ADDIS ABABA UNIVERSITY
SCHOOL OF GRADUATE STUDIES
FACULTY OF SCIENCE
DEPARTMENT OF STATISTICS

Predictors of Burden on caregivers of patients of Schizophrenia and Bipolar disorder: the case of Butajira, Ethiopia

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July, 2008

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A Thesis submitted to the Office of Graduate Programs of Addis Ababa
University for the partial fulfillment of the requirement for the Degree of
Master of Science in Applied Statistics

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ABSTRACT

The aim of the study was to investigate the prevalence and nature of the objective burden experienced by caregivers of schizophrenia and bipolar disorder patients. Also to compare the results from the two statistical methods, polytomous logistic regression and discriminant analysis in correctly classifying and selecting important explanatory variables of burden on caregivers in psychiatric patients. A total of 514 patients were included in this study. Burden on the caregivers was assessed in terms of how much the caregiver's life was affected by the presence of the illness in the family. Results indicate that 36.5% of the caregivers experienced no burden, whereas 36.9% of them experienced moderate burden. The polytomous ordinal logistic regression classified 67.2% of the caregivers in their respective burden group, whereas the discriminant analysis classified 64.7% of the caregivers correctly. The polytomous ordinal logistic regression shows a slight improvement in correctly classifying caregivers over multiple discriminant analysis. Based on the findings of the present study we conclude that high burden on the caregivers is significantly characterized by dependency status of the patient, emotional helps given to the care giver from the society, negative and positive symptom of the patient. The results call for more attention to be given to reduce patients' positive and negative symptoms, to create awareness in the society to give emotional helps to the caregivers and to economically support the patients so as to minimize their dependency on their caregivers.

ACKNOWLEDGEMENT

Thanks to the Almighty GOD for all He has done for me. First and for the most, I owe a lot to my advisor, Dr. Fentaw Abegaz. He taught me research at the best. It has been a great pleasure and experience to work under his guidance and get his support, encouragement and a share of his wisdom. I also would like to thank him for his many valuable comments and suggestions on the whole improving the quality and readability of my dissertation. I would also like to thank all colleagues from department of Statistics, accounting for the nice working environment. Also I would like to thank my department, 'Department of Statistics' for giving me opportunity to study. My thank goes to all the staff members of the Butajira project of the course and outcome of Schizophrenia and Bipolar disorder and my co-advisor Dr. Teshome Shibre. Of course, I cannot forget to thank my brother Tekle Wakwaya for his invaluable support by providing me Laptop computer.

Finally, I have to say `Thank you' to all my friends and family. They have given me strength during my research work. Therefore this dissertation is also part of their work. I might not always show it, but I really appreciate their interest, support and involvement in everything I do. They are the best!
To end, "Thank you" everyone for every support you gave and ever will give!

Merga Belina
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July, 2008

CHAPTER ONE

INTRODUCTION

1.1 Background

Mental health is a term used to describe either a level of cognitive or emotional wellbeing or an absence of a mental disorder. From perspectives of the discipline of positive psychology or holism, mental health may include an individual's ability to enjoy life and procure a balance between life activities and efforts to achieve psychological resilience. In low income countries where malnutrition and infectious diseases are common, mental disorders, which are regarded as non life-threatening, are given very low priority. Research on the burdens experienced by families caring for a mentally ill member originated in the 1950s with the implementation of conventional antipsychotic treatments enabling more patients to be reintegrated into their family units (Platt, 1985). Mental health problem contribute 8.1% to the global burden of disease as estimated by World Bank (Atalay, 2006); whereas in low income countries, mental disorder contributes 12 % of global burden of disease. Consistent with this finding, a recent study in Ethiopia showed that Mental illness contributes over 12 % of the burden (Atalay, 2006). Although the burden of illness resulting from psychiatric and behavioural disorders is enormous, it is grossly under represented by conventional public health statistics, which have tended to focus on mortality rather than morbidity or dysfunction.

Some Ethiopians believe that mental illnesses are afflictions caused by supernatural forces, and traditional methods are the most frequently used treatments to individuals who develop mental illness. There is very little demand for health research for planning interventions. Ethiopia is not exception to this. However, there have been thriving epidemiological research activities in various population groups (Atalay, 2006). Mental health disorders are classified into groups with some overlap. The major groups of disorders as they are classified are: anxiety, bipolar, borderline personality, depression, obsessive-compulsive, phobic, narcissistic, schizophrenic, substance abuse, and eating disorders (Kaplan and Sadock's, 2003).

This thesis focuses on two of the more common and devastating ones, Schizophrenia and Bipolar disorder. Sometimes people confuse two mental disorders, only one of which could be referred to as "common" within the population — bipolar disorder (also known as manic-depression), and schizophrenia. This confusion has largely resulted from the common use of some of these names in popular media, and as short-hand by people referring to someone who is grappling with a mental health issue. The disorders, however, have little in common other than the fact that many who have them are still stigmatized by society.

Bipolar disorder is a fairly common mental disorder compared with schizophrenia. It is also well-understood and readily treated by a combination of medications and psychotherapy. It is characterized by alternating moods of mania and depression, both of which usually last weeks or even months in most people who have the disorder. People who are manic have a high energy level and often irrational beliefs about the amount of work they can accomplish in a short amount of time. During the manic phase of the disease, the person experiences a state of extreme euphoria (feeling good). During the depressive phase, the person becomes increasingly despondent and inconsolable (Kaplan and Sadock's, 2003).

On the other hand, Schizophrenia is less common than bipolar disorder and is usually first diagnosed in a person's late teens or early to late 20's. Hallucinations are seeing or hearing things that aren't there. Delusions are the belief in something that isn't true. People who have delusions will continue with their delusions even when shown evidence that contradicts the delusion. That's because, like hallucinations, delusions are "irrational" — the opposite of logic and reason. Since reason doesn't apply to someone who has a schizophrenic delusion, arguing with it logically gets a person nowhere (Kaplan and Sadock's, 2003).

Schizophrenia is a group of disorders characterized by some form of psychosis or disconnected thought processes. The symptoms associated with schizophrenia vary, and can affect thinking, behavior, and emotions. Schizophrenics suffer from delusions, hallucinations, and/or emotional unresponsiveness. Schizophrenia is also challenging to treat mainly because people with this disorder don't function as well in society and have difficulty maintaining the treatment regimen. Such treatment usually involves medications and psychotherapy, but can also involve a day program for people who have more severe or treatment-resistant forms of the disorder.

Because of the nature of the symptoms of schizophrenia, people with this disorder often find it difficult to interact with others, and conduct normal life activities, such as holding down a job. Many people with schizophrenia go off of treatment (sometimes, for instance, because a hallucination may tell them to do so), and end up homeless.

Schizophrenia has long been recognized as a devastating disorder for patients and their families. The burden on caregivers of patients with schizophrenia is enormous. The socioeconomic costs of patients with schizophrenia include the direct treatment costs, and indirect costs associated with lost earnings and family burden. The burden of having a schizophrenic patient in the family is not simply monetary. Life quality and psychiatric morbidity assessments of schizophrenic families may provide a measure of the non-monetary impact of the illness.

Schizophrenia, which afflicts approximately one percent of the world population, usually begins before the age of 25, persists throughout life, and affects persons of all social classes. Both patients and their families often suffer from poor care and social ostracism because of widespread ignorance about the disorder. The magnitude of the clinical problem of schizophrenia has consistently attracted the attention of major researchers in psychiatry and neurology throughout the history of the disorder (Kaplan and Sadock's, 2003).

Families of persons with mental illness witness the devastating effects of this disorder on their ill relative and struggle to manage their situation in a society that provides little assistance (Susan and Allan, 1995). Over the past 35 years, families of persons with severe and persistent mental illness have increasingly assumed caregiving responsibilities for their adult family members. Recent estimates indicate that between one-third and two-thirds of persons with long-term psychiatric disabilities currently reside with family members. Studies indicate that families are significantly affected by the responsibility of their caregiving function (Dennis, 1999).

The term family or caregiver burden commonly refers to the effects of the mental illness of one family member on the emotional well-being of other family members, as well as on the family members' use of time, finances, and general living conditions (Magliano, 2002). Although most studies of burden have focused solely on the challenges to families of caring for a mentally ill relative, research in schizophrenia has suggested that families' experiences of burden may have adverse repercussions for persons with the illness (Lowyck et al., 2002 and Schene et al., 1998).

The family caregiving burden of persons with severe mental illness includes financial responsibilities, missed work, disturbance of domestic routines, constraints on social and leisure activities, and reduced attention to other family members (Dennis, 1999). The financial strain due to medical costs and the patient's economic dependency are considerable Often family members forego work outside the home to provide care for the person with mental illness. In addition, behavioral problems of the patient contribute to the experience of burden, including frequent and intense arguments, withdrawal, bizarre behavior that is disturbing to neighbors, and threatened or actual harm to self or others. Also identified as sources of burden are a variety of household complaints about patient behavior, such as being noisy at night, failing to adhere to a regular time schedule, being generally uncooperative, refusing to do household chores, being verbally abusive, and making unreasonable demands The caregiver often suffers from severe mental and emotional drain, feels utterly defeated, and has feelings of anxiety, resentment, and anger, with stress being cumulative over time

The concept of family burden in schizophrenia refers to a wide range of social, financial, work and family related stress and psychological reactions that result from the impact of the illness. In Ethiopia, as in most developing countries, services which could help people who suffer from mental disorder are insufficient; thus families are the sole care givers to their severely mentally ill relatives. While understanding the magnitude of the family burden and coping strategies is important to plan family intervention programmes, very little is known about the extent of relatives' care giving-related distress in Ethiopia (Atalay, 2006).

A naturalistic, prospective study by Perlick and colleagues (Perlick *et al.,* 2007) recently demonstrated that patients with bipolar disorder were more likely to meet criteria for a major affective episode at the 15-month follow-up when their families reported higher levels of burden during the patients' acute episode at baseline. This finding remained significant when the analysis controlled for the baseline symptom level. Earlier studies that used two symptom dimensions indicate that the caregiver burden for patients with schizophrenia is significantly determined by their negative symptoms. Personal traits, tension, distress and disorganized symptoms were found to predict the caregiver burden (Wolthaus *et al.*, 2002).

Schizophrenia is a severe mental illness, which is stressful not only for patients, but also for family members. Providing care to family members dealing with chronic illness may result in feelings of burden or strain for caregivers that can diminish their quality of life. Numerous studies have demonstrated that family caregivers of persons with a severe mental illness suffer from significant stresses, experience moderately high levels of burden, and often receive inadequate assistance from mental health professionals (Stanley and Shwetha, 2006).

We can classify family burden into two main categories as subjective burden and objective burden. It is important to distinguish between caregivers' experience of this subjective burden and objective burden as externally appraised. Caregivers' previous experiences of health services may influence their beliefs about the illness. A distinction between objective and subjective burden was made and have been subsequently used. Objective burden has been defined as the observable concrete costs to the family resulting from the mental illness, such as disruption to everyday life in the household, financial problems, limitations on personal activities, and social interactions. Subjective burden has been defined as the individual personal appraisal of the situation and the extent to which caregivers perceive they are carrying a burden (Hoening and Hamilton, 1966).

In identifying unit attributes of interest we need to keep in mind not only which variables to measure but also how to measure them. Agreement about what constitutes burden is limited and some have suggested abandoning the term altogether (Szmukler et al, 1996).When the term is used there are differences of opinion regarding how to sub-classify and measure it adequately. Different variables in subjective and objective burden (social stigma, dependency, marital disharmony, financial stress, physical abuse) might have different levels of impact on different care-givers, and the outcome of that stress might not be the same for all individuals. Perhaps because of these disagreements there is a wide variety of burden instruments used in research. These have been reviewed by Platt (1985) and more recently by Schene et al (1994). These reviews make three broad points:-

(a) There is no agreement on the definition of the term burden;

(b) There is more or less an agreement on the dimensions that comprise burden; and

(c) There is a need for further work to establish adequate psychometric properties of reliability and validity for the various scales used to measure burden. It is possible to identify certain key dimensions of burden that have been assessed.

These key dimensions are:-

Symptom-specific burden- impact of the disability associated with the illness itself, both in terms of demands for assistance and supervision, and regarding the potential stigma associated with the illness.

*Social burden-*refers to impact on family and other social relationships.

Emotional burden- refers to impact on mental and emotional well-being.

Financial burden- refers to impact on work and the general financial costs of care-giving.

By social burden it means that living with a relative who has a major mental illness has a severe impact on the care-giver's social and leisure activities. Social contacts can be reduced and care-givers can find themselves becoming increasingly isolated. A relative may perceive psychiatric illness as a stigma and might not mix with others, or the ill relative's behavioural disturbance might make socialization difficult. This is viewed by many relatives as a burden, as their own leisure activity sometimes cannot be undertaken (Vaddadi, 1997). In other cases the patient ceases to go out, imposing further limitations on the social life of their partner. The patient may contribute very little to household tasks and their contribution may not be welcome because their relative feels that any tasks performed simply add to their own work. Quarrels and tension over domestic responsibilities may lead to an oppressive atmosphere within the home. This in turn can lead to the gradual erosion of visits from friends, neighbours and other family members.

The other dimension of burden is emotional burden; relatives of mentally ill people make great sacrifices in their role as care-givers. They tend to tolerate disturbed behaviour and rarely complain. The feelings and conflicts produced by their caregiving responsibilities can have considerable impact. Worry about what will happen when they die or become too frail to help can affect older care-givers and some family members can experience a sense of guilt or feel that they are to blame for their relative's illness .

Financial burden is one of the dimensions of burden on caregiver due to having a mentally ill family member. Mental illness imposes an economic as well as a social cost to individuals, and to their families. Sometimes, a care-giver has to give up work to look after their ill relative. It is not uncommon for parents of an adult with schizophrenia to bail him or her out of debt. When parents as care-givers are elderly and on a pension, this can lead to poverty, social isolation, poor dietary habits, overcrowding (when a schizophrenic child returns home) and lack of leisure activities.

The other dimension of burden is symptom-specific impact; there are several psychiatric symptoms, especially in people suffering from schizophrenia, that their care-givers find it difficult to deal with and which cause them to feel distressed and helpless. Behavioural disturbance, physical and verbal abuse, threatening and other dangerous irresponsible behaviour, are commonly found in schizophrenia and bipolar disorder. Relatives show a surprising tolerance to disturbed behaviour. However, they reach a point of distress at which even they cannot continue coping with it. Relatives find aggressive behaviour, delusions, confusion, lack of self-care, apathy, anhedonia and extreme reclusiveness very burdensome (Hoening & Hamilton, 1966).

How do researchers measure burden? Researchers use questionnaire and with questions related to symptom and social behavior of the patients and socio-demographic characteristics of the caregivers they try to see whether they suffer from caregiving burden. Deborah and his colleagues (Deborah, 2006) evaluated Family burden with an adapted version of the Family Experience Interview Schedule (FEIS) and by the help of Hierarchical regression analyses and Factor analysis they tried to identify correlates of burden. Moreover, Perlick et al (2007) used the Social Behavior Assessment Scale (SBAS), a semi-structured interview, to assess caregivers' experience of objective burden and mean scores of burden was used with Hierarchical multinomial logistic regression analysis to examine which characteristics contributed significantly to the classification of caregivers into the burden categories.

A substantial body of research has documented that up to 83 percent of friends and family members of people diagnosed as having schizophrenia experience considerable financial, emotional, and social burdens (Perlick *et al.,* 2007). They report time lost from work, unreimbursed medical and other patient-related expenses, limited time for leisure and socializing, elevated symptoms of psychological distress, and feelings of stigmatization as components of burden. In addition to its impact on caregiver quality of life, caregiving strain has been associated with other adverse effects, including poorer self-rated health, chronic medical conditions, or both; increased visits to a primary care physician ; greater use of psychotropic drugs, such as tranquilizers and antidepressants and increased risk of medical hospitalization.

Although theorists have identified multiple aspects of patient behavior that influence the caregiver's experience of burden, few studies have examined the impact of aspects of the patient's life and functioning other than his or her symptom level on caregiver burden. To our knowledge, no study has evaluated the association between patient quality of life and family burden in schizophrenia beyond the impact of symptoms in Ethiopia. To the extent that patients are optimally medicated with relatively stable symptom profiles, patients' quality of life, cognitive status, or both might carry greater prognostic weight than symptom measures. This difference might arise because patients who are more socially interactive outside the home, who have the cognitive capacity to be productively employed, and who have more satisfying interpersonal relationships with others, make fewer demands on the caregiver or present fewer subjective concerns or worries to him or her (Perlick *et al.,* 2007).

Caregivers of people with bipolar disorder may experience a different quality of burden than is seen with other illnesses. A better understanding of their concerns is necessary to improve the training of professionals working with this population. Conceptualizing caregiver burden in a conventional medical framework may not focus enough on issues important to caregivers, or on cultural and social issues. Perceptions of caregivers about bipolar disorder have important effects on levels of burden experienced.

1.2 Significance of the study

The purpose of this study is to examine the relationships among potential predictors of burden within a conception of burden as the objective consequences of providing ongoing care to a mentally ill relative. Caregiver burden is associated with depression, which affects patient recovery by adding stress to the living environment. Caregivers of bipolar patients have high levels of expressed emotion, including critical, hostile, or over-involved attitudes. In this study we deal with the objective burden on the caregiver.

Despite the importance of assessing caregiver burden in bipolar disorder, relevant literature is scarce. The specific effects of mania and inter-episode symptoms have not been adequately addressed, and there is a lack of existing measures to assess burden adequately, causing uncertainty regarding how best to structure family interventions to optimally alleviate burden. Clinically effective, well-targeted and practically viable interventions are needed. However, services cannot be enhanced on a rational basis without an improved understanding and capacity to measure and target caregiver burden and the impact of any change in services are evaluated. This study is important because it can be used to develop interventions, quality of care and effectiveness of interventions and also to investigate different aspects of family burden, need for support and participation in care situations specifically considering whether the relative and the patient are living together or apart. In addition it shows the statistical methods one prefers to use, based on the performance of the methods, in mental health researches.

Caregiver burden, particularly which closely involved family members such as parents, is important as an outcome measure in mental health care, so as to assess and reduce it for the well-being of both caregivers and the mentally ill. Indeed, the measurement of caregiver burden has been shown to enhance worker and administrator awareness of the need to reduce such burden in the health care field in general (Rudnick, 2004).

Based on previous theoretical and empirical findings, the study by Susan and Allan, (1995) examines the relationship between the content and consequences of caregiving, and the extent to which selected factors predict burden. Because people who suffer from mental illness often experience ongoing psychotic symptoms and impaired social functioning, the content of family caregiving includes dealing with disruptive behaviors and providing concrete and emotional support. Prior research documents family management of behaviors and the burden associated with this aspect of caregiving.

Although the stress paradigm predicts a direct relationship between burden and the amount of assistance that caregivers provide, there is little empirical evidence to support this relationship because caregiving behaviors are often confounded with the measurement of burden; while we view disruptive behaviors and social support as essential predictors of burden, there are several important factors that may affect the experience of burden. Among the most obvious but poorly understood factors is living arrangements. Many burden studies include only those family members who coreside with their ill relative (Susan and Allan, 1995).

1.3 Objectives

- ✓ To investigate the prevalence and nature of the burden experienced by care givers of bipolar and schizophrenia patients under the study.
- ✓ To study components and correlates of caregiver burden in schizophrenia and bipolar disorder.
- ✓ To describe the impact of caring for cases with schizophrenia and Bipolar disorder on relatives in terms of social leisure, family relation, work and financial burden in a traditional society.
- ✓ To compare the performance of polytomous logistic regression and discriminant analysis in correctly classifying and selecting important explanatory variables of burden on caregivers in psychiatric patients for the data under the study.

1.4 Application of the results

- The result of this study will forward the way family interventions and support can be done; in at least educating the family members about schizophrenia and bipolar disorder.
- It will also help to identify factors that ameliorate and/or exacerbate the degree of burden experienced by care givers of patients with bipolar disorder and schizophrenia.
- The result also serves to identify the models to be used with their respective conditions under which they are valid for the current data.
- The result will also help as a basis for further studies in this area.

1.5 Limitation of the study

- ♦ Since the sample size is not large enough for the proposed method of analysis, the study of caregivers' burden is not done for Schizophrenia and Bipolar disorder patients separately.
- ♦ In this research work we were unable to include exhaustively all the variables that are supposed to be predictors of burden on caregivers, instead we dealt with only the variables on which we have data at hand.
- ♦ Lack of literature on our country related to the subjects under the study.

CHAPTER TWO

LITERATURE REVIEW

2.1 Overall review

The schizophrenia research community has shared a belief that the incidence of schizophrenia shows little variation. However, there is now robust evidence that the incidence of schizophrenia is characterized by substantial variability. There is prominent variation in the incidence of schizophrenia between sites. The incidence of schizophrenia is significantly higher in males than in females (male: female ratio = 1.4). Migrants and those living in urban areas have a higher incidence of schizophrenia. The incidence of schizophrenia has fluctuations across time. In addition, the prevalence of schizophrenia is also characterized by prominent variation (McGrath, 2006). The realization that schizophrenia is characterized by rich and informative gradients will serve as a catalyst for future research.

Care for severely mentally ill individuals, particularly in the community, may carry a heavy burden, more so than care for other disabled individuals such as mentally retarded people. While this is true for any person involved in such care, it is particularly true for close family members such as parents, many of whom take care of their mentally ill children for long. Such burden manifests in reduced caregiver well-being, which admittedly depends in part on caregiver factors such as caregiving style. Moreover, such burden may manifest in reduced well-being of the mentally ill individuals themselves, for instance, due to impaired caregiver support (Rudnick, 2004).

Although caring for a relative with a major psychiatric disorder imposes some degree of burden on all caregivers, caregivers of patients with schizophrenia and dementia perceive varying rates of burden, ranging from 55% to 90% (Perlcik, 2007). Dementia is the loss (usually gradual) of mental abilities such as thinking, remembering, and reasoning. It is not a disease, but a group of symptoms that may accompany some diseases or conditions affecting the brain. Like schizophrenia, bipolar disorder is a chronic illness with early adult onset. In contrast to schizophrenia, bipolar disorder has a variable course characterized by recurrent episodes of depression. Therefore, the experiences and consequences of burden for caregivers of patients with bipolar disorder may differ from those of the caregivers of patients with schizophrenia (Perlcik, 2007).

A study was conducted on Israel family members of mentally ill individuals to evaluate a caregiver burden and association of caregiver burden with kinship relationship to the mentally ill individual. This problem was not assessed as nearly all participants (94%) were parents of mentally ill individual. On the other hand, the study showed that age was not associated with burden and females were more significantly burdened than males (Rudnick, 2004).

Several predictors of family burden are proposed by researchers at different times, for instance, distracted from activities, upset household routine, family frictions, reduced leisure time, changed plans, financial strain, reduced social contacts, neglect family members, missed work, frictions with others are variables identified as factors contributing to objective burden. Susan and Allan, based on data which stem from interviews with 163 parents and siblings of seriously mentally ill adults, found that most parents report at least some negative consequences of caregiving. The three most frequently reported areas of objective burden are distracted from activities (72%), upset household routines (64%), and family frictions (58%), (Susan and Allan, 1995).

According to the study by Dennis (1999), age of the caregiver and patient correlated inversely with burden, and male caregivers reported less burden than did female caregivers. Older caregivers also had fewer infectious illness episodes. Several demographic characteristics may also influence the meaning of caregiving and the burden experience. Some research indicates that ethnicity relates to both the content and the consequences of caregiving. Black caregivers, for example, appear to suffer lesser burden than Whites from equivalent levels of responsibilities this difference may be due to cultural factors that influence conceptions of disordered behaviors and functioning, as well as responsibilities to help manage these problems (Susan and Allan, 1995). This is not the case in our study since we are considering only one ethnic group.

Studies have provided consistent evidence that care-givers for persons with chronic mental illness suffer from a number of significant stresses and moderately high levels of burden; the care-giver is usually a relative of the ill person and the care given is invariably continuous. The care-giver often has additional responsibilities in the family and many of the ill recipients do not acknowledge or even recognize the assistance and help they are receiving. The care is given because of emotional bonding (capacity to love and a fierce need to protect; parents take on the role of provider, problem solver and advisor), duty, guilt (grief responses) and/or the lack of other available services in the community (Vaddadi, 1997).

A study from India shows that the majority of the caregivers were females (53.3%) and their age ranged from 23 to 75 years with a mean age of 54.9 years. While the majority of them were parents (76.7%), 16.7 per cent of the caregivers were spouses and the remaining (6.6%) were siblings of the patient. The majorities of the caregivers were married (70%) and had availed of basic school level education (Stanley and Shwetha, 2006).

The family caregiving burden perspective is that caring for a family member with severe mental illness imposes a caregiving burden, and the degree of the burden will vary according to the factors included in the study. Reconceptualization of the burden framework should include the possibility that gratifying, positive aspects of caring can also result from the caregiving experience. Somporn and his colleagues in their study included variables on Patient's characteristics (Age, Gender, Duration of illness and symptoms) and Caregiver's characteristics (Age, Gender, Relationship, Ethnicity and Socioeconomic status) to study burden on caregivers of mentally ill people (Somporn, et al., 2000).

One of the statistical methods used by researchers is factor analysis. The purpose of factor analysis is to discover simple patterns in the pattern of relationships among the variables. In particular, it seeks to discover if the observed variables can be explained largely or entirely in terms of a much smaller number of variables called factors. For example, Deborah and his colleagues used factor analysis and reduced the caregiver burden data into four orthogonal factors: assessing perceptions of patient problem behavior, patient impairment in activities of daily living, patient helpfulness, and resource demands and disruptions in the caregiver's personal routine.

Also, the researchers evaluated Family burden with an adapted version of the Family Experience Interview Schedule (FEIS), which evaluates patient problem behavior, activities of daily living, role functioning, disruption of household routine, caregiver contributions in time and money to the patient's general support and treatment, and the amount of practical and emotional support provided to the caregiver by the patient. Because the FEIS comprises scales and items selected conceptually on the basis of findings of prior studies of family burden, an approach adopted by more recent studies as well, they used factor analysis to reduce the FEIS to dimensions that were statistically as well as conceptually meaningful. The pool of 44 variables and scales derived from the FEIS were subjected to an exploratory principal-components factor analysis with orthogonal (varimax) rotation. Data were randomly divided into two approximately equal samples of 304 and 319 with the SPSS sample procedure for use in their exploratory and confirmatory analyses (Deborah *et al.,* 2007).

Moreover, researchers are often interested in testing theoretical assumptions and examining the influence of several predictor variables in a sequential way, such that the relative importance of a predictor may be judged on the basis of how much it adds to the prediction of a criterion, over and above that which can be accounted for by other important predictors. Further, Deborah and his colleagues used hierarchical regression analyses to demonstrate differential correlates of burden for each factor, explaining 34 percent of variance each for problem behavior and resource demands and disruption, 21 percent for impairment in activities of daily living, and 38 percent for patient helpfulness (Deborah *et al.,* 2007).

Despite these adverse effects of caregiving, efforts to identify contributing factors have mostly been limited to investigations of the impact of different types of patient symptoms, with mixed conclusions. Although one study found that higher levels of burden were associated with higher levels of negative but not positive symptoms, others found that increased burden was associated with higher levels of both positive and negative symptoms or with positive symptoms alone (Deborah et al., 2006).

Up to now we have been looking at literature review of the predictors of burden; now we consider the statistical methods used to identify the factors/predictors of burden. In the first place we see the details of the two models, binary logistic regression (since polytomous logistic regression is just the extension of the binary one), and discriminant analysis which will be used in this study.

2.2 Logistic Regression and Discriminant Analysis

Regression methods have become an integral component of any data analysis concerned with describing the relationship between a response variable and one or more explanatory variables. In such a case one can use logistic regression or discriminant analysis. It is often the case that the outcome variable is discrete taking on two or more values. The goal of an analysis using logistic regression method is to find the best fitting and most parsimonious, yet statistically reasonable model to describe the relationship between an outcome (dependent or response variable) and a set of independent (predictor or explanatory) variables. The second method of data analysis we consider is discriminant analysis. Discriminant analysis captures the relationship between multiple independent variables and a categorical dependent variable in the usual multivariate way, by forming a composite of the independent variables.

Also, logistic regression allows one to predict a discrete outcome such as group membership from a set of variables that may be continuous, discrete, dichotomous, or a mix (Tabachnick and Fidell, 1996). On the other hand, the objective of Discriminant function analysis is to predict group membership from a set of predictors (Tabachnick and Fidell, 1996), in other words, the objective of discriminant analysis is identifying a set of variables that "best" discriminates between two or more groups, thus, it appears that the same research questions can be answered by both methods. There are two primary reasons for choosing logistic distribution. The first is, from mathematical point of view, it is an extremely flexible and easily used function and secondly it leads itself to meaningful interpretations (Hosmer and Lemeshow, 1989).

However, the real difference in determining which one to use depends on the assumptions regarding the distribution and relationship among the independent variables and the distribution of the dependent variable. For both methods the categories in the outcome (i.e. the dependent variable) must be mutually exclusive. One of the ways to determine whether to use logistic regression or discriminant analysis in the cases where there are more than two groups in the dependant variable is to analyze the assumptions pertinent to both methods (Tabachnick and Fidell, 1996).

The logistic regression is much more relaxed and flexible in its assumptions than the discriminant analysis. Unlike the discriminant analysis, the logistic regression does not have the requirements of the independent variables to be normally distributed, linearly related, nor equal variance within each group (Tabachnick and Fidell, 1996). Being free from the assumption of the discriminant analysis posits the logistic regression as a tool to be used in many situations. However, "when assumptions regarding the distribution of predictors are met, discriminant function analysis may be more powerful and efficient analytic strategy" (Tabachnick and Fidell, 1996).Even though the logistic regression does not have many assumptions, thus usable in more instances, it does require larger sample size, at least 50 cases per independent variable might be required for an accurate hypothesis testing, especially when the dependant variable has many groups (Grimm and Yarnold, 1995).

However, given the same sample size, if the assumptions of multivariate normality of the independent variables within each group of the dependant variable are met, and each category has the same variance and covariance for the predictors, the discriminant analysis might provide more accurate classification and hypothesis testing (Grimm and Yarnold, 1995). The rule of thumb though is to use logistic regression when the dependant variable is dichotomous and there are enough samples.

In this research work many of the independent variables included are categorical. The sample size is not large enough as compared to the number of independent variables so that one can not prefer the other in advance. Therefore, both logistic regression and discriminant analysis will be considered.

CHAPTER THREE

DATA AND METHODOLOGY

3.1 Data

The Stanley Medical Research Institute (SMRI) is a nonprofit organization supporting research on the causes of, and treatments for, schizophrenia and bipolar disorder.The Stanley Medical Research Institute's (SMRI) involvement in psychiatric research in Ethiopia began in 1996 in collaboration with Addis Ababa University and Amanuel Psychiatric Hospital. The site of the first and biggest research activity was the rural town of Butajira, which is situated 135 kilo meters south of the Ethiopian capital, Addis Ababa. The town and its surrounding rural villages, which were already site for ongoing studies by the Department of Community Health in the Faculty of Medicine, Addis Ababa University, presented a suitable location for Mental Health research. This department made the data available for this research work. Basic Information on the Study Subject (BISS), Basic Information on the Informant (BII) and Family Interview schedule (FIS) were used to obtain data on family caregiver burden due to mental health problem. Family Burden was assessed in terms of how much the relative's (Caregiver) life was affected by the presence of the illness in the family, (Atalay *et al.*, 2006). A total of 514 patients were included in this study. Socio-demographic characteristics of the caregiver's (age, marital status, relation to the patients, average time spent with the case per day, educational status, relation to the patient) and patient's characteristics (sex, marital status, age, living status, employment, negative symptoms (Decreased spontaneous movement, poor eye contact, poverty of speech, etc) and positive symptoms (Auditory hallucination, visual hallucination, delusions of being controlled, etc)) are the variables included in the study.

3.2 Variables in the study

The aim of this study is to predict the burden experienced by the care givers; here the dependent variable of interest is burden. Throughout the literature on burden the importance of objective and subjective burden is debated. But this study is concerned with the objective burden only. In judging this burden caregivers were asked thirty four questions to rate degree to which each problem(Symptom and social behaviour) was present on scale of '0' (almost never), '1'(some times), '2'(often), '3'(almost always). Out of those thirty-four items included in the instrument (questionnaire) twenty items are considered to generate the burden score; we included variables that previous studies have found to predict burden; and are directly taken from the questionnaire (symptoms and social behaviour: Just sits, has bad dreams, acting as if people are not there, does strange thing with out reason, getting anger breaking things, showing little change in facial expression, thinking people talk about him /her, act as if he/she is suspicious of people, gets into fight with people, curses at people, avoid eye contact when talking with others, seems emotionally detached from people, is very slow to react, stay in one position for a long period, says that he/she lacks freedom, threatens to tell people off, shows little interest in social activities, talks about strange things going on inside him/her, believes in strange things and has a difficulty in carrying on conservation); and four question of impact on the caregiver (Difficulty in participating in social activities, strain caused between family members, difficulty to be employed, financial difficulty); we used the average score of these items to get single burden score for each respondent.

Studies have shown that there are many ways of obtaining an index for objective burden. Factor analysis and averaging of scores are the most commonly used. Here in this study an index for objective burden was computed by averaging the mean of all items for each care giver, which is similar to that of Perlick (2007). As a matter of averaging the value of the new score became continuous and we categorized it into three classes as no burden, moderate burden and severe burden.

To estimate the extent of objective burden in the study sample, a mean objective burden (i.e., Symptom and social behaviour) rating was calculated for each caregiver across all items. Caregivers whose mean rating was '0' were categorized as having no burden or 'none,' caregivers whose mean rating was >0 and <0.33 were categorized as 'moderate' and caregivers whose mean rating was $>0.33^*$ were categorized as having a 'high' level of objective burden. The reason why we selected 0.33 as cut point for the two categories moderate burden and severe burden is that in the first place the primary scale on which data were collected is likert scale '0' (almost never), '1'(some times), '2'(often), '3'(almost always). After averaging these scales across all items we came up with new scores which are continuous and since the caregivers with zero averages of response are already classified in category of 'no burden', then it is logical to classify the remaining caregivers with non zero average scores into two categories; assigning those having scores greater than the mean value of the averages in 'severe burden' category and those with lesser value than the mean value in 'moderate burden' category.* *It is the averages of none zero scores.*

The following are the dependent variable and explanatory variables:

1. Response variable:
   - ✓ Burden (No burden, Moderate burden, High burden)
2. The explanatory variables included are :
   - ✓ Dependency status of the cases (Dependent or Independent).
   - ✓ Employment status of the caregiver. (Not employed, part-time, full-time)
   - ✓ Emotional help to informant. (Absent, present)
   - ✓ Marital status of the patient. (Never married, Married, Common law marriage, Separated, Divorced, Widowed)
   - ✓ Marital status of the caregiver. (Never married, Married, Common law marriage, Separated, Divorced, Widowed)
   - ✓ Gender of the caregiver. (Male, Female)
   - ✓ Gender of the patient. (Male, Female)
   - ✓ Age of the care giver. (in years)
   - ✓ Age of the patient. (in years)
   - ✓ Educational status level of caregivers (illiterate, literate)
   - ✓ Relation to the patient. (Spouse, Parent, sibling, child, other relative, friend)
   - ✓ Living situation(Live with patient or not)
   - ✓ Positive symptoms.
   - ✓ Negative symptoms.

Statistical methods employed are: discriminant analysis, polytomous ordinal logistic regression with proportional odds model and also other statistical methods will be employed. The statistical software used is SPSS.

3.3 Methodology

3.3.1 Introduction

The choice of a particular model will depend to some extent on the goals of the analysis and the stage of model development. Several statistical methods were used by different researchers at different time; such as Factor analysis, hierarchical regression analyses, hierarchical multinomial logistic regression analysis, and multiple stepwise regression models and so on, to study the magnitude of burden on the caregivers of mentally ill people. Hierarchical multinomial logistic regression analysis is used by Perlick and his colleagues to examine which characteristics contributed significantly to the classification of caregivers into the burden tertiles, using the low burden group as the comparison (Perlick et al., 2007). Dennis et al., (1999) used multiple regression analysis for predicting burden and infectious illness.

3.3.2 Logistic Regression model

Logistic regression (or logit regression) is a form of regression analysis that is specifically tailored to the situation in which the dependent variable is dichotomous (or binary). For example, among a sample of people under investigation, a researcher might be interested in what factors are associated with the likelihood of someone being schizophrenic patient or non-schizophrenic, being bipolar patient or non-bipolar patient, or living in rural or in urban and so on. However, so-called multinomial logistic regression is increasingly common, involving analyses in which the possible causal effects of independent variables on a categorical dependent variable having three outcome categories or more. For example, the probability of someone identifying themselves as not burdened rather than moderately burdened or severely burdened (taken together); as compared with the probability of someone claiming severely burdened rather than a moderately burdened or have no burdened (again with these last two taken together). The multinomial dependent variable is assessed via comparison of a series of dichotomous outcomes.

In order to simplify notation we will use the quantity $\pi(x) = E(Y|x)$ to represent the conditional mean of Y given $X = (x_1, x_2, \ldots, x_p)$ when the logistic distribution is used. For a dichotomous response variable, this expected value is simply the probability, π, that the response variable takes the value 1. The specific form of the logistic model usually used is as follows:

$$\pi(x) = \frac{e^{\beta_o + \beta_1 x_1 + ... + \beta_p x_p}}{1 + e^{\beta_o + \beta_1 x_1 + ... + \beta_p x_p}} \tag{1}$$

In a logistic regression model the parameter β_i, associated with explanatory variable x_i represents the expected in logit when x_i is increased by one unit, conditional on the other explanatory variables remaining the same.

3.3.2.1 Estimation of the parameters

Although logistic regression finds a "best fitting" equation just as linear regression does, the principles on which it does so are rather different. Instead of using a least-squared deviations criterion for the best fit, it uses a maximum likelihood method, which maximizes the probability of getting the observed results given the fitted regression coefficients. A consequence of this is that the goodness of fit and overall significance statistics used in logistic regression is different from those used in linear regression. Maximum likelihood is used to estimate the parameters in the logistic regression model; the log-likelihood function is: $l(\beta; y) = \sum_{i=1}^{n} \{y_i \log[\pi(\beta' X_i)] + (1 - y_i)\log[1 - \pi(\beta' X_i)]\}$, where $y' = [y_1, y_2, \ldots, y_n]$ are the n observed values of the dichotomous response variable and $x'_i = [x_{i1}, x_{i2}, \ldots, x_{iq}]$ is the vector of values of the explanatory variables associated with the i^{th} observation.

3.3.2.2 Goodness of fit

The lack of fit of logistic regression model can be measured by a term known as deviance, which is essentially the ratio of the likelihood of the model of interest to the saturated model that fits the data perfectly. Explicitly, deviance is defined as:

$D = 2\sum_{i=1}^{n}\{y_i \log(\frac{y_i}{\hat{y}_i}) + (n_i - y_i)\log(\frac{n_i - y_i}{n_i - \hat{y}_i})\}$, where $\hat{y}_i$ is the predicted number of event of interest under the current model, i.e., $\hat{y}_i = n_i\hat{\pi}_i$. This statistics, D, compares the observed values y_i with their fitted values, $\hat{y}_i$ under the current model. More on this can be found on Hosmer and Lemeshow, 1998.

3.3.2.3 Polytomous Ordinal Logistic Regression

Logistic regression is most frequently used to model the relationship between a dichotomous response variable and a set of predictor variables. On occasion, however, the response variable may have more than two levels. For instance the relation between severity of disease (Mild, Moderate and severe), the presence of burden (No burden, Moderate burden, High burden) and some explanatory variables may be of interest. Logistic regression can still be employed, by a means of polytomous logistic regression model. Polytomous logistic regression models are used in many fields. Polytomous logistic regression is an extension of the simple logistic regression analysis where the response variable has two outcomes. Various complexities arise from the extension, but the basic ideas of modeling, the use of deviance and making inference also apply here (John *et al.,* 1996). An approximate way of carrying out polytomous logistic regression analysis is to fit several individual binary logistic models. The estimates of the logistic regression coefficients so obtained are consistent estimates of the polytomous logistic regression parameters and often involve only a moderate loss of efficiency (John *et al.*, 1996). An important advantage of this approach is that it outputs an estimate of the probability that an object belongs to each of the possible classes.

Polytomous logistic regression can be divided into two cases: ordinal response (the dependent variable is ordinal, for example, mild, moderate and severe), and nominal response (the dependent variable is nominal categorical variable, for example, single, married and divorced). When response categories are ordered, logits can directly incorporate the ordering. This results in models having simpler interpretations and potentially greater power than ordinary multicategory logits models (Agresti, 1996).

The proportional odds model for ordinal regression provides a useful extension of binary logistic model to situations where the response variable takes on values in a set of ordered categories. The model may be by a series of logistic regressions for dependent binary variables, with common regression parameters reflecting the proportional odds model assumption. Key to the valid application of the model is the assessment of the proportionality assumption.

3.3.2.4 Proportional odds model (A cumulative logit model)

The proportional odds model for ordinal regression described by McCullagh (1980) provides a useful extension of the binary logistic model to situations where the response variable takes on ordered categorical values. It is based on the assumption that the effects of the explanatory variables X_1, ..., X_p are the same for all categories, on the logarithmic scale. Polytomous logistic regression for ordinal responses commonly uses logits of cumulative probabilities, often called cumulative logits (Agresti, 2005). For ordinal response, cumulative logits can be modeled with the proportional odds model.

The proportional odds model assumes that the cumulative logits can be represented as parallel linear functions of independent variables, that is, for each cumulative logit the parameters of the models are the same, except for the intercept. This model uses cumulative probabilities. For a J-category ordinal response variable Y and a set of predictors $X = (x_1,...,x_p)$ with corresponding effect parameters $\boldsymbol{\beta} = (\beta_1,...,\beta_p)$, the model has the form:

$\mathrm{logit}[\mathrm{P}(\mathrm{Y} \le \mathrm{j} \mid \mathrm{X})] = \alpha_{\mathrm{j}} - \beta' X$, $\mathrm{j} = 1, 2,..., \mathrm{J} - 1$.

The minus sign in the predictor term makes the sign of each component of $\boldsymbol{\beta}$ have the usual interpretation in terms of whether the effect is positive or negative, but it is not necessary to use this parameterization (Agresti, 2005). The parameters $\{\alpha_j\}$, called the cut points, are usually nuisance parameters of little interest. This model applies simultaneously to all J-1 cumulative probabilities and it assumes an identical effect of the predictors for each cumulative probability. Specifically, the model implies that odds ratios for describing effects of explanatory variables on the response variable are the same for each of the possible ways of collapsing a J-category to a binary. Explanatory variables in cumulative logit models can be continuous, categorical or of both types.

Maximum likelihood fitting process uses an iterative algorithm simultaneously for all J categories. When the categories are reversed in order, one gets the same fit but the sign of $\hat{\beta}$ reverses (Agresti, 1996). Let the response $Y = 1, 2, ..., J$ where order is relevant. The associated probabilities are $\{\pi_1, \pi_2, ..., \pi_j\}$, and a cumulative probability of a response less than equal to *j* is:

$F_j = P(Y \le j) = \pi_1 + \cdots + \pi_j$, $j = 1, \cdots, J$

The cumulative probabilities reflect the ordering with $P(Y \le 1) \le P(Y \le 2) \le \ldots \le P(Y \le J) = 1$ Models for cumulative probabilities do not use the final one, $P(Y \le J)$ since it necessarily equals one. The Logit of the first J-1 cumulative probabilities are:

$$\log(\frac{P(Y \le j)}{P(Y > j)}) = \log(\frac{P(Y \le j)}{1 - P(Y \le j)}) = \log(\frac{\pi_1 + \cdots + \pi_j}{\pi_{j+1} + \cdots + \pi_J}), \ j = 1, \ldots, J - 1 \ .$$

This describes the log-odds of two cumulative probabilities; that is how likely is the response to be a category *j* or bellow *j* versus a response that's higher than *j*. Each cumulative logit uses all J response categories. A model for the jth cumulative logit looks like an ordinary logit model for binary response in which categories 1 to j combine to form a single category and categories j+1 to J from a second category. In other words, the response collapses into two categories. Ordinal models simultaneously provide a structure for all J -1 cumulative logits. This model is a more common way to approach the modeling of a J-category response variable through the use of cumulative logits as follows:

$L_j = \log it(F_j) = \log(\frac{F_j}{1 - F_j}), \ j = 1, \ldots, J - 1$, where F_j is the cumulative probability up to and including category j. In this notation, L_j is the log-odds of falling into or below category *j* versus falling above it. The Proportional Odds Model (McCullagh, 1980) can be expressed as follows:

$$L_j = \beta_{j0} + \sum_{i=1}^{p} \beta_{ji} X_i \quad , \ j = 1, \ldots, J - 1$$

Now suppose that we simplify the model by requiring the coefficient of each *X*-variable to be identical across the J −1 logit equations. Then, changing the names of the intercepts to α's, the model becomes:

$$L_j = \alpha_j + \sum_{i=1}^{p} \beta_i X_i = \alpha_j + \beta'\mathrm{X}, \mathrm{j} = 1, \ldots, \mathrm{J} - 1$$

This model, called the proportional-odds cumulative logit model, has (J − 1) intercepts plus *p* slopes, for a total of J + p − 1 free parameters. We have to note that intercepts can differ, but that slope for each variable stays the same across different equations.

A single parameter describes the effect of X_i on *Y* and β_i is the increase in log-odds of falling into or below any category associated with a one-unit increase in X_i, holding the other entire X-variables constant. Constant slope β_i; the effect of X_i is the same for all J-1 ways to collapse *Y* into dichotomous outcomes.

Let's consider only one predictor; $\mathrm{logit}[\mathrm{P}(\mathrm{Y} \le \mathrm{j})] = \alpha_\mathrm{j} + \beta\mathrm{X}$ in this model, β does not have a j subscript, so the model assumes an identical effect of X for all J-1 collapsing of the response into binary out comes. The cumulative probabilities are given by:

$$\mathrm{P}(\mathrm{Y} \le \mathrm{j}) = \frac{\mathrm{e}^{\alpha_\mathrm{j} + \beta X}}{1 + \mathrm{e}^{\alpha_\mathrm{j} + \beta X}}$$

. Since β is constant, the curves of cumulative probabilities plotted against X are parallel.

When the proportional odds model holds for a given response scale, it also holds with the same effects for any collapsing of the response categories. For instance, if a model for categories (None, Questionable, mild, moderate, marked, severe) fits well, approximately the same estimated effects result from collapsing the response scale to (None, Mild, Severe). This invariance to the choice of response categories is a nice feature of the model. Two researchers who use different response categories in studying the association will come up with similar conclusion (Agresti, 1996).

3.3.2.5 Estimation of parameters

Maximum likelihood estimation is used to obtain the estimates of the model parameters. Suppose that the dependent variable Y has three categories that takes ordered values 1 (mild), 2 (moderate) and 3 (severe) and let $p_1 = P(Y=1)$, $p_2 = P(Y=2)$ and $p_3 = P(Y=3)$. The ordinal logistic regression models the relationship between the cumulative logits of Y, that is,

$$\log\left(\frac{p_1}{1-p_1}\right) = \log\left(\frac{p_1}{p_2+p_3}\right) \text{and } \log\left(\frac{p_1+p_2}{1-(p_1+p_2)}\right) = \log\left(\frac{p_1+p_2}{p_3}\right)$$

In this case and independent variables are $(x_1,\ldots,x_p)$. The model assumes a linear relationship for each logit and parallel regression lines; for J=3 we have, J-1=3-1=2, two simultaneously cumulative link-functions for solving the model parameters in the following equations:

$$\log\left(\frac{p_1}{1-p_1}\right) = \alpha_1 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p,$$

$$\log\left(\frac{p_1+p_2}{p_3}\right) = \alpha_2 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p,$$

That is, the intercepts are different, but the remaining regression parameters are the same. It is easy to see that the odds $\frac{p_1}{1-p_1}$ and $\frac{p_1+p_2}{p_3}$ are proportional,

$$\frac{p_1}{1-p1} = e^{\alpha_1} e^{\beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p} \quad ,$$

$$\frac{p_1+p_2}{p_3} = e^{\alpha_2} e^{\beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p} = C*\left(\frac{p_1}{1-p_1}\right),$$

Where C= exp (α_2- α_1), hence the name the proportional odds model. Proportional odds imply that odds ratios for Y being severe (1) vs. moderate or mild (2 or 3) and for Y being severe or moderate (1 or 2) vs. mild (3), are the same.

After the parameters α_1, α_2, β_1, β_2, ..., β_p are estimated, it is easy to compute predicted probabilities using the following formulas derived from the above equations.

$$\hat{p}_1 = \frac{e^{\alpha_1 + \hat{\beta}_1 x_1 + \ldots + \hat{\beta}_p x_p}}{1 + e^{\alpha_1 + \hat{\beta}_1 x_1 + \ldots + \hat{\beta}_p x_p}}, \quad \hat{p}_1 + \hat{p}_2 = \frac{e^{\alpha_2 + \hat{\beta}_1 x_1 + \ldots + \hat{\beta}_p x_p}}{1 + e^{\alpha_2 + \hat{\beta}_1 x_1 + \ldots + \hat{\beta}_p x_p}} \quad \text{and}$$

$$\hat{p}_3 = 1 - (\hat{p}_1 + \hat{p}_2)$$

Interpretation of the sign of the coefficients is as follows: If parameter b_i is positive, then p_1, predicted probability of (Y=0, none), as well as cumulative probability of (Y=1, moderate, or Y=2, severe), p_1+p_2, are higher for higher values of X_i. If parameter b_i is negative, p_1 and p_1+p_2 are lower for higher values of X_i.

3.3.2.6 Model Fitting

As with any type of regression modeling, it is important to be able to assess the quality of model fit, because under fitted models can lead to biased estimation of important effects. An assessment of model fit may include detection of when important covariates or interactions are omitted, when the link function is not appropriate, when the functional form of modeled covariates is not correct, or when assumptions like proportional odds do not hold. Currently, goodness-of-fit in the ordinal setting is often assessed using the Pearson chi-square and deviance tests, which are widely available in commercial software. The methodology proposed in this manuscript is appropriate for ordinal logistic models that contain both categorical and continuous covariates and is a modification of the deviance and the Pearson chi-square tests of goodness-of-fit in the binary logistic regression setting.

In modeling with many independent variables one is usually concerned with the goal of selecting those variables that can result in "best" with in the scientific context of the problem. To fit proportional odds model, it is unnecessary to assign scores to the response categories. One can motivate the model by assuming that the ordinal response Y has an underlying continuous response Y*, such an unobservable variable is called latent variable (Agresti, 2005). One reason for the proportional-odds cumulative-logit model's popularity is its connection to the idea of a continuous latent response.

Suppose that the categorical outcome is actually a categorized version of an unobservable (latent) continuous variable. Letting Y* have mean linearly related to X, and have logistic conditional distribution with constant variance. Then for the categorical variable Y obtained by chopping Y* into categories (with cut points $\{\alpha_j\}$), the proportional odds model holds for predictor X, with effects proportional to those in the continuous model. If this latent variable model holds, the effects are invariant to the choices of the number of categories and their cut points (Agresti, 2005). The model is also referred to as the grouped continuous model, since it can be constructed by supposing that observations on a latent variable following a logistic distribution with conditional mean $\mu=\beta'X$, have been grouped in intervals with cut points α_j.

Ordinal Regression Model assumes that the categories of an ordinal response can be ranked, but the distances between the categories are unknown. Since cumulative logits are correlated asymptotically, simultaneous estimation is required. In Ordinal Regression Model, observed response categories (y_i) are tied to the latent variable (y_i^*) by a measurement model that divides y_i^* into J ordinal categories so that J-1 cut points are estimated.

Proportional odds model employs a strict assumption that odds ratio does not depend on the cut point, and therefore we need to test the proportional odds assumption, which is also called "parallel regression assumption." Approximate likelihood ratio test of proportionality of odds across response categories ominously tests that the coefficients for all variables are simultaneously equal. It compares the log likelihood from proportional odds assumption (Wolfe & Gould 1998) to the log likelihood obtained from pooling J-1 binary models, adjusting for the correlation between the binary outcomes defined by $Y \leq j$. On the other hand, Wald test (Brant 1996) tests the "parallel regression assumption" for each variable individually. In both tests, if p-value is small, the parallel regression assumption can be rejected.

There is no guarantee, however, that a particular model of this form is appropriate or that it provides a good fit to the data. The test of the null hypothesis that the model holds compares the fitted and observed counts using a Pearson χ^2 or likelihood-ratio G^2 test statistic. Large χ^2 or G^2 values provide evidence of lack of fit and the P-value is the right-tail probability above the observed value. When the fit is poor, residuals and other diagnostic measures describe the influence of individual observations on the model fit and highlight reasons for the inadequacy.

Given ordinal response data on *N* subjects and the cumulative logit model with *k* categorical covariates, observed and expected counts, the Pearson chi-square goodness-of-fit statistic compares the observed (O) to expected (E) counts with the following formula:

$$\chi^2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\frac{(O_{ij} - E_{ij})2}{E_{ij}}$$

The deviance statistic also compares observed to expected counts, but instead uses the formula given by:

$$D^2 = 2\sum_{i=1}^{I}\sum_{j=1}^{J} O_{ij}\log\frac{O_{ij}E_{ij}}{E_{ij}}$$

These test statistics are based on an approximate central chi-square distribution with degrees of freedom equal to (I -1)*(J-1)-k, and reject the hypothesis of no significant lack-of-fit when they exceed the corresponding upper α critical value (Gerhard, 2007).

On the other hand, in logistic regression the generalized coefficients of determination, pseudo $R^{2,}$ statistic is available to summarize the strength of the relationship. It does not assume linearity of relationship between the independent variables and the dependent, does not require normally distributed variables, does not assume homoscedasticity, and in general has less stringent requirements. It does, however, require that observations are independent and that the independent variables be linearly related to the logit of the dependent. The success of the logistic regression can be assessed by looking at the classification table, showing correct and incorrect classifications of the dichotomous, ordinal, or polytomous dependent. In addition, goodness-of-fit tests such as model chi-square are available as indicators of model appropriateness as is the Wald statistic to test the significance of individual independent variables.

3.3.3 Discriminant analysis

Discriminant function analysis is used to determine which variables discriminate between two or more naturally occurring groups. When the purpose of the research is either to describe the group difference or to predict group membership on the basis of response variable measures, discriminant analysis techniques are appropriate (Huberty, 1994). Linear discriminant is originally developed in 1936 by R.A. Fisher. It often produces models whose accuracy approaches (and occasionally exceeds) more complex modern methods. Discriminant analysis can be used only for classification (i.e., with a categorical target variable), not for regression. The target variable may have two or more categories. If discriminant function analysis is effective for a set of data, the classification table of correct and incorrect estimates will yield a high correct percentage. Multiple discriminant analysis (MDA) is an extension of discriminant analysis, sharing many of the same assumptions and tests. MDA is used to classify a categorical dependent variable which has more than two categories, using as predictors a number of continuous or dummy independent variables.

There are several purposes for discriminant analysis some of these are: to classify cases into groups, to test theory by observing whether cases are classified as predicted, to investigate differences between or among groups, to determine the most parsimonious way to distinguish among groups, to determine the percent of variance in the dependent variable explained by the independents, to determine the percent of variance in the dependent variable explained by the independents over and above the variance accounted for by control variables using sequential discriminant analysis, to assess the relative importance of the independent variables in classifying the dependent variable and to discard variables which are little related to group distinctions.

The dependent variable in a discriminant analysis can be categorical and may have any number of categories. The categories should be mutually exclusive and jointly comprehensive, allowing each case to be assigned to a single category. It is assumed that all of the independent variables are measured on at least an interval scale. Including other types of variables using dummy coding will produce meaningful results. However, the more discrete variables that are included, the less trustworthy the results will be in terms of finding the optimum separation of the groups. In this situation it is usually wiser to resort to logistic regression, which can accommodate any mix of independent variable types.

3.3.3.1 Assumptions required for discriminant analysis

The statistical assumptions required for discriminant analysis are essentially the same as for OLS (Ordinary Least Square) regression, though some of them take on a slightly different form. The independent variables are assumed to have a multivariate normal distribution in each population from which the category samples are drawn. As in OLS regression, the consequences of violating this assumption are not usually serious if the sample size requirements are met. Discriminant analysis requires that the population variances and covariances for all independent variables are equal across the dependent variable groups; which is also called the homogeneity of variance-covariance matrices assumption. The status of the assumption can be explored by inspecting the group variances and covariances, examining appropriate plots, and testing with statistics such as Box's M. If the sample sizes in each category are reasonably large and approximately equal, violation of this assumption has little effect on statistical tests, but classification analyses may be distorted. If there is a clear violation, remedies may be found in transformations of variables, or possibly in an alternative approach to classification called quadratic discrimination.

3.3.3.2 The Fisher's linear discriminant function

One of the methods of classification by discriminant analysis is by the use of discriminant score. The Fisher's linear discriminant function for two groups is given by:

$$y = (\overline{X}_1 - \overline{\mathrm{X}}_2)'\mathrm{S}^{-1}\mathrm{X},$$

where $\overline{X}_1$ and $\overline{X}_2$ are the sample mean vectors and S is the pooled estimate of Σ. The Fisher's linear discriminant function was developed under the assumption that the two populations, whatever their form, have a common variance matrix. The primary purpose of Fisher's linear discriminant analysis is to separate populations. It can, however, also be used to classify. In a case where we have g populations; it is not necessary to assume that the g populations are multivariate normal, however, the population covariance matrices are equal and of full rank (Johnson, 1992).

To use the linear discriminant function for classifying an observation of unknown population we begin by computing the mean values of the score for the two samples:

$\bar{y}_1 = (\bar{X}_1 - \bar{X}_2)'S^{-1}\bar{X}_1$, $\bar{y}_2 = (\bar{X}_1 - \bar{X}_2)'S^{-1}\bar{X}_2$.

The mid point of these means on discriminant function scale is: $\frac{1}{2}(\bar{X}_1 - \bar{X}_2)'S^{-1}(\bar{X}_1 + \bar{X}_2)$

and we might adopt the classification rule; $W = X'S^{-1}(\bar{X}_1 - \bar{X}_2) - \frac{1}{2}(\bar{X}_1 + \bar{X}_2)'S^{-1}(\bar{X}_1 - \bar{X}_2)$

And assign the individual with observation X to population 1 if W > 0 and otherwise to population 2, and this is called Anderson's classification function (Statistic).

That is, sampling units are assigned to the group with the closer discriminant mean score. For three groups we have two discriminant functions and the linear discriminant scores are defined as:

$$W_{12} = X'S^{-1}(\bar{X}_1 - \bar{X}_2) - \frac{1}{2}(\bar{X}_1 + \bar{X}_2)'S^{-1}(\bar{X}_1 - \bar{X}_2) \quad ,$$

$$W_{13} = X'S^{-1}(\bar{X}_1 - \bar{X}_3) - \frac{1}{2}(\bar{X}_1 + \bar{X}_3)'S^{-1}(\bar{X}_1 - \bar{X}_3) \quad \text{and}$$

$$W_{23} = X'S^{-1}(\bar{X}_2 - \bar{X}_3) - \frac{1}{2}(\bar{X}_2 + \bar{X}_3)'S^{-1}(\bar{X}_2 - \bar{X}_3)$$

Because $W_{23} = W_{13} - W_{12}$, it is only necessary to use the statistics W_{12} and W_{13} (Morrison, 1976). The classification rule is defined as follows:

Classify X as from Population 1 if $W_{12} > 0$ and $W_{13} > 0$, Population 2 if $W_{12} < 0$ and $W_{13} > W_{12}$ and Population 3 if $W_{13} < 0$ and $W_{12} > W_{13}$. For the details one can refer Morrison (1976).

Fisher suggested that the classification should be based on a linear combination of discriminating variables such that group differences are maximized and variation within groups is minimized by using the pooled within-groups covariance matrix.

For cases with an equal sample size for each group, the classification function coefficient C_j is expressed by the following equation:

$C_j = c_{j0} + c_{j1}x_1 + c_{j2}x_2 + ... + c_{jp}x_p$, where C_j is the score for the j^{th} group, $j = 1 \ldots k$, c_{jo} is the constant for the j^{th} group, and x = raw scores of each predictor. If W = within-group variance-covariance matrix and M = column matrix of means for group j, then the constant is

$$c_{jo} = (\frac{-1}{2})C_j M_{j.}$$

3.3.3.3 Assessing the significance of discriminant functions

The eigenvalue, the characteristic root of each discriminant function, reflects the ratio of importance of the dimensions which classify cases of the dependent variable. There is one eigenvalue for each discriminant function. For two-group discriminant analysis, there is one discriminant function and one eigenvalue, which accounts for 100% of the explained variance. If there is more than one discriminant function, the first will be the largest and most important, the second next most important in explanatory power, and so on. In our case since we are dealing with three groups discriminant analysis, we have two discriminant functions; the first function being the largest and most important, the second next most important in explanatory power. The eigenvalues assess relative importance because they reflect the percents of variance explained in the dependent variable, cumulating to 100% for all functions. That is, the ratio of the eigenvalues indicates the relative discriminating power of the discriminant functions.

The canonical correlation, R*, is a measure of the association between the groups formed by the dependent and the given discriminant function. When R* is zero, there is no relation between the groups and the function. When the canonical correlation is large, there is a high correlation between the discriminant functions and the groups and for two-group DA, the canonical correlation is equivalent to the Pearsonian correlation of the discriminant scores with the grouping variable.

In discriminant analysis the so called Wilks' lambda statistic is used to test the significance of the discriminant function as a whole. The researcher wants a finding of significance, and the larger the lambda, the more likely it is significant. A significant lambda means one can reject the null hypothesis that the two groups have the same mean discriminant function scores and conclude the model is discriminating. The Wilks' lambda coefficient, which represents what model Wilks' lambda would be if that variable were dropped, leaving only the other one.

Wilks' lambda difference tests are also used in a second context to assess the improvement in classification when using sequential discriminant analysis. There is an F test of significance of the ratio of two Wilks' lambdas, such as between a first one for a set of control variables as predictors and a second one for a model including both control variables and independent variables of interest. The second lambda is divided by the first (where the first is the model with fewer predictors) and an approximate F value for this ratio is found using calculations reproduced in Tabachnick and Fidell (2001).

Wilks' lambda can also be used to test which independents contribute significantly to the discriminant function. The smaller the variable Wilks' lambda for an independent variable, the more that variable contributes to the discriminant function. Wilks' Lambda varies from 0 to 1 (Huberty, 1994), with 0 meaning group means differ (thus the more the variable differentiates the groups), and 1 meaning all group means are the same. The F test of Wilks's lambda shows which variables' contributions are significant.

Conceptually, there are three ways of finding correlations between variables and linear discriminant functions, namely total group-group correlations, between group structure correlations and within-group structure correlations. Although the use of total-group correlation has been advocated, it seems reasonable to focus on the within-group structure r's, which take into consideration group differences of mean vectors (Huberty, 1994).

Standardized discriminant coefficients, also termed the standardized canonical discriminant function coefficients, are used to compare the relative importance of the independent variables (Huberty, 1994), much as beta weights are used in regression; the importance is assessed relative to the model being analyzed. Addition or deletion of variables in the model can change discriminant coefficients markedly.

To summarize, when interpreting multiple discriminant functions, which arise from analyses with more than two groups and more than one variable, one would first test the different functions for statistical significance, and only consider the significant functions for further examination. Next, we would look at the standardized beta coefficients for each variable for each significant function. The larger the standardized beta coefficient, the larger is the respective variable's unique contribution to the discrimination specified by the respective discriminant function. In order to derive substantive "meaningful" labels for the discriminant functions, one can also examine the factor structure matrix with the correlations between the variables and the discriminant functions. Finally, we would look at the means for the significant discriminant functions in order to determine between which groups the respective functions seem to discriminate.

CHAPTER FOUR

STATISTICAL DATA ANALYSIS AND DISCUSSION

4.1 Introduction

Identifying predictors of family burden in caregivers of patients with schizophrenia and Bipolar disorder has been the focus of several investigations. The impact of the burdens experienced by caregivers on the course of illness in bipolar affective disorder has not been investigated to date. Because bipolar disorder is an episodic, cyclical illness, the relationship between the stressful experiences of family members and the patient's clinical status over time may differ from that observed in schizophrenia, and at different phases of the patient's illness. Moreover, because 93% of families of patients with bipolar affective disorder report experiencing burdens in relation to the patients' illness (Perlick et al., 2007), the role played by such experiences in predicting patient outcome among patients diagnosed with bipolar affective disorder deserves further investigation.

The response variable, burden score, is a polytomous out come assuming three values 0, 1 and 2. That is if the response is 0 the caregiver experiences no burden, if the response is 1 the caregiver experiences moderate burden and if the response is 2 the caregiver experiences severe burden. We have used ordinal logistic regression with polytomous out come in our analysis of the magnitude of burden experienced by the caregivers. In other words, we have tried to see the proportion of the study subjects falling in each category via the help of proportional odds model. In addition, we also performed the classification by linear discriminant analysis to observe the proportion of study subjects falling in the three categories so as to compare the results with the findings from the ordinal logistic regression. We start our data analysis by giving the summary statistics for the variables considered in the study; then we proceed to the bivariate analysis and complete the final model in the multivariate analysis. Calculations were carried out using the Statistical Package for the Social Sciences (SPSS) version 13.

4.2 Summary of descriptive Statistics

Table 1 shows the socio-demographic characteristics of caregivers and the patient included in the sample at fifth year (Cross-sectional) of the project. The sample consisted of 514 persons with a diagnosis of schizophrenia or Bipolar disorder and their primary family caregivers. Patient participants were between 20 and 54 years of age, about 72% of the patients were adults, older than thirty year, with the mean age of 36.27 (SD = 8.487) years. They were predominantly men (63%). Less than half of the patients lived with their relatives, friends and others (33.7 %), but mostly the caregiver was a spouse (39.4%) and married or living with a partner (70.8%). Almost half, about 49%, of the caregivers were younger in the age range of 15 to 30 with the mean age of caregivers was 34.88 (SD = 14.58) years. Like the patients, caregivers were not predominantly women or men rather both participated approximately equally (Men 49.5%). More than three-fourth (77.8%) of the caregiver's were living with the patient. Approximately all, 98.5% of caregivers attend the patient seven and more hours per day and this variable is excluded from further analysis as there is no variation among the responses.

From Table 1 we can see that out of the total of 514 respondents, 448 (87.5%) of them mostly depend on their caregiver. This implies that caregivers are expected to cover almost all costs needed to sustain the patient, thus the caregiver experiences burden. It can be seen from the proportion of the caregivers educational status that more than half (55.6%) of the caregivers were illiterate, out of which 28.8 % of them were male. Out of the total of our sample, about two-third (66.1%) of them have no positive symptom, whereas 21% of them reported that they had moderate negative symptom. Also, few of the caregivers (1.9%) reported that they had severe positive symptom and more than two-third (67.9%) of them had no positive symptom.

About 60 percent of the patients were not married, 25.6% of them were single and the remaining were not living together or separated. Only 10% of the caregivers were not employed and 76.7% of the employed caregivers were living with the patients.

Table 1: Demographic characteristics for the 514 caregivers studied at the fifth year (cross-sectional)

Characteristics	(% or mean ± SD)
Patient	
Gender	
Male	63
Female	37
Age (years)	36.27 ± 8.5
Minimum, Maximum	20, 59
≤ 30 years	27.9
> 30 years	72.1
Marital status	
Never married	25.6
Married	59.5
Separated	14.9
Whether the patient depends most on the caregiver	
Yes	87.5
No	12.5
Negative symptom	
None	66.1
Moderate	21
Severe	12.9
Positive symptom	
None	67.9
Moderate	30.2
Severe	1.9

Characteristics	(% or mean ± SD)
Caregiver	
Gender	
Male	49.5
Female	50.5
Age (years)	34 ± 14.6
Minimum, Maximum	15, 95
15-30 years	48.8
> 30 years	51.2
Marital status	
Never married	22.5
Married	70.8
Separated	6.7
Relation to the patient	
Spouse	39.4
Parent	14.8
Child	12.2
Other	33.7
Living situation	
Ever lived with patient	77.8
Not	22.2
Employment status	
Employed	90
Not currently employed	10
Emotional help to the caregiver	
Yes	12.4
No	87.6
Average number of hours the Caregiver Spent with patient Per day (7 and more hours)	98.5
Educational status of caregiver	
Illiterate	55.6
Literate	44.4

4.3 Bivariate analysis the explanatory variables

In bivariate analyses, using Pearson chi-square test the variables that are found to be significantly associated with caregiver burden are marital status of the patient, gender of the patient, relation of caregiver to the patient, employment status of the caregiver, dependency status of the patient, emotional help to the caregiver, positive symptom and negative symptom of the patient. Details are shown in Table 2 below.

Table 2: Variables in the bivariate analysis

Explanatory Variables	Pearson chi-square	df	Asymptotic sig.
Marital status of the patient	32.249	4	0.000*
Gender of the patient	20.881	2	0.000*
Age of the patient	0.420	2	0.811
Relation of caregiver to the patient	15.420	6	0.017*
Gender of the caregiver	1.482	2	0.477
Age of caregiver	3.708	2	0.157
Ever lived with patient	1.535	2	0.464
Marital status of the caregiver	2.483	4	0.648
Employment of the caregiver	22.002	2	0.000*
Whether the patient depends most on the caregiver	44.264	2	0.000*
Emotional help to the caregiver	32.787	2	0.000*
Negative symptom	173.377	4	0.000*
Positive symptom	171.562	4	0.000*
Educational status of caregivers	4.081	2	0.130

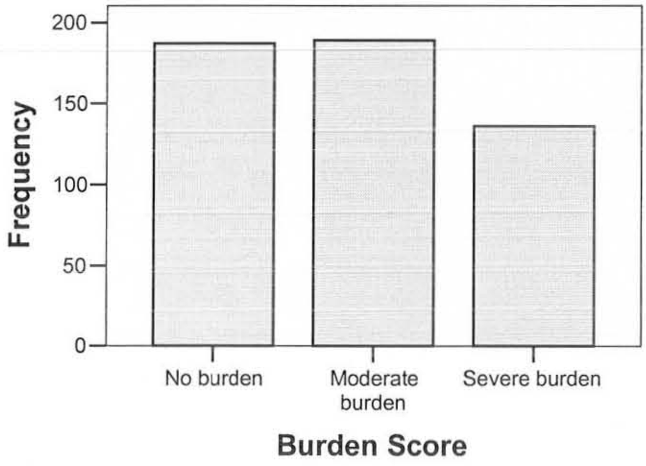
* Significant ($p<0.05$)

4.4 Polytomous ordinal logistic regression analysis

4.4.1 Link function

The link function, a transformation of the cumulative probabilities of the ordinal outcome, is needed in the estimation of the model. One way to choose a link function is to see the distribution of the response variable. The response variable, burden, is an ordinal outcome and the frequency distribution is displayed in figure 1 using bar chart. The three outcomes no burden, moderate burden and severe burden are quite evenly distributed, thus the appropriate link function to be used is logit link function (Chan, 2005).

Figure 1: Distribution of Burden of caregivers



4.4.2 Testing for proportional odds model assumption

Using the result in the Table 3 below, we perform the test of parallel lines to assess whether the assumption of all categories having the same parameters (the proportional odds assumption) is reasonable or not, i.e. whether one set of coefficients for all the categories is appropriate. Since the ordered logit model estimates one equation over all levels of the response variable (as compared to the multinomial logit model, which models, assuming no burden is our reference level, an equation for medium burden versus no burden, and an equation for sever burden versus no burden), the test for proportional odds tests whether our one-equation model is valid. We want to test the null hypothesis which states that the ordered logit coefficients are equal across the levels of the outcome against the alternative that the ordered logit coefficients are not equal across the levels of the outcome at least for one category at 5% level of significance. Using logit link function the likelihood chi-square statistic is computed as difference of -2 log likelihood of the null and general model. If we were to reject the null hypothesis based on the significance of the Chi-Square statistic, we would conclude that ordered logit coefficients are not equal across the levels of the outcome, and we would fit a less restrictive model (i.e., multinomial logit model). If we fail to reject the null hypothesis, we conclude that the assumption holds. For the data under consideration, Chi-Square statistic is not significant ($p>0.05$) and as a result the proportional odds assumption appears to be appropriate. The p-value for parallel line test is sensitive to the sample size and the number of independent variables included into a model. Most of the time if it has $p<0.05$, we could assess the model via its pseudo R-square and classification table of accuracies.

Table 3: Test of Parallel Lines

Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Null Hypothesis	618.001			
General	595.133	22.868	20	.295

4.4.3 Parameter estimation of the polytomous ordinal logistic regression

In the discussion that follows, the categories are order as none < moderate<severe. In Table 4 below, the "Dependent variable" rows contain the intercepts estimated for all but the highest level of the ordinal dependent variable and represent the response variable in the ordered logistic regression. The “Explanatory variable” rows contain the logit coefficients (parameter estimates) for the independent variables. Significant predictors (for explanatory variables) are dependency status of the patient, emotional help to the caregiver, patient’s positive symptom and negative symptom. And this is in line with the results from bivariate analysis even though some variables (Marital status of the patient, patient’s gender, relation of caregiver to patient and employment status of the caregiver) which were statistically significant in the bivariate analysis are not significant here in multivariate analysis. A negative relationship ($\hat{\beta}$= -1.393) exists between the probability of falling in higher ordinal outcome (burden score) and the dependency status of the patient. This means that as dependency status of the

patient decreases, so does the probability of being in one of the higher categories of burden. Similarly, negative symptom of the patient has a negative relationship. For a negative symptom of the patient, those who have no negative symptom ($\hat{\beta}$=-2.428) and moderate negative symptom ($\hat{\beta}$=-1.150) as compared to those having severe negative symptom had a lower probability to be in the higher category burden. Since our link function is logit, taking the exponential of the estimates gives us the Odds ratios. Here for instance, when the dependency status of the patient takes a value of '1' (that means the patient depends most on the caregiver) will result in an odds ratio of exp (-1.393) = 0.25 increase in odds of being in a higher category of the ordinal outcome. The other significant explanatory variable is the emotional help given to the caregiver; as compared to the caregivers who did not had emotional help, those who experienced the emotional help have inverse relationship to the out come variable ($\hat{\beta}$=-0.910), this implies that those care givers who experienced emotional help will have lower probability of being in the higher category of burden, in other words, the more emotional help the caregivers experience the lesser will be the burden. The remaining significant explanatory is one of the symptoms of patients, that is patient's positive symptom, this variable is also inversely related to the out come variable, no positive symptom ($\hat{\beta}$=-19.166) and moderate positive symptom ($\hat{\beta}$=-17.583), when we compare patients with no positive symptom and moderate symptom to patients with sever positive symptom, no and moderate positive symptoms have lower probability of being in the higher category of outcome variable (sever burden), with odds of being in the higher category for both is approximately zero, $\exp(-19.166)\approx 0 \approx \exp(-17.583)$.

Table 4: Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Dependent Variable	[BSc = 0] †	-22.239	0.689	1041.530	1	0.000*	-23.590	-20.889
	[BSc = 1]	-19.818	0.659	905.411	1	0.000*	-21.109	-18.528
Explanatory Variables	[n8maritals=0]	0.401	0.356	1.270	1	0.260	-.297	1.099
	[n8maritals=1]	-0.109	0.306	0.128	1	0.721	-.710	0.491
	[n8maritals=2]	0	.	.	0	.	.	.
	[n1sex=1]	0.043	0.217	0.039	1	0.843	-.382	0.468
	[n1sex=2]	0	.	.	0	.	.	.
	[n2curage=0]	-0.070	0.235	0.090	1	0.764	-.531	0.390
	[n2curage=1]	0	.	.	0	.	.	.
	[n2relation=1]	0.312	0.371	0.708	1	0.400	-.415	1.039
	[n2relation=2]	-0.349	0.380	0.841	1	0.359	-1.094	0.397
	[n2relation=3]	-0.082	0.392	0.044	1	0.834	-.850	0.686
	[n2relation=4]	0	.	.	0	.	.	.
	[n3gender=1]	0.260	0.221	1.389	1	0.239	-.173	0.693
	[n3gender=2]	0	.	.	0	.	.	.
	[age=0]	0.146	0.245	0.356	1	0.551	-.335	0.627
	[age=1]	0	.	.	0	.	.	.
	[n5everliv=0]	0.025	0.313	0.006	1	0.937	-.589	0.639
	[n5everliv=1]	0	.	.	0	.	.	.
	[n1marital=0]	0.385	0.527	0.534	1	0.465	-.648	1.419
	[n1marital=1]	0.000	0.436	0.000	1	0.999	-.855	0.855
	[n1marital=2]	0	.	.	0	.	.	.
	[n4employme=0]	-.614	0.393	2.437	1	0.119	-1.385	0.157
	[n4employme=1]	0	.	.	0	.	.	.
	[n1familyme=0]	-1.393	0.372	14.051	1	0.000*	-2.122	-0.665
	[n1familyme=1]	0	.	.	0	.	.	.
	[emot=0]	-.910	0.314	8.416	1	0.004*	-1.525	-0.295
	[emot=1]	0	.	.	0	.	.	.
	[Negsym=0]	-2.428	0.412	34.698	1	0.000*	-3.236	-1.620
	[Negsym=1]	-1.150	.387	8.842	1	0.003*	-1.908	-0.392
	[Negsym=2]	0	.	.	0	.	.	.
	[Posym=0]	-19.166	0.269	5084.996	1	0.000*	-19.693	-18.639
	[Posym=1]	-17.583	0.000	.	1	.	-17.583	-17.583
	[Posym=2]	0	.	.	0	.	.	.
	[edustatusinfor=1]	-.261	0.193	1.824	1	0.177	-0.640	0.118
	[edustatusinfor=2]	0	.	.	0	.	.	.

(•) *Reference category*

† *see acronym in the appendices*

* *Significant ($p < 0.05$)*

4.4.4 Model fitting for the proportional odds model

Table 5 presents information model fitting. This table gives the overall test of the model, based on the difference between the model we specified and the null (intercept-only) model. A well-fitting model is significant by this test.

Table 5: Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Intercept Only	881.779			
Final (Model with explanatory variables)	618.001	263.778	20	.000

The inclusion of predictor variables maximizes the log likelihood that is the "Final" model has improved upon the "Intercept Only" model. This can be seen in the differences in the -2(log likelihood) values associated with the models. By the use of Chi-Square we can test the hypothesis that at least one of the predictors' regression coefficients is not equal to zero in the model. The likelihood ratio based Chi-Square statistic 263.778 is significant and would lead us to conclude that at least one of the regression coefficients in the model is not equal to zero.

4.4.5 Goodness of fit (chi-square goodness of fit)

From Table 6, the chi-square goodness of fit test is used to assess how much predicted cell frequencies differ from observed frequencies. Both Pearson chi-square and deviance chi square coefficients are reported in Table 6. A well-fitting model is non-significant by these tests. As can be seen from Table 6 both the Pearson and deviance statistics are not significant implying our model fits well, which is in agreement with the previous likelihood ratio test.

Table 6: Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	653.982	656	.515
Deviance	545.725	656	.999

In the next section, discussion is based on alternative statistical method of analysis, which is discriminant analysis.

4.5 Discriminant Function Analysis

4.5.1 Multi-variate analysis of the explanatory variables

In the ANOVA table below, the smaller the Wilks's lambda, the more important the independent variable to the discriminant function. Wilks's lambda resulted in significant F test for the variables gender of the patient, employment status of the caregiver, whether the patient depends most on the caregiver, emotional help given to the care giver, negative and positive symptom of the patient; we might consider to drop the others from the model. But most of the time dropping of these statistically non-significant variables may be misleading.

Table 7: Tests of Equality of Group Means

Explanatory variables	Wilks' Lambda	F	df1	df2	Sig.
Marital status of the Patient	.993	1.605	2	481	0.202
Gender of the patient	.959	10.189	2	481	0.000*
Age of the patient	.999	.294	2	481	0.745
Relation of the caregiver to the patient	.993	1.767	2	481	0.172
Gender of the caregiver	.997	.641	2	481	0.527
Age of the caregiver	.995	1.307	2	481	0.271
Ever lived with the patient	.995	1.213	2	481	0.298
Marital status of the caregiver	.997	.774	2	481	0.462
Employment status of the caregiver	.960	10.025	2	481	0.000*
Whether the patient depends most on the caregiver	.921	20.639	2	481	0.000*
Emotional help to caregiver	.939	15.576	2	481	0.000*
Negative symptom	.658	124.973	2	481	0.000*
Positive symptom	.651	129.212	2	481	0.000*
Educational status level of caregivers	.992	1.906	2	481	0.150

df: Degrees of freedom
*: Significant ($p< 0.05$)

4.5.2 Testing the assumption of homogeneity of covariance matrices

Box's M test is used to the assumption of homogeneity of covariance matrices. The probability value of F should be greater than .05 to demonstrate that the assumption of homoscedasticity is upheld. For our data, the test is not significant (Table 8), so we conclude the groups do not differ in their covariance matrices, meeting assumption of discriminant analysis.

Table 8: Box's Test of Equality of Covariance Matrices

Box's M		867.482
F	Approx.	3.960
	df1	210
	df2	527266.085
	Sig.	.056

Discriminant analysis is generally robust to small deviations, which is important since field data rarely meet assumptions precisely. The larger the sample size, the more robust the analysis is to violation of assumptions. When sample sizes are small, more attention to violations is needed. It is assumed that the data (for the variables) represent a sample from a multivariate normal distribution. However, note that violations of the normality assumption are not "fatal" and the resultant significance test are still reliable as long as non-normality is caused by skewness and not outliers, which are a more serious problem (Tabachnick and Fidell 1996).Violations of normality mean the computed probabilities are not exact and will not be optimal in the sense of minimizing the number of misclassifications, even though they may still be quite useful if interpreted with caution.

4.5.3 Significance test

Since the dependent variable, burden score, has three groups, the number of discriminant functions computed is two; the eigenvalues show how much of the variance in the dependent variable, burden score, is accounted for by each of the functions. To attach meaning to the functions (like to factors in factor analysis) we will use the structure matrix later in the Table 13. The first function accounts for 87.3% of the total among-groups variability and the second accounts for the remaining 12.7%.

Table 9: Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.834	87.3	87.3	.674
2	.121	12.7	100.0	.328

SPSS is used to assess the significance of the discriminant functions. The Wilks' Lambda that has a chi-square distribution is used to test the null hypothesis that in the population the groups do not differ from one another on mean discriminant score for any of the discriminant functions. In both cases the chi-square test provided significant results, which imply the group can be discriminated based on the explanatory variables.

Table 10: Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 and 2	.486	341.989	28	.000
2	.892	54.150	13	.000

Table 11: Standardized Canonical Discriminant Function Coefficients

	Function	
Explanatory Variables	1	2
Marital status of the Patient	-.093	.063
Gender of the patient	-.033	-.006
Age of the patient	-.002	.095
Relation of the caregiver to the patient	-.075	.261
Gender of the caregiver	-.078	-.153
Age of the caregiver	-.118	.154
Ever lived with the patient	.017	-.079
Marital status of the caregiver	-.064	-.118
Employment status of the caregiver	.039	.371
Whether the patient depends most on the caregiver	.149	.778
Emotional help to caregiver	.156	.065
Negative symptom	.573	.083
Positive symptom	.601	-.294
Educational status level of caregivers	.006	.310

The standardized discriminant function coefficients presented in Table 11 serve the same purpose as beta weights in multiple regression; they indicate the relative importance of the independent variables in predicting the dependent variable. The larger the standardized beta coefficient, the larger is the respective variable's unique contribution to the discrimination specified by the respective discriminant function. To interpret the discriminant functions, let us first look at the standardized discriminant function coefficients. The first discriminant function is most heavily weighted on patients' positive symptom and negative symptom. The second function is most heavily weighted on the variables 'dependency status of the patient' followed by the employment status of the caregiver.

In order to see which groups are separated by the discriminant function, the group means on each of the discriminant functions shown in Table 12 can be considered. The first discriminant function separates the severe burdened caregivers from the caregivers in the other two groups. The second discriminant function separates the moderately burdened caregivers from the remaining group of caregivers.

Table 12: Functions at Group Centroids

	Function	
Burden Score	1	2
No burden	-.803	-.339
Moderate burden	-.269	.447
Severe Burden	1.447	-.142

Figure 2 (Territorial plot) in the appendix, allows for visual inspection of the relationship between the predicted group membership and the two discriminant function.

The structure matrix in Table 13 shows the correlations of each variable with each discriminant function. The standardized discriminant function coefficients Table 11 indicate the partial contribution of each variable to the discriminant function(s), controlling for other independents entered in the equation whereas the structure coefficients in Table 13 indicate the simple correlations between the variables and the discriminant functions. The correlations serve like factor loadings in factor analysis, that is, by identifying the largest absolute correlations associated with each discriminant function we gains insight into how to name each function.

As a result, the first discriminant function has high correlations with explanatory variables: 'positive' and 'negative symptoms' of the patients whereas the second discriminant function is highly correlated with 'dependency status of the patient' and 'employment status of the caregiver'.

Table 13: Structure Matrix

	Function	
Explanatory variables	1	2
Positive symptom	.798(*)	-.220
Negative symptom	.789(*)	.036
Emotional help to caregiver	.279(*)	-.010
Gender of the patient	-.225(*)	.023
Relation of the caregiver to the patient	.094(*)	.016
Marital status of the Patient	-.088(*)	.036
Age of the patient	.038(*)	.018
Whether the patient depends most on the caregiver	.134	.766(*)
Employment status of the caregiver	.076	.552(*)
Educational status level of caregivers	-.004	.256(*)
Age of the caregiver	.042	.180(*)
Gender of the caregiver	-.004	-.148(*)
Marital status of the caregiver	.047	.108(*)
Ever lived with the patient	.070	-.087(*)

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.
* Largest absolute correlation between each variable and any discriminant function

4.5.4 Classification Statistics

Once the discriminant functions are determined and groups are differentiated, the utility of these functions can be examined in terms of their ability to correctly classify each data point to their a priori groups. There are many methods for performing classifications. All procedures involve defining some notion of distance between each observation and its group centroid. Then the observation is classified into the closest group. These procedures use either the discriminating variables themselves or the canonical functions.

The Fisher's linear discriminant functions coefficients are presented in Table 14. As can be seen in Table 14, a set of coefficients of explanatory variables are obtained for each burden group: no burden, moderate burden and severe burden. For groups with unequal sample sizes (n_j) the classification coefficients with explanatory variables $(x_1,..,x_{14})$ can be arranged in linear form as follows. Let Cij be the score for the ith, (i=1,..., nj) observation in the jth group (j=1,2,3).

$$\begin{aligned} C_{i1} = &-40.130 + 2.126x_{i,1} + 7.498x_{i,2} + 4.049x_{i,3} + 6.547x_{i,4} + 7.193x_{i,5} + 4.820x_{i,6} + 12.783x_{i,7} + \\ &3.311x_{i,8} + 9.363x_{i,9} + 7.017x_{i,10} - 1.016x_{i,11} - 1.617x_{i,12} - 0.517x_{i,13} + 6.173x_{i,14} \end{aligned}$$

$$\begin{aligned} C_{i2} = &-43.598 + 2.126x_{i,1} + 7.450x_{i,2} + 4.212x_{i,3} + 6.674x_{i,4} + 6.870x_{i,5} + 4.937x_{i,6} + 12.654x_{i,7} + \\ &3.061x_{i,8} + 10.457x_{i,9} + 9.244x_{i,10} - 0.604x_{i,11} - 0.980x_{i,12} - 0.298x_{i,13} + 6.670x_{i,14} \end{aligned}$$

$$\begin{aligned} C_{i3} = &-43.357 + 1.809x_{i,1} + 7.339x_{i,2} + 4.078x_{i,3} + 6.456x_{i,4} + 6.782x_{i,5} + 4.350x_{i,6} + 12.839x_{i,7} + \\ &2.983x_{i,8} + 9.923x_{i,9} + 8.591x_{i,10} + 0.103x_{i,11} + 0.622x_{i,12} + 2.663x_{i,13} + 6.322x_{i,14} \end{aligned}$$

The classification rule is that for each caregiver calculate its score on the three groups. Then the caregiver is assigned to the group for which it has the largest discriminant score. The resulting classification is presented in Table 15.

Table 14: Classification Function Coefficients (Fisher's linear discriminant functions)

Explanatory variables		Burden Score		
		No burden	Moderate burden	Severe Burden
X_1	Marital status of the Patient	2.126	2.126	1.809
X_2	Gender of the patient	7.498	7.450	7.339
X_3	Age of the patient	4.049	4.212	4.078
X_4	Relation of the caregiver to the patient	6.547	6.674	6.456
X_5	Gender of the caregiver	7.193	6.870	6.782
X_6	Age of the caregiver	4.820	4.937	4.350
X_7	Ever lived with the patient	12.783	12.654	12.839
X_8	Marital status of the caregiver	3.311	3.061	2.983
X_9	Employment status of the caregiver	9.363	10.457	9.923
X_{10}	Whether the patient depends most on the caregiver	7.017	9.244	8.591
X_{11}	Emotional help to caregiver	-1.016	-.604	.103
X_{12}	Negative symptom	-1.617	-.980	.622
X_{13}	Positive symptom	-.517	-.298	2.663
X_{14}	Educational status level of caregivers	6.173	6.670	6.322
	(Constant)	-40.130	-43.598	-43.357

Discriminant function plots were created in which the two axes are two of the discriminant functions and rectangles within the plot locate the centroids of each category being analyzed. The farther apart one point is from another on the plot, the more the dimension represented by that axis differentiates those two groups. Figure 3 in the appendix is the plot of "Combined-groups" on the space dimension formed by the two discriminant functions and it depicts discriminant function space.

As can be seen from Table 15, the discriminant function correctly classifies about 65% of the caregivers. The classification result in each group indicates that 79 % of severely burdened caregivers, about 61% of the moderately burdened caregivers and about 58% of the caregivers were classified correctly. The diagonal elements in the count part of the table below shows the number of cases correctly classified into the groups.

Table 15: Classification Results (*)

Burden Score			Predicted Group Membership			Total
			No burden	Moderate burden	Severe Burden	
Original	Count	No burden	102	62	13	177
		Moderate burden	35	108	33	176
		Severe Burden	11	17	103	131
	%	No burden	57.6	35.0	7.3	100.0
		Moderate burden	19.9	61.4	18.8	100.0
		Severe Burden	8.4	13.0	78.6	100.0

(*) 64.7% of original grouped cases correctly classified.

4.6 Discussion and Interpretation of results

From the analysis of polytomous ordinal logistic regression, dependency status of the patient, emotional help to the caregiver, patient's positive symptom (Positive symptoms are those that characterize schizophrenia during an acute exacerbation of the illness (i.e relapse)) and negative symptom (Negative symptoms, are those more persistently stable characteristics of schizophrenia) are found as important determinants of caregivers burden. Efforts in the past to identify contributing factors have mostly been limited to investigations of the impact of different types of patient symptoms and reached with mixed conclusions. That is some studies found that higher levels of burden were associated with higher levels of negative but not positive symptoms and others found that increased burden was associated with higher levels of both positive and negative symptoms or with positive symptoms alone (Deborah, 2006). In the present study we found that both negative and positive symptoms were found to be associated with caregivers' burden. That is caregivers of patients who have no negative and positive symptom and moderate negative and positive symptom, as compared to caregivers of patients those having severe negative and positive symptoms had a lower probability to be highly burdened. In other words, it implies that caregivers of patients with severe positive and negative symptom were more likely to experience severe burden than those with no positive or negative symptoms, which means as both negative and positive symptoms of the patient increases so does the burden on the caregivers.

The other important variable identified as predictor of caregivers' burden is the dependency status of the patients on the caregiver. It is found that as dependency status of the patient decreases, burden on caregivers' decrease as well and vice versa. Here for instance, when the dependency status of the patient takes the value 1 (that means the patient depends most on the caregiver) will result in an odds ratio of exp (-1.393) = 0.25 increase in odds of being in a highly burdened.

The other statistically significant explanatory variable is the emotional helps (showing that others help in caregiving) given to the caregiver; as compared to the caregivers who did not had emotional help, those who experienced the help have inverse relationship to the out come variable ($\hat{\beta}$=-0.910), this implies that those caregivers who experienced emotional help will have lower probability of being in the higher category of the outcome variable, category of burden, in other words, the more emotional help the caregivers experience the lesser will be the burden.

Though, sex of patient is not statistically significant in the multivariate study, results from the univariate and bivariate analysis are in line with those of Hoening & Hamilton (1966), who found that relatives of male patients reported objective burden than those of female patients; in the present study 78.7% of the caregivers of male patients reported that they experienced sever burden.

A preliminary analysis for discriminant analysis using Wilks' lambda we found differences in the three groups of burden with respect to 'gender of the patient', 'employment status of the caregiver', 'whether the patient depends most on the caregiver', 'emotional help given to the care giver', 'negative' and 'positive' symptom of the patient; which we might consider the others dropping from the model. Among these variables positive and negative symptoms are heavily weighted on the first function and employment status of the caregiver and dependency status of patients on the caregivers have relatively high weight on the second function. Although these variables are similar to those variables found to be significant in bivariate analysis, only four of them namely, 'whether the patient depends most on the caregiver', 'emotional help given to the care giver', 'negative' and 'positive' symptom of the patient were significant in polytomous ordinal logistic regression analysis.

The standardized discriminant function coefficients obtained from the multiple discriminant analysis in Table 11 indicate the relative importance of the independent variables in predicting the caregivers' burden, group membership. 'Employment status of the caregiver', 'dependency status of the patient', 'Emotional help to caregiver', 'patients' Negative symptom' and 'Positive symptom' were variables found to have relatively high contribution on the discrimination of caregivers into the respective categories.

Similar results are also obtained from the structure matrix (Table 13). This helps to assign meaningful labels to the discriminant functions. Since negative and positive symptoms are highly correlated with the first function this function can be labeled as health related factors. On the other hand employment status of the caregiver and dependency status of the patient are highly related to the second function; we can label it as economic factors. Further, it can be noted that health related factors explain 87.3% and economic factor 12.7% of the total variation in caregivers' burden. Moreover, the classification result indicates that the variables under consideration in the linear discriminant function be able to correctly classify about 65% of the caregivers in the caregivers burden groups.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Our prime concern is identification of predictors of burden on caregivers of patients of Schizophrenia and Bipolar disorder; and comparison of the results from the polytomous ordinal logistic regression and discriminant analysis. From Table 16 in the appendices we can see that 36.5% of the caregivers reported that they experienced no burden, whereas 36.9% of them experienced moderate burden.

In the vast literature on determining the association between negative and positive with burden of caregivers, the results were not consistent. Discrepancies in the research findings may be explained in two ways. First, these symptom types may lack sensitivity or specificity to dimensions of burden that differ from those we measured. Second, the discrepancies may be caused by variations in the degree and relative proportion of positive and negative symptoms represented in different clinical samples. In other words, the may be sensitive to some explanatory variables and the sample may not be representative of the populations. In the present study however, both negative and positive symptoms of patients are found the most contributing factors in determining burden of caregivers. The more the patient shows negative and positive symptoms the higher will be the severity of burden on caregivers.

In the multivariate analyses carried out in polytomous ordinal logistic regression and discriminant analysis four of the explanatory variables: positive symptom, negative symptom, emotional helps to the caregiver and dependency status of the caregiver are found to be important predictors of burden on caregivers of schizophrenia and bipolar disorder patients. All the significant variables in discriminant analysis, two more than that of logistic regression, were also significant in univariate analysis. In addition, though some variables are not significant in the multivariate set up due to the relationship with other explanatory variables, in the bivariate analysis age of the patient, gender of the caregiver, age of caregiver, ever lived with patient, marital status of the caregiver, educational status of caregivers are found to be significantly associated with caregiver burden.

The dependency status of the patient has negative relationship with the probability of falling in higher ordinal outcome (burden score). This means that as the patient depends most on the care giver, the caregiver suffers from severe burden. The emotional help given to the caregiver is also another important variable contributing to burden experienced by the caregivers; as compared to the caregivers who did not had emotional help, those who experienced the help had less burden, in other words, the more emotional helps the caregivers experience the lesser will be the burden.

In the discriminant analysis, in order to discriminate among no burden, moderate burden and high burden groups using explanatory variables; two discriminant functions are constructed. The first discriminant function is highly correlated to negative and positive symptom and named as health related factors. The second one mainly related to dependency status of the patient and employment status of the caregiver and identified as economic factor. The health related factors explains most of the variation as compared to the economic related factors. The health related factors mainly discriminate the severely burdened caregivers from the caregivers in the other two groups. The economic related factors mainly discriminates the moderately burdened caregivers from the remaining group of caregivers.

In comparing the results obtained by the multivariate analysis, explanatory variables such as positive and negative symptoms and dependency status of the patient, employment status of the caregiver found most contributing factors in determining the burden of caregivers. However, the polytomous ordinal logistic regression classified 67.2%* of the caregivers in their respective burden group, whereas the discriminant analysis correctly classified 64.7%*. The polytomous ordinal logistic regression shows a slight improvement in correctly classifying caregivers over multiple discriminant analysis. *(* See Tables in the appendix).*

Based on the findings of the present study we conclude that high burden on the caregivers is significantly characterized by dependency status of the patient (whether the patient depends most on the caregiver), emotional helps given to the care giver from the society, negative and positive symptom of the patient.

5.2 Recommendations

Intervention strategies for family members or caregivers of mentally ill people have frequently focused on modifying the family's affective response and behavior toward the patient. Such interventions are based on findings that expressed emotion, an index of the family's emotional response to the patient, predicts relapse. Besides such interventions, our findings on patient helpfulness draw attention to the importance of reducing burden on caregivers in maintaining a more positive affective climate.

The findings suggest that attention should be given towards the patients symptom reduction (provision of treatment to reduce severity of the symptoms) and creating awareness about mental illness in the society. Interventions to support and develop the patients' ability to contribute to the household and management of his or her own care, such as skills training or wellness recovery, are most likely to meet the needs and enhance the quality of life of people with mental illness and their families. Therefore we recommend the health policy makers and the health workers as follows:

- The existing limited resource for the purpose of mental health service should be used for caregivers' interventions and support at least in educating caregivers about the nature of schizophrenia and Bipolar disorder and how to deal with its burden on them.
- Health centers for the service of mentally ill patients should be expanded so as to minimize the patients' symptom of disease; and creating awareness by teaching the society so that the caregivers experience emotional help from the society.
- To help both the patients as well as their caregivers with the regard to the financial aspect, employment opportunity at least for the caregivers should be created.

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APPENDICES

Figure 2: Territorial Map

Canonical Discriminant Function 2

```
       -6.0      -4.0      -2.0        .0       2.0       4.0       6.0
         ⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳
     6.0 ⇳                                         23                ⇳
         ⇔                                          23               ⇔
         ⇔                                         23                ⇔
         ⇔                                         23                ⇔
         ⇔                                        23                 ⇔
         ⇔                                       23                  ⇔
     4.0 ⇳         ⇳         ⇳         ⇳         23        ⇳         ⇳
         ⇔222                                   23                   ⇔
         ⇔11122                                 23                   ⇔
         ⇔  11222                              23                    ⇔
         ⇔    11122                            23                    ⇔
         ⇔       11222                        23                     ⇔
     2.0 ⇳         11122     ⇳         ⇳     23  ⇳         ⇳         ⇳
         ⇔            11222                   23                     ⇔
         ⇔              11122                23                      ⇔
         ⇔                 11222             23                      ⇔
         ⇔                   11122          23                       ⇔
         ⇔                      1122  *     23                       ⇔
      .0 ⇳         ⇳         ⇳    11222⇳  23   * ⇳         ⇳         ⇳
         ⇔                         *1112223                          ⇔
         ⇔                             1123                          ⇔
         ⇔                               13                          ⇔
         ⇔                               13                          ⇔
         ⇔                               13                          ⇔
    -2.0 ⇳         ⇳         ⇳         ⇳ 13      ⇳         ⇳         ⇳
         ⇔                               13                          ⇔
         ⇔                                13                         ⇔
         ⇔                                13                         ⇔
         ⇔                                13                         ⇔
         ⇔                                13                         ⇔
    -4.0 ⇳         ⇳         ⇳         ⇳  13     ⇳         ⇳         ⇳
         ⇔                                13                         ⇔
         ⇔                                13                         ⇔
         ⇔                                 13                        ⇔
         ⇔                                 13                        ⇔
         ⇔                                 13                        ⇔
    -6.0 ⇳                                13                         ⇳
         ⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳⇩⇩⇩⇩⇩⇩⇩⇩⇩⇳
       -6.0      -4.0      -2.0        .0       2.0       4.0       6.0
```

Canonical Discriminant Function 1

Symbols used in territorial map

Symbol	Group	Label
------	-----	--------------------
1	0	No burden
2	1	Moderate burden
3	2	Severe Burden
*		Indicates a group centroids

Figure 3: Scatter plot for the combined group

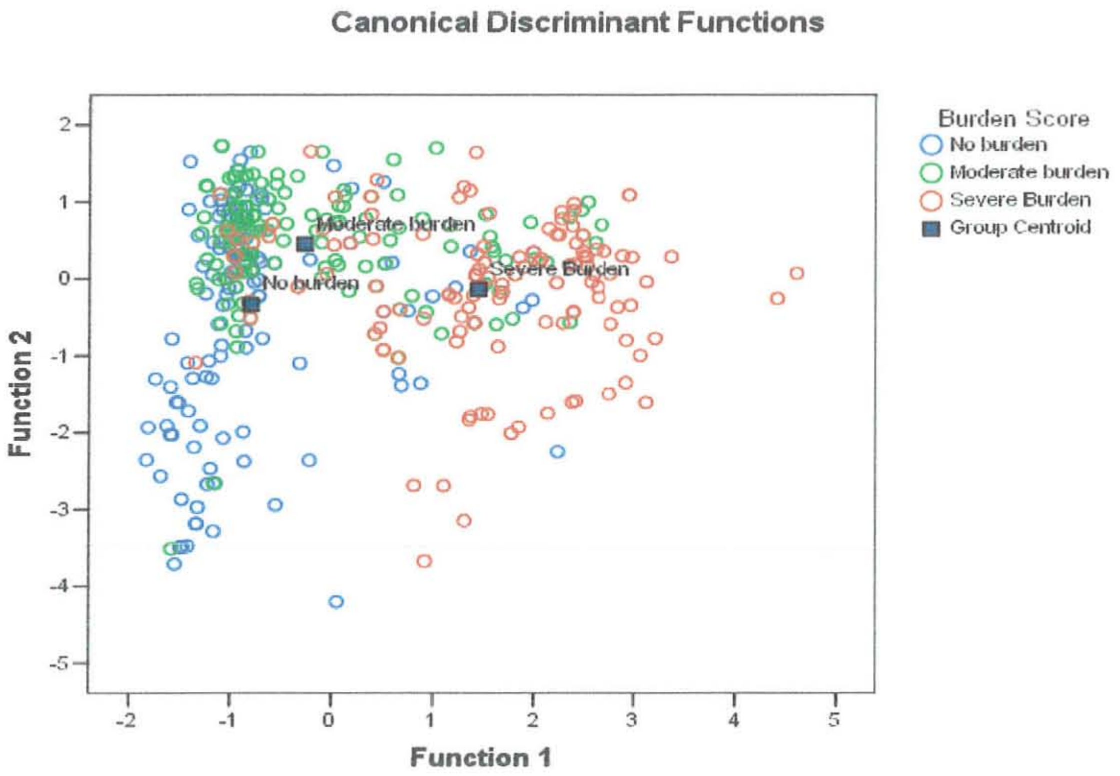

Table 16: Percentage distribution of Burden Score

		Frequency	Percent	Valid Percent
Valid	No burden	187	36.4	36.5
	Moderate burden	189	36.8	36.9
	Severe Burden	136	26.5	26.6
	Total	512	99.6	100.0
Missing	System	2	.4	
Total		514	100.0	

Table 17: Classification table for polytomous ordinal logistic regression

	Predicted			
Observed	No burden	Moderate burden	Severe Burden	Percent Correct
No burden	128	40	9	72.3%
Moderate burden	54	96	26	54.5%
Severe Burden	14	19	98	74.8%
Overall Percentage	40.5%	32.0%	27.5%	67.2%

Table for the acronyms used in the discussion.

Acronym	Description	Value labels
[BSc]	Burden score	No burden (0)
		Moderate burden (1)
		Severe Burden (2)
[n8maritals]	Marital status of the patient	Never married (0)
		Married (1)
		Separated (2)
[n1sex]	Gender of the patient	Male (1)
		Female(2)
[n2curage]	Current age of the patient	Less than or equal to 30 (0)
		Greater than 30 (1)
[n2relation]	Relation to the patient	Spouse(1)
		Parent(2)
		Child(3)
		Other(4)
[n3gender]	Gender of the caregiver	Male (1)
		Female(2)
[age]	Age of the caregiver	15-30 years(0)
		Greater than 30 years(1)
[n5everliv]	Whether the patient lived with patient	Yes(0)
		No(1)
[n1marital]	Marital status of the caregiver	Never married (0)
		Married (1)
		Separated (2)
[n4employme]	Employment status of the caregiver	Not currently employed (0)
		Employed (1)
[n1familyme]	Dependency status of the patient	Not dependent(0)
		Dependent(1)
[emot]	Emotional helps given to the caregiver	No(0)
		Yes(0)
[Negsym]	Patients negative symptom	None (0)
		Moderate (1)
		Severe(2)
[Posym]	Patients positive symptom	None (0)
		Moderate (1)
		Severe(2)
[edustatusinfor]	Educational status of the caregiver	Illiterate (1)
		Literate (2)

DECLARATION

I, the undersigned, declare that the thesis is my original work, has not been presented for degrees in any University and all sources of material used for thesis have been duly acknowledged.

Name: Merga Belina

Signature: ______________

Place: Faculty of Science, Addis Ababa University

Date: July 22, 2008

This thesis has been submitted for examination with my approval as a University advisor.

____

Fentaw Abegaz (PhD)