the SCID). Second, for Specific Aims 2 and 3, access to care is defined by having a usual source of care. Third, quality of mental healthcare is defined by physician recognition of having depression among those with screened depression, and communication about mental disorders between physicians and patients among those who were recognized by the physician as having mental disorders.

(1). Depression:

Each instrument used to identify people with depression has different sensitivity and specificity. The sensitivity of the test is defined as the ability of the test to identify correctly those who have the disease (Gordis, 2000). The specificity of a test is defined as the proportion of non-diseased people who are correctly identified as negative by the test. Since depression is a prevalent chronic disease among the elderly, it is associated with heavy social and economic burden, and can be treated effectively, early detection and early treatment is highly preferred. From this point of view, instruments with higher sensitivity will be better at defining mental health needs.
<table>
<thead>
<tr>
<th>Measure</th>
<th>Question</th>
<th>Definition</th>
<th>Data source</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCID diagnosis</td>
<td>At least 2 weeks of persistent depressed mood or anhedonia were present, accompanied by a total of at least 5 or more of the 9 DSM-IV symptoms of major depression in the past year.</td>
<td>Yes/No</td>
<td>NESARC</td>
</tr>
<tr>
<td>PHQ-2 Scale</td>
<td>In the past 12 months, have you had a time when you felt sad, blue, depressed, or down most of the time for at least 2 weeks? In the past 12 months, have you had a time, lasting at least 2 weeks, when you didn’t care about the things that you usually cared about, or when you didn’t enjoy the things that you usually enjoyed?</td>
<td>Yes/No</td>
<td>NESARC</td>
</tr>
<tr>
<td>Single-Item Screen</td>
<td>In the past 4 weeks, how often have you felt downhearted and depressed?</td>
<td>Yes/No</td>
<td>NESARC</td>
</tr>
<tr>
<td>ICD-9 Codes</td>
<td>ICD-9 codes for all mood disorders with depressed mood in the past year.</td>
<td>Yes/No</td>
<td>Medicare claims</td>
</tr>
<tr>
<td>Two-Item Screen</td>
<td>In the past 12 months, how much of the time did (you/SP) feel sad, blue, or depressed? Would you say (you were/SP was) sad or depressed all of the time, most of the time, some of the time, a little of the time, or none of the time? In the past 12 months, (have you/has SP) had 2 weeks or more when (you/he/she) lost interest or pleasure in things that (you/he/she) usually cared about or enjoyed?</td>
<td>Yes/No (either depressed or anhedonia)</td>
<td>MCBS</td>
</tr>
</tbody>
</table>
The outcome variable (depression) in Question 1 was measured by the following five measures: the Structured Clinical Interview for DSM disorders (SCID), the Population Health Questionnaire-2 (PHQ-2), a single-item screen, the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM), and a two-item screen. The presentation of results will focus on the comparison between the two-item screen and the SCID in order to prove that the two-item screen is a good measure to estimate disparities in depression prevalence in different racial/ethnic groups, and to use it to test other hypotheses in this dissertation.

The DSM-IV includes the American Psychiatric Association’s definition of major depression and other mental disorders. This definition is based on the presence of symptoms. Five (or more) of the following symptoms must have been presented during the same 2-week period and represent a change from previous functioning; and at least one of the symptoms is either (1) depressed mood or (2) loss of interest or pleasure. Other symptoms include: (1) significant weight loss when not dieting or weight gain (e.g., a change of more than 5% of body weight in a month), or a decrease or increase in appetite nearly every day; (2) insomnia or hypersomnia nearly every day; (3) psychomotor agitation or retardation nearly every day (observable by others, not merely subjective feelings of restlessness or being slowed down); (4) fatigue or loss of energy nearly every day; (5) feelings of worthlessness or excessive or inappropriate guilt (which may be delusional) nearly every day (not merely self-reproach or guilt about being sick); (6) diminished ability to think or concentrate, or indecisiveness, nearly every day (either by subjective account or as observed by others); (7) recurrent thoughts of death (not just fear
of dying), recurrent suicidal ideation without a specific plan, or a suicide attempt or a specific plan for committing suicide (APA, 1994).

The 9-item depression module of the Patient Health Questionnaire (Pfizer, 1999), the PHQ-9 is one of the most popular screening instruments for depression among persons living in the community. The PHQ-9 serves as both a depression severity measure as well as a diagnostic instrument for DSM-IV depressive disorders (Kroenke, 2001). The PHQ-2 (Kroenke et al., 2003) is a short version of the PHQ-9, including the first two symptoms in the DSM-IV. The validity of these two questions for screening depression in the community has been widely supported (Almeida et al., 1999; Lowe et al., 2004; Blank et al., 2004; Corson et al., 2004; Whooley et al., 1997; Kroenke et al., 2003). However, the PHQ-2 has been applied differently in previous studies. For example, Kroenke utilized scaled responses and a time frame of the past two weeks, Whooley employed yes/no answers and the last month, and NESARC used yes/no answers and the past 12 months. There is no information on how these various approaches to measurement compare. The PHQ-2 has been consistently found to be as effective (sensitivity and specificity) as using longer screening measures (such as the PHQ-9) based on different formats of questions about those two symptoms (Whooley, 1997; Sharp, 2002; Kroenke, 2003). Virtually all people with depression have replied "yes" on one or both questions (Aroll et al., 2003). The two-item screening tool in the MCBS asked about the same symptoms but over a different time frame compared with the PHQ-2. We assume that the two-item screen included in the MCBS has comparative validity with the PHQ-2 used in those previous studies.
In defining depression using the ICD-9-CM, individuals were required to have at least one inpatient or outpatient claim with a depression syndrome code. The depression codes include 293.83 (mood disorder, due to general medical conditions), 296.2-296.3 (major depressive disorder, single/recurrent episode), 296.5-296.6 (Bipolar I Disorder), 298.0 (depressive type psychosis), 300.4 (neurotic depression), 309.0-309.1 (brief or prolonged depressive reaction), and 311 (depressive disorder, not otherwise classified).

Dummy variables (0/1) were generated for each measure, with 1 indicating “yes” and 0 otherwise.

(2). Access to Healthcare

In this dissertation, access to healthcare was evaluated by a structural measure, usual source of care. The definition of having a usual source of care is based on respondent self-report for the following question in the MCBS: “Is there a particular medical person or a clinic (you/SP) usually go to when (you are/he is/she is) sick or for advice about (your/his/her) health?”

Site of usual source of care include: (1) doctor’s or group practice office; (2) clinics (doctor’s clinic, neighborhood or family health center, rural health clinic, company clinic, other clinic, and hospital outpatient department); (3) Veterans Affairs (VA) facility; (4) HMO; and (5) other (freestanding surgery center, walk-in urgent care center, at home, hospital emergency room, mental health center and other). Here, HMO may include private insurance plan through an HMO.
A dummy variable (0/1) was generated for having a usual source of care. When people responded “yes” to the question mentioned above, they were defined as having a usual source of care (USOC = 1, otherwise USOC = 0). If the site of usual source of care was the other category (category 5 above), then it was identified as not having a USOC (USOC = 0) in the statistical analyses.

(3). Ambulatory Care Visit

An ambulatory care visit (hospital outpatient visit or physician office visit) was defined using the summary variables in the MCBS data for the utilization of services rendered and reimbursed under traditional fee-for-service Medicare in each calendar year using Medicare claims. A physician office visit was identified by the Healthcare Common Procedure Coding System (HCPCS) codes in the series 90000-90090 and 99201-99215 in the Part B line item trailer groups. If an individual had one or more hospital outpatient visit bills and/or one or more physician office visits in the past year then s/he was identified as having at least one ambulatory care visit in the last 12 months. A dummy variable was then generated for use or no use. In Specific Aim 4, four dummy variables were generated for 4 categories of number of ambulatory care visits (0-6, 7-12, 13-18, 19+).

Only ambulatory care visits were considered here because older adults are most likely to go to primary care settings for their health problems (Cooper-Patrick, 1999). Only community-dwelling participants were included in the present study, and usual source of care was restricted to ambulatory care. Other kinds of health services use (for example, inpatient services and home health care) were excluded from the analysis.
Ambulatory care visits analyzed here included any ambulatory visits. They were not limited to mental health visits. Chronic conditions including both mental and physical health problems are prevalent among the elderly. Older adults experiencing mental disorders such as major depression are more likely to experience general medical conditions (such as congestive heart failure, myocardial infarction, diabetes, stroke, cancer, dementia, and urinary incontinence) (Shine, 1997; Reynolds, 1998). In addition to improving physical health, treatment of physical health problems can improve people’s mental health status (Spiegel et al., 1999).

(4). Quality of Mental Healthcare

The quality of mental healthcare studied here was evaluated by two measures: (1) physician recognition of mental health problems among people with mental health needs; and (2) communication about mental disorders between physician and patient when patients were recognized by the physician as having mental health problems.

Physician recognition was identified when either one of the following conditions was met: (1) physician diagnosis based on ICD-9 codes (see section of depression measure) in Medicare claims; (2) treatment for depressive symptoms, i.e. self-report of antidepressants use in the MCBS (see Appendix A). Outpatient treatments for depression include prescription drugs, psychotherapy, and electroconvulsive therapy (ECT). Only antidepressants were considered here because the other two types of treatment are almost impossible to receive without a physician diagnosis (ICD-9 codes).
Communication about mental disorders between physician and patients among patients who were recognized as having mental health problems was defined as a dummy (0/1) by the following question in MCBS: “Since a year ago, did a doctor tell (you/SP) that (you/he/she) had a mental or psychiatric disorder, including depression?”

3.4.2.2 Independent Variables

Independent variables are factors contributing to disparities in mental health needs, access to care and quality of mental healthcare (see Table 3.2). Independent variables were categorized into three levels, i.e. individual factors, community factors, and healthcare system factors.

Racial/ethnic disparities in depression prevalence

To test Hypothesis 1, in order to compare depression prevalence across different measures common risk variables in the MCBS and the NESARC data were controlled for to estimate the “pure” racial/ethnic effect. A “pure” effect is defined as the differences in depression prevalence across racial/ethnic groups based on the distribution of population characteristics of a standard population. Those variables include demographic characteristics (age, gender, race, marital status, living arrangement, number of children, and Metropolitan Statistical Area [MSA] status), socioeconomic characteristics (education, income, and health insurance), and health status (self-rated health, chronic conditions, and BMI) and health behaviors (smoking).
Racial/ethnic disparities in access and quality of care

Based on Andersen’s Behavioral Model, enabling, predisposing, and need factors along with system characteristics work together to determine people’s healthcare access and use.

Predisposing factors: Age, gender, race, marital status, living arrangement, and number of children

Enabling factors: Education, income, health insurance, MSA status

Need factors: Self-reported health, chronic conditions, and disability (ADLs, IADLs).

System characteristics: availability of health professionals, convenience to care

Effect of access to care on healthcare utilization and prevalence of screened depression

Similar to Question 2, independent variables were constructed based on the Andersen’s Behavioral Model. Predisposing factors include age, gender, race, marital status, living arrangement, and number of children; Enabling factors include education, income, health insurance; Need factors included self-reported health, chronic conditions, and disability (ADLs, IADLs); System characteristics include availability of health professionals, and convenience to care. As mentioned above, it is important to control for potential endogeneity among USOC, healthcare use, and/or health status. A simultaneous-equations model was used for Question 3 (see Section 3.4.3.2). Restriction exclusions were required for the identification of the simultaneous-equations model mentioned below. In this dissertation, two variables were included as the restriction exclusions in the USOC equation and the ambulatory care use equation: (1) primary care practitioner shortage area; and (2) percentage of residents with mean travel time of 45
minutes or more to work for people aged 16+ at the county level. These variables are associated with having a usual source of care and ambulatory care visits, but are not directly associated with people’s mental health status (depression) among the elderly.

The shortage of primary care practitioners (PCPs) is assumed to affect people’s health indirectly by acting as a barrier to access care and/or resulting in lower quality of care. No direct correlation between health professional distribution and people’s health status has been found (CHWS, 2006). Travel barriers have been found to be related to lower healthcare utilization, such as lower number of visits among people with depression (Fortney et al., 1999). Average amount of travel time to work for people aged 16+ is a general proxy for the inconvenience of transportation and barriers to access care in a county (Hillemeier et al., 2003). It is argued that the average amount of travel time indirectly affects people’s mental health through healthcare access and use.

A geographic area was designated as having a shortage of primary medical care professionals if the following three criteria are met: (1) It is a rational area for the delivery of primary medical services; (2) One of the following conditions prevails within the area: The area has a population to full-time-equivalent primary care physician ratio of greater than 3,000:1 and has unusually high needs for primary care services, or it has insufficient capacity of existing primary care providers; (3) Primary medical care professionals in contiguous areas are overutilized, excessively distant or inaccessible to the area population under consideration (Health Resources and Services Administration, 2002).

*Racial/ethnic disparities in quality of mental healthcare*
In addition to the independent variables included in the analysis for Question 3, USOC and number of ambulatory care visits in the past year were included in the analysis for Question 4. A USOC and higher number of visits are associated with better physician-patient relationship, which may affect the outcome. Clinical variables such as length of visit time are missing in the dataset used. This limitation will be discussed in Chapter V.

<table>
<thead>
<tr>
<th>Table 3.2 Definitions of Independent Variables</th>
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<tbody>
<tr>
<td>Variable</td>
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<tr>
<td>Individual level</td>
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<tr>
<td>Calendar year</td>
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<tr>
<td>Demographic</td>
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<td>Gender</td>
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<td><strong>Medicare Supplementary insurance</strong></td>
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<td><strong>Community level</strong></td>
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<tr>
<td><strong>System level</strong></td>
</tr>
</tbody>
</table>
3.4.3 Analytical Models

3.4.3.1 Descriptive Analysis

Univariate analyses were used to describe population statistics: frequency, mean, standard deviation, median, 95% confidence interval (CI), missing data, and extreme values.

3.4.3.2 Statistical Analysis

The Chi-square test, t-test, and analysis of variance (ANOVA) were used to test the distribution of categorical and continuous variables across race and ethnicity.

Multiple regression analysis: Weighted logistic and probit models, trivariate probit models, and bivariate probit were applied to test the hypotheses in this dissertation. Complicated sampling design was taken into consideration in all the analyses. STATA 8.2 was used for the analysis.

Specific Aim 1

Weighted logistic model was used to test Hypothesis 1.1. The total study sample was used as a standard population to estimate the “pure” race/ethnicity effect. Common variables in the NESARC and the MCBS were controlled in the model, including age, gender, race, education, annual income, supplementary Medicare insurance, rural/urban, living alone, marital status, number of children, comorbidity, BMI, and smoking. A dummy variable was generated to indicate having any comorbidity.

\[
Y_i^* = \beta_0 + \beta_1 X_{ij} + \beta_2 \text{race}_i + \beta_3 \text{year}_i + \varepsilon_i
\]  

(1)

Where
i indexes individual,

j indexes the year of information observed,

$Y_{ij}^*$ is the probability of having depression for person i in year j,

X is the vector of individual characteristics,

Race is the race and ethnicity of individual i,

Year is the dummy variable for the year the survey was conducted,

$\varepsilon$ is the random error in explaining $Y_{ij}^*$.

$Y_{ij}^*$ is an unobserved (latent) variable for the probability of having mental health needs.

For example, although we do not observe $Y_{ij}^*$, we do observe whether each individual screened positive for depression or not based on the two-item screen. The observed form $Y$ takes two forms:

$Y_i = 1$ if $Y_{ij}^* > 0$

$= 0$ if $Y_{ij}^* \leq 0$

Therefore, $\text{Prob}(Y_i = 1) = \text{Prob}(Y_{ij} > 0) = \text{Prob}(\varepsilon_i > -\beta_iZ_i) = 1 - F(-\beta_iZ_i) = F(\beta_iZ_i)$, where $Z_i$ is a vector of independent variables and $F(.)$ is the cumulative distribution function for $\varepsilon_i$. I assume $\varepsilon_i$ logistically distributed.

$$F(-Z_i\beta_i) = \frac{\exp(-Z_i\beta_i)}{1 + \exp(-Z_i\beta_i)}$$

Sensitivity analyses were conducted to examine whether the results vary using different study subsamples including: (1) sample met the inclusion criteria; (2) sample met the inclusion criteria excluding people reported dementia; (3) sample met the
inclusion criteria excluding residents in Puerto Rico; (4) sample met the inclusion criteria excluding residents in Puerto Rico and people with dementia.

**Specific Aim 2**

A weighted logistic regression model was used to estimate disparities in access to care (having a usual source of care) across racial/ethnic groups, controlling for potential risk factors at the individual and system levels. A standardized population was used to estimate the pure racial/ethnic effect.

\[
Y_{ij}^* = \beta_0 + \beta_1 X_{ij} + \beta_2 PCP\text{ shortage}_i + \beta_3 \text{race}_i + \beta_4 \text{year}_{ij} + \epsilon_{ij}
\]  

(2.1)

The marginal differential effects (interactions) between race and supplementary Medicare insurance and between race and shortage area for primary care physicians were tested. 1) Supplemental Medicare insurance: Minorities are much less likely to have supplemental Medicare insurance compared with whites (DHHS, 1989). Individuals at risk for mental health problems are less likely to have health insurance (Sturm et al., 2000). Also, minorities with fewer financial resources are at higher risk for distress (Kaiser Foundation, 2008). 2) Primary Care Physician (PCP) shortage: Minorities are more likely to live in a PCP shortage area (GAO, 2002), so PCP shortage areas will have a disproportionately higher effect among minorities compared with whites. 3) Convenience to care: similarly, minorities are more likely to reside in areas with longer travel time (or lower convenience to care). Longer travel time has been to be associated with less access and use (GAO, 2006).

\[
Y_{ij}^* = \beta_0 + \beta_1 X_{ij} + \beta_2 PCP\text{ shortage}_i + \beta_3 \text{race}_i + \beta_4 \text{year}_{ij} + \beta_5 \text{race}_i \times \text{PCP shortage}_i + \\
+ \beta_6 \text{race}_i \times \text{insurance}_{ij} + \beta_7 \text{race}_i \times \text{convenience}_i + \epsilon_{ij}
\]  

(2.2)
Where

\(i\) is individual,

\(j\) is the year of information observed,

\(Y_{ij}^*\) is the probability of having a usual source of care for person \(i\) in year \(j\).

\(X\) is the vector of individual characteristics,

\(PCP_{shortage}\) is the dummy variable for shortage area of PCPs

\(Race\) is the race and ethnicity of individual \(i\),

\(Year\) is the dummy variable for the year survey was conducted,

\(race*PCP_{shortage}\) is the interaction term between race and PCPshortage,

\(race*insurance\) is the interaction term between race and Medicare supplemental insurance,

\(race*convenience\) is the interaction term between race and convenience to care,

\(\epsilon\) is a random error in explaining \(Y_{ij}^*\).

Sensitivity analyses were conducted using different subsamples: (1) a sample based on the inclusion criteria, (2) a non-demented inclusion sample, and (3) an inclusion sample excluding people that used a proxy during the survey.

**Specific Aim 3**

To test the effect of having a usual source of care on the prevalence of screened depression, one strategy for addressing this issue would be to apply a single-equation weighted logistic model. I began with such a model, given by

\[
Depression_{ij}^* = \alpha_iUSOC_{ij} + \alpha_2visit_{ij} + X_{ij}\beta + \epsilon_{ij}
\]

\(Depression^* = 1\) if \(Depression^* > 0\), \(Depression = 0\), if otherwise
where $i$ indexes individuals,

$j$ indexes the calendar year,

$Depression^*$ is a latent variable, the propensity to be screened positive for depression,

$Depression$ is the observed status of screened depression,

$USOC$ is an indicator for having a usual source of care in the past year,

$visit$ is an indicator for having at least one ambulatory care visit,

$X$ is a vector of observable characteristics and a constant, and

$\varepsilon$ is the error term.

As mentioned above, it is possible that unobservable individual- or system-specific characteristics may jointly affect having a usual source of care, health care utilization and/or screened depression. For example, people who live in a community of low socioeconomic status (such as a neighborhood with a high poverty or crime rate) may be less likely to have a usual source of care due to a shortage of health professionals and may be more likely to develop depression due to living in a disadvantaged environment. Failure to account for this endogeneity could lead to biased estimation of the effect of $USOC$ on the prevalence of screened depression. Consequently, the Geweke-Hajivassiliou-Keane (GHK) simulator technique (Tarrecol, 2002) was applied and a simultaneous-equations model is developed in which the error terms were allowed to be correlated across equations in order to take account of unobserved endogeneity.

Evaluation of the likelihood function requires the computation of trivariate normal integrals. The GHK technique relies on a trivariate normal distribution of the error terms.

In this model, having a usual source of care directly affects having at least one ambulatory care visit and – through the ambulatory care visit equation – has an indirect
effect on being screened positive for depression, and also has a direct effect on being screened positive for depression in the depression equation. It is assumed that a usual source of care is a resource for social support for elderly people. Older adults have a high demand for healthcare services and having a usual source of care may be associated with a lower stress level compared with those without a usual source of care. Depression was not included in the usual source of care equation because in theory coping resources (such as a usual source of care) may be unchanged by exposure to stress (Kaplan, 1996).

Given this, the following trivariate probit model was used:

\[ USOC_i^* = \beta_1 X_{ij} + \beta_2 \text{race}_{ij} + \beta_3 \text{pcpshortage}_{ij} + \beta_4 \text{timetowork}_{ij} + \epsilon_{1ij} \]

\[ \text{Visit}_{ij}^* = \gamma X_{ij} + \gamma_2 \text{race}_{ij} + \gamma_3 \text{timetowork}_{ij} + \gamma_4 \text{PCPshortage}_{ij} + \gamma_5 \text{USOC}_{ij} + \epsilon_{2ij} \]  \hspace{1cm} (4)

\[ \text{Depression}_{ij}^* = \kappa X_{ij} + \kappa_2 \text{race}_{ij} + \kappa_3 \text{USOC}_{ij} + \kappa_4 \text{Visit}_{ij} + \epsilon_{3ij} \]

Where

- \( i \) indexes individuals,
- \( j \) indexes the calendar year,
- \( USOC^* \) = the latent variable propensity to have a usual source of care,
- \( USOC = 1 \) if \( USOC^* > 0 \) observed having a usual source of care, otherwise, \( USOC = 0 \),
- \( X \) are common variables for individual characteristics (demographic, socioeconomic characteristics, and health status) and a constant,
- Race is the race and ethnicity of individual \( i \),
- \( \text{PCPshortage} \) = shortage area for primary care physicians,
- \( \text{timetowork} \) = percentage of residents with a mean time of 45 minutes or more traveling to work among people aged 16+ at the county level,
- \( \text{Visit}^* \) = the latent variable propensity to receive ambulatory visit; \( \text{Visit} = 1 \) if \( \text{Visit}^* > 0 \) observed having at least one ambulatory visit; otherwise, \( \text{Visit} = 0 \),
Depression* = the latent variable propensity to have screened depression,

Depression = 1 if Depression* > 0 observed screened depression; otherwise, Depression = 0,

Γ, κ, and β are vectors of coefficients.

E[ε₁] = E[ε₂] = E[ε₃] = 0

Cov[ε₁, ε₂] = ρ₁₂, Cov[ε₁, ε₃] = ρ₁₃, Cov[ε₂, ε₃] = ρ₂₃

σ₁ = σ₂ = σ₃ = 1

The error terms were assumed to have a trivariate normal distribution.

ρ is the correlation between the pair-wised unobserved explanatory variables. If ρ₁₂ = ρ₁₃ = ρ₂₃ = 0 can be rejected, this implies that the equations need to be estimated as a system. This possibility was tested using a likelihood ratio (LR) test.

The likelihood ratio is the ratio of the maximum probability of a result under two different hypotheses. Let L₁ be the maximum value of the likelihood of the data without the additional assumption. In other words, L₁ is the likelihood of the data with all the parameters unrestricted and maximum likelihood estimates substituted for these parameters. Let L₀ be the maximum value of the likelihood when the parameters are restricted (and reduced in number) based on the assumption. Assume k parameters were lost (i.e., L₀ has k less parameters than L₁). Form the ratio \(\lambda = L₀/L₁\). This ratio is always between 0 and 1 and the less likely the assumption is, the smaller \(\lambda\) will be. \(\chi^2 = -2 \ln \lambda\). The likelihood ratio test computes \(\chi^2\) and rejects the assumption if \(\chi^2\) is larger than a Chi-Square percentile with \(k\) degrees of freedom, where the percentile corresponds to the confidence level chosen by the analyst.
Convenience to care (travel time to work) and shortage area for PCPs identify the USOC regression and the ambulatory visit regression from the depression regression, and ensure that the results do not merely depend on the distributional assumptions imposed on the error terms. If no reasonable exclusion restrictions in a simultaneous-equations model, it may be that the system fails the autonomy requirement (Wooldrige, 2001).

For ease of interpretation, the incremental effect (calculated at means) and the standard error (calculated using the delta method) of having a usual source of care on ambulatory care use and being screened positive for depression, and the incremental effect and the standard error of having at least one ambulatory care visit on being screened positive for depression were calculated to test the impact on the probability of observing a change in being screened positive for depression. The delta method is a method for deriving an approximate probability distribution for a function of an asymptotically normal statistical estimator from knowledge of the limiting variance of that estimator. The delta method, in its essence, expands a function of a random variable about its mean, usually with a one-step Taylor approximation, and then takes the variance (Feiveson, 2005). For example, if we want to approximate the variance of G(X) where X is a random variable with mean mu and G() is differentiable, we can try

\[ G(X) = G(mu) + (X-mu)G'(mu) \] (approximately)

so that

\[ \text{Var}(G(X)) = \text{Var}(X)[G'(mu)]^2 \] (approximately)

where G'(\(\cdot\)) = dG/dX. This is a good approximation only if X has a high probability of being close enough to its mean (mu) so that the Taylor approximation is still good.
This idea can easily be expanded to vector-valued functions of random vectors,

$$\text{Var}(G(X)) = G'(\mu) \text{Var}(X) [G'(\mu)]^T$$

and that in fact is the basis for deriving the asymptotic variance of maximum-likelihood estimators. In the above, $X$ is a $1 \times m$ column vector; $\text{Var}(X)$ is its $m \times m$ variance–covariance matrix; $G()$ is a vector function returning a $1 \times n$ column vector; and $G'(\cdot)$ is its $n \times m$ matrix of first derivatives. $T$ is the transpose operator. $\text{Var}(G(X))$ is the resulting $n \times n$ variance–covariance matrix of $G(X)$.

Sensitivity analysis using different model specifications (with one or two restriction exclusions and without restriction exclusion) and F-test (a ‘rule-of-thumb’ that helps determine whether exclusion restrictions are relevant or not. If the F-test value exceeds 10 then the instrument could be taken highly relevant.) were applied to test the validity of the exclusion restrictions. Likelihood ratio test was also used to test the goodness-of-fit between models (one with the two exclusion restrictions and one without any restriction exclusion).

**Specific Aim 4**

**Hypothesis 4.1**

A multivariate logistic model was applied to test whether there are disparities in physician recognition of mental health problems among people who screened positive for depression and at least one ambulatory care visit in the last year. An interaction term between race/ethnicity and USOC was included in the model because USOC should be
associated with better communication, less stigma and increased physician recognition. Minorities are disproportionately less likely to have a USOC and more limited English proficiency. Having a USOC is more important for minorities to have better communication with physicians and get accurate recognition compared with non-Hispanic whites. USOC defined in this dissertation is places where people regularly receive healthcare services. I had no information on whether this is a specific provider or not. I assumed that people with a USOC are more likely to have a stable relationship with a healthcare provider and are more likely to receive an accurate diagnosis compared with those without a USOC.

\[ Y_{ij}^* = \beta_0 + \beta_1 X_{ij} + \beta_2 \text{race} + \beta_3 \text{year}_{ij} + \beta_4 \text{nvisits}_{ij} + \beta_5 \text{USOC}_{ij} + \beta_6 \text{race}^* \text{USOC}_{ij} + \varepsilon_{ij} \]  

(5)

Where

i indexes individual,

j indexes the year of information observed,

\( Y_{ij}^* \) is the probability of physician recognition for person i in year j,

X is the vector of individual characteristics,

Race is the race and ethnicity of individual i,

year is the dummy variable for the year the survey was conducted,

nvisits is the number of ambulatory care visits in the past year,

USOC is the dummy variable for having a usual source of care or not,

race*USOC is the interaction term between USOC and race,

\( \varepsilon \) is the random error in explaining \( Y_{ij}^* \).

Sensitivity analysis was done by defining physician recognition of depression as:

(1) antidepressants use only; (2) depression diagnosis only; (3) either depression diagnosis or antidepressants use.
There may be unobserved factors affecting both healthcare utilization and physician recognition among people screened positive for depression (such as stigma and belief in health and healthcare). A seemingly unrelated bivariate probit model was also used to examine the differences in physician recognition of depression among people screened positive for depression, with one equation for ambulatory care visit and another equation for physician recognition. Area shortage for primary care physicians and convenience to care were included in the ambulatory care visit equation but not in the physician recognition equation. Number of ambulatory care visits was controlled for in the physician recognition equation.

**Hypothesis 4.2**

The probability of physician-patient communication about mental disorders for people recognized by physicians as having depression was examined to test whether there are disparities in quality of mental healthcare across racial and ethnic groups. Unobserved characteristics at the patient and provider levels (such as stigma, stereotype, and discrimination) may affect physician recognition of mental health problems and physician-patient communication about them at the same time, so a seemingly unrelated bivariate probit model was used to allow for the correlation between the error terms of those two equations. A set of equations that has contemporaneous cross-equation error correlation is called a seemingly unrelated regression (SUR) system (Greene, 2003). I modeled the joint outcome \((Y_1, Y_2)\) using two marginal probabilities for each dependent variable, and the correlation parameter \(\rho\), which describes how the two dependent
variables are related. The stochastic component is described by two latent (unobserved) continuous variables which follow the bivariate normal distribution:

\[
\begin{pmatrix}
Y_1^* \\
Y_2^*
\end{pmatrix}
\sim N_2\left(\begin{pmatrix}
\mu_1 \\
\mu_2
\end{pmatrix}, \begin{pmatrix}
1 & \rho \\
\rho & 1
\end{pmatrix}\right)
\]

where \(\mu_i\) is a mean for \(Y_j^*\) and \(\rho\) is a scalar correlation parameter. The following observation mechanism links the observed dependent variables \(Y_j\) with these latent variables

\[
Y_j = \begin{cases} 
1 & \text{if } Y_j^* \geq 0, \\
0 & \text{otherwise.}
\end{cases}
\]

Given this, I adapt the model as follows:

\[
\begin{align*}
\text{phyrecog}_i &= 1(Y_{1ij}^* > 0) = \beta_1 X_{ij} + \beta_2 \text{race}_{ij} + \beta_3 \text{USOC}_{ij} + \beta_4 \text{nvisits}_{ij} + \beta_5 \text{year}_{ij} + \varepsilon_{ij} \\
\text{communication}_i &= 1(Y_{2ij}^* > 0) = \gamma_1 X_{ij} + \gamma_2 \text{race}_{ij} + \gamma_3 \text{USOC}_{ij} + \gamma_4 \text{nvisits}_{ij} + \gamma_5 \text{year}_{ij} + \varepsilon_{2ij}
\end{align*}
\]

(6)

Where

i indexes individual,

j indexes the year of information observed,

phyrecog is the probability of physician recognition,

X is the vector of individual sociodegrphic characteristics,

Race is the race and ethnicity of individual i,

USOC is the dummy variable for having a usual source of care,

nvisits is the number of ambulatory care visits in the past year,

communication is the dummy variable of physician communication about mental disorders,

Year is the dummy variable for the year the survey was conducted,
$\varepsilon_{ij}$ is a random error in explaining $Y_{ij}^*$.

$E[\varepsilon_1] = E[\varepsilon_2] = 0$

$\text{Cov}[\varepsilon_1, \varepsilon_2] = \rho$

$\sigma_1 = \sigma_2 = 1$