The Pennsylvania State University

The Graduate School

College of Health and Human Development

APPLYING MULTILEVEL MODELS TO HEALTH SERVICES RESEARCH FOR CHILDREN WITH MENTAL HEALTH PROBLEMS

A Thesis in

Health Policy and Administration & Demography

by

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Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

May 2005

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ABSTRACT

This dissertation uses multilevel modeling to study health services for youth with mental health and substance abuse problems. This dissertation is composed of three studies. The first study examines whether racial/ethnic variation in use of medication among youth with attention problems can be explained by factors related to where the youth live. The second study examines determinants of length of stay in inpatient facilities for youth with mental health and substance abuse problems. The third examines determinants of receipt of follow-up and readmission among youth with mental health and substance abuse problems who have been discharged.

The first study examines racial variation in receipt of medication among youth with attention problems using data from the National data from the evaluation of the Comprehensive Community Mental Health Services for Children and Their Families program (CCMHSCF) were analyzed. The sample for these analyses consisted of 4193 youth in 40 communities aged 3-22 whose parents reported that they had attention problems. Estimation involved a multi-level model of receipt of medication management as a function of child characteristics (age, internalizing, externalizing, or substance abuse disorder, special education status), family characteristics (income, structure, number of children in the family) and county-level characteristics (percent Hispanic, black, urban, children living in poverty and designation as a mental health provider shortage area). Reflecting potential racial differences in the processes shaping medication use, separate models were estimated by race and gender. Our results suggest that among boys with attention problems, blacks and Hispanics were roughly 15 percent less likely to receive medication than whites (p<.001). Among girls with attention problems, blacks were 12 percent less likely than whites to receive medication (p<.05). Thus, controlling for a wide array of determinants of health services does not explain the racial disparity in receipt of medication. Further research needs to explore the underlying reasons for these differences.

The second study examines variation in inpatient length of stay (LOS) for youth with mental health and substance abuse disorders. A primary goal of this analysis is to examine whether patient-level factors are poor predictors of LOS because LOS is primarily determined by facilities rather patients. These analyses also demonstrate a method for profiling healthcare facilities whose patients on average have exceptionally long or short LOS. This study uses Tennessee Medicaid claims data from 1996 to 2001. The data include information on 16,217 observations related to 9,4183 patients (aged 12-21) from 197 facilities. We estimate LOS using a Bayesian cross-classified model. Covariates include patient characteristics (age, gender, race, qualification for Medicaid, diagnosis) and facility characteristics (facility type and primary specialty of the facility). Our results suggest that about 4 percent of the variation in LOS is explained at the patient-level while 42 percent is explained at the facility-level. These analyses also demonstrate that having a cross-classified data structure rather than a completely nested data structure improve the precision of our patient-level variance estimate by 84 percent. By presenting shrinkage estimates of the residuals, we demonstrate a method for pooling information across patients and facilities to identify facilities whose average LOS is truly exceptionally long or short. To conclude, given the vulnerable nature of youth who are in need

of inpatient psychiatric care, it may be particularly important to monitor provider-level processes and outcomes. Measuring facility or provider level quality is complicated because of difficulties in adjusting for case-mix severity across providers. The methodology presented here represents a general framework that can be widely used in health services research. Potential applications of multilevel modeling include broadening models of utilization to simultaneously include attributes of patients, providers and communities and it identify providers whose outcomes or costs are relatively exceptional in some way.

The third study examines both patient and provider-level determinants of aftercare services for youth with mental health and substance abuse disorders following inpatient hospitalizations. This study uses Tennessee Medicaid claims data from 1996 to 2001. The data include information on 9,181 youth aged 12-21 discharged from 170 facilities. We estimate the hazard of receiving aftercare services using a multilevel discrete-time event history model. Covariates include patient characteristics (gender, race,), facility characteristics (type, specialty), episode characteristics (length of stay prior to discharge, year, child's qualification for Medicaid, age, and diagnosis) and duration from discharge until receipt of follow-up services. Twelve percent of youth in our sample received aftercare services within four months of discharge. Relative to youth with mental health problems, the hazard of receiving aftercare services was 26 percent lower for youth with substance abuse problems. Relatively little (9%) of the variation in aftercare services was determined at the facility level, and 16 percent was explained by patient and family characteristics. A relatively small percentage of youth discharged from inpatient facility received the appropriate level of aftercare services. Further research should examine factors that could improve this low rate. Because relatively little of the variation in aftercare is determined at the facility level, these results call into question the use of aftercare receipt as a measure of quality of care.

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ACKNOWLEDGMENTS

There are a large number of individuals who were invaluable in helping prepare this thesis and more importantly complete graduate. I'd like to thank my committee, Linda Collins, Marianne Hillemeier, Wayne Osgood, Rebecca Wells and Eric Ford. I appreciate their comments and willingness to move quickly so that I could pursue opportunities such as submitting an NIH dissertation grant and starting a new job.

I'd like to thank my graduate school friends, such as Paige Powell, Kristine Pringle, EJ Kang, Lousie Meret-Hanke, Jill Rumberger, Francis Burden and Gretchen Ruth. Some days were better than others but it was nice to have a group of friends going through the same process. I'd like to thank Isis without whom I'm quite sure I would have completely lost my mind. It's hard to imagine how something so seemingly frivolous as a frisbee team can change ones life.

Of course, I'd like to thank my family-- most notably my mother who took the brunt of my stress and anxiety over the last seven years. The more that I study families, the more that I understand how essential family support is.

Somehow this section wouldn't be complete without acknowledging Mike Foster. Most people think that the advisor puts the graduate student through hell. I assure you that I did my darnest to make that a two way street. For whatever reason, Mike continued to work with me and I'm better researcher for it. I benefitted from working with Mike in terms of organization, statistical knowledge, writing ability and general professional development.

Finally, I'd to thank the agencies that supported this research. I'd like to thank the staff at ORC Macro International for allowing us to use the data from the evaluation of the Comprehensive Community Mental Health Services for Children and Their Families (CCMHSCF) program. I'd like to thank Craig Anne Heflinger for allowing me to use data collected through the Tennessee Impact Study data. I'd like to thank Robert Saunders for his help in understanding the Tennessee Impact Study data. Collection of the Tennessee Impact study data used in this study was funded by the Center for Substance Abuse Prevention (CSAP grant # CSAP:UR7 TI11304, Principal Investigator: C.A. Heflinger) in the Substance Abuse and Mental Health Services Administration. Preparation of this article was supported by Center for Substance Abuse Treatment (CSAT grant # 1KD1, TI112328, Principal Investigator: C.A. Heflinger), the National Institute on Drug Abuse (NIDA grant # R01 DA12982, Principal Investigator: C.A. Heflinger), and the National Institute on Alcohol Abuse and Alcoholism (NIAAA grant # R21 AA12432, Principal Investigator: C.A. Heflinger). Its contents are the authors' responsibility and do not necessarily represent the official view of the funding agency. Special thanks to the families who shared their lives and experiences to make this research possible.

CHAPTER ONE

The Use of Multilevel Models in Health Services Research

Health services researchers are interested in questions related to cost, quality and access to health care. Determinants of these three components are based on a host of interwoven forces. For instance, whether an individual seeks care is partly based upon his or her illness, age, gender, race/ethnicity, education, family income and insurance status. At the same time, individuals live within communities. The types of providers that are available to the individual partly depend upon community resources. For instance, remote areas often lack specialty care for populations with specific needs such as women with substance abuse problems. Meanwhile, providers play a large role in making decisions for their patients regarding the type of care they should receive. In fact, providers from different geographic regions of the United States have different practice styles (Birkmeyer et al. 1998; McPherson, and al. 1982). Differences in practice style mean patients with the same illness will likely receive different treatments simply based upon where they live.

In order to answer questions related to cost, quality and access to health services, health services researchers frequently frame their models by employing the Andersen/Aday Behavioral Model of Health Services Utilization (Andersen 1995) (see figure 1.1). This framework has been developed over the last 40 years. It summarizes the various factors thought to influence whether an individual receives care as well as the quantity and quality of the care he or she receives.

One of the most important determinants of use of health services is an individual's need for care. However, "need" for health services is relatively subjective. Individuals with the same ailment, or in the case of preventive medicine–in the same situation, may differ in their perceived

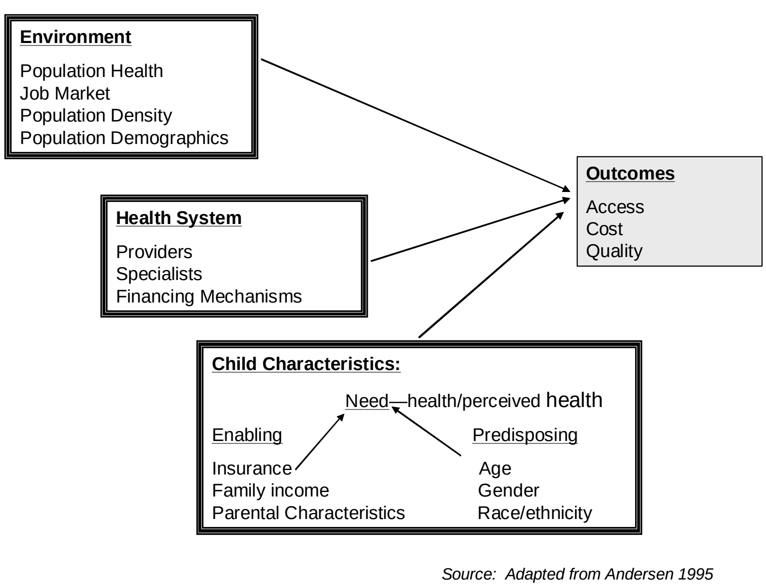

Figure 1.1 Behavioral Health Services Model

need for care. Decisions to use services will be influenced by how one perceives need for care–is the person ill, is the illness affecting his or her ability to function, are there services that can improve his or her health and is it worth spending X amount of dollars to improve health status by X amount.

The Behavioral Model also includes an individual's predisposing characteristics. These are thought to be biological characteristics which influence a person's need for health services such as age, gender, race/ethnicity. For instance, young children and the elderly are more likely to need vaccinations. Boys and girls often manifest psychological problems differently and may benefit from different treatments. At the same time, an individual's beliefs, values and attitudes about health and health care can also influence whether he or she will seek services.

A second factor is enabling characteristics. These are factors that promote or prohibit an individual from engaging in the health care system. Enabling factors include family income, health insurance and having a usual source of care. Education can also be thought of as an enabling factor because it influences whether one knows how to access care. In fact, for children, enabling characteristics can include predisposing and enabling characteristics of the caregiver. A more highly educated caregiver may be better equipped to identify a child's ailment and seek services earlier.

The Behavioral Model of Health Services Utilization also includes environment characteristics such as the health care system and the external environment. The health care system includes features such as the number and types of providers in the area and the training of the health care providers. It may also include the payment systems that operate within a community or the managerial practices used by local providers. These factors influence the availability of services. Since providers play an important role in choosing the best course of treatment for a patient, differences in local health care systems are an important determinant of health services utilization (Buchanan 1988; Grossman, and Hart 1983; Ross 1973).

One final factor that influences health services utilization is the external environment. The external environment can impact features of the model in many ways. For instance, areas with few financial resources may have difficulty attracting and retaining highly trained physicians and specialists. Similarly, areas with a large low income population may have higher rates of certain illnesses that correlated with poverty such as mental retardation, asthma and exposure to lead. High rates of need in underserved areas may make it difficult for some individuals to obtain care and may increase the amount of time an individual waits for services. Similarly, in high poverty areas with few doctors, patients with Medicaid may find it difficult to find a doctor who will see them.

Because these factors are operating simultaneously, models of health services utilization should use sophisticated statistical tools to incorporate each component. However, health services researchers have typically studied the influence of each actor separately. For example, economists have studied individual determinants of length of inpatient stay without examining factors about who was providing care (English et al. 1986; Frank, and Lave 1986). Organization theorists have studied how different managerial practices affect provider decisions without including differences in patient-level characteristics (Stiffman et al. 2001).

The samples in the data used by health services researchers often reflect the separation of the different disciplines. Often the samples for our studies are based on many patients from one or a few facilities (ex. a hospital, an emergency room), patients from one or a few geographically close counties, or are based on a national sample but exclude provider level factors altogether. Conceptually, collecting samples under the scheme encourages the researcher to ignore the nesting of individuals within higher order units. A child lives within a family, receives services from within a facility. That facility is located within a community.

From a statistical stand point, the consequences of ignoring the nesting of individuals within higher order units is potentially severe. By so doing, we are violating the assumption that observations from the sample are identically and independently distributed. When this assumption is violated our standard errors will be too small because we are ignoring the fact that our sample is not a simple random sample but rather that these observations are clustered in some way. Even more importantly, by ignoring the fact that the observations are clustered within higher order units, researchers may be missing an important source of variation altogether.

When health services researchers have accounted for the clustering in the data, they have primarily relied on one of two approaches taken from economists–the fixed effect or random effect approach. These approaches are extensions of ordinary regression techniques. For instance, in the fixed effect approach, the regression model includes a dummy variable for each higher order unit. Thus, each higher order unit has it's own intercept. This model assumes that across higher order units, the effect of each covariate in the model is the same (ex. the effect of being black would be constant across hospitals). One advantage of this approach is that it makes no assumptions about the distribution from which the higher order units were sampled. However, the major disadvantage of the fixed effects approach is that it uses many degrees of freedom (one degree of freedom fewer than the number of level two units). In comparison, the random effects approach assumes that each higher order unit has a unique error term. While this approach uses fewer degrees of freedom than the fixed effect approach, it lacks some flexibility in terms of modeling decisions. For instance, this model would not allow the slope of a parameter to vary across higher order units.

Multilevel modeling offers health services researchers a host of tools to answer research questions than they otherwise could not. For instance, one limitation of both the fixed and random effects approach is that they assume that the effects of the covariates are the same across higher order units. However, in multilevel modeling the researcher can allow the slope of a variable to vary across higher order units. For example, we may be interested in whether the effect of being a minority on health services utilization varies across communities. A second benefit of multilevel modeling relative to the random effects approach is that it can allow for more than two levels. For instance, our data may contain information on each visit that a patient makes to various facilities. These facilities may be located in different communities. Multilevel modeling allows the researcher several modeling options. For example, the researcher could model the nesting of repeated observations on individuals who receive treatment within facilities that are located within communities. As an extension, the researcher could use a cross-classified model to incorporate information on the same individual who is treated at different facilities (see Chapter 5 for an example). A third use of multilevel modeling partitioning the variance in an outcome across different levels. This feature of multilevel modeling is potentially valuable to health services researchers. As researchers seek ways to improve quality and decrease the costs of care, understanding what level explains the large amounts of the variance may provide insight into the types of interventions that will be most beneficial. For instance, does patient compliance with provider recommendations vary at the individual or provider level? One final use of multilevel modeling is in the area of provider profiling. As health care costs rise and providers are increasingly held accountable for their outcomes, attention has been growing as to ways to identify providers whose care is extreme. Yet, accurately identifying providers whose behavior is extreme is challenging. This is because providers do not treat a homogeneous set of patients, may only treat a few patients with a given illness and because the quality of information that we have on different providers is not uniform. In chapter 5, we demonstrate a Bayesian mulitilevel modeling method for profiling facilities. This type of method may have broad applicability in the future as profiling becomes more common.

This dissertation presents three studies using multilevel modeling to examine different issues in health services for children with mental health and/or substance abuse problems. While each study addresses an important substantive issue in the area of children's mental health services research, each study also demonstrates a methodologically sophisticated way to address the research question.

The purpose of the first study is to examine whether racial variation in receipt of medication by youth with attention problems. This is an important area of research because roughly four percent of youth aged 6-17 are afflicted with attention deficit disorder (National Institute of Mental Health, 2001). The prevailing expert opinion is that stimulant medication is a safe and effective manner for treating these youth. However, a series of studies have found that among youth with attention problems, Blacks and Hispanics are substantially less likely to receive medication than their white counterparts (LeFever, Arcona, and Antonuccio 2003; Leslie et al. 2003; Rowland et al. 2002a). The current study uses multilevel models to examine whether the racial variation in receipt of medications can be explained by where the youth. In order to do this we take advantage of two features of the data. First, we use the fact that individuals within are dataset are clustered within 40 sites. Second, using geographic information systems, we incorporate county-level demographic information in the analyses.

The second study examines determinants of inpatient length of stay for youth with mental health and substance abuse disorders. This study draws on Medicaid claims data of children aged 12-21 from the Tennessee Impact Study. The importance of this study lies in the fact that inpatient care is typically the most costly component of treatment. Often, managed care plans, insurance plans and policy makers are interested in curbing these costs. The purpose of this study is twofold. First, we partition the variation in length of stay for youth with mental health and substance abuse disorders across provider-level and patient-level characteristics. This is a relatively novel idea in the area of health services researchers where economists have typically focused on individual level determinants of health services. Second, we demonstrate a method for identifying providers who's pattern of health care is extreme (average length of stay is extremely short or long). As accountability for outcomes because increasingly important, identifying providers whose care is extreme will grow in importance. However, methodologically, there are several reasons why it is challenging to identify providers whose care truly is extreme (Zaskavsky 2001). First, providers do not treat a homogeneous population. Given available data sources, it is typically difficult to accurately risk adjust across providers. In addition, some providers will only treat a small number of patients with a given condition. While frequentist approaches work well when we have large numbers, it is difficult to say with certainty whether a providers behavior is extreme when only a few cases are observed. This study uses a Bayesian approach which allows the researcher to pool information across providers. Estimates produced from the Bayesian approach reflect the greater amount of uncertainty for providers which we observe fewer events.

The third study examines provider-level and patient level determinants in a commonly used measure of quality of care for youth who have been hospitalized, receipt of timely aftercare services. This study uses Medicaid claims data from the Tennessee Impact study to examine timing of follow-up services. The contribution of this study is that it uses multilevel modeling with event history techniques. There by we are able to examine factors that affect timing of services while taking into account factors related to the individual as well as the provider.

Together these studies demonstrate several techniques related to multilevel modeling that have many potential applications in researching issues related to children's mental health services. Multilevel modeling offers health services researchers a means for incorporating the observed clustering (ex. patients within hospitals; patients with communities) that affects health care decisions. Using more sophisticated tools that take into account this clustering will provide researchers with more accurate and precise estimates for questions of interest.

CHAPTER TWO

Race and place: Does local area variation explain the racial disparity in use of therapeutic psychostimulants?

ABSTRACT

Objective: To examine racial variation in receipt of medication among youth with attention problems.

Method: National data from the evaluation of the Comprehensive Community Mental Health Services for Children and Their Families program (CCMHSCF) were analyzed. The sample for these analyses consisted of 4193 youth in 40 communities aged 3-22 whose parents reported that they had attention problems. Estimation involved a multi-level model of receipt of medication management as a function of child characteristics (age, internalizing, externalizing, or substance abuse disorder, special education status), family characteristics (income, structure, number of children in the family) and county-level characteristics (percent Hispanic, black, urban, children living in poverty and designation as a mental health provider shortage area). Reflecting potential racial differences in the processes shaping medication use, separate models were estimated by race and gender.

Results: Among boys with ADD, blacks and Hispanics were roughly 15 percent less likely to receive medication than whites ($\underline{p}$<.001). Among girls with ADD, blacks were 12 percent less likely than whites to receive medication ($\underline{p}$<.05).

Conclusions: Controlling for a wide array of determinants of health services does not explain the racial disparity in receipt of medication. Further research needs to explore the underlying reasons for these differences.

Attention deficit disorder (ADD) affects about 4 percent of youth aged 6-17 (National Institute of Mental Health (NIMH) 2001). ADD Symptoms include impulse control, hyperactivity and difficulty paying attention. Because ADD can affect an individual's ability to function in various settings such as the classroom, failure to treat ADD can have long lasting effects. For example, children with ADD may not achieve their full potential in school which in turn could negatively affect future employment (NIH Consensus Statement Online 1998).

Effective treatments for the disorder exist (American Academy of Pediatrics 2001; Jadad et al. 1999; NIH Consensus Statement Online 1998). For many youth, treatment includes stimulant medication. According to a review by the Perrin et al (2001) for youth with ADD, stimulant medication improves a youth's impulse control and decreases emotional hyperactivity. These behaviors affect functioning in school, peer and family settings. While the long-term effects of stimulant medication are unknown, negative side effects are thought to be mild and short lasting such as decreased appetite, stomach or head ache, jitteriness, or social withdrawal (Gaub, and Carlson 1997). More troubling are the potential for enduring consequences, such as stunting or developing a substance abuse disorder (Greydanus, Sloane, and Rappley 2002) (Wilens et al. 2003).

Prior research suggests that white youth with attention-related disorders are substantially more likely to receive medication than their nonwhite counterparts (LeFever, Dawson, and Morrow 1999; Leslie et al. 2003; Rowland et al. 2002b; Safer, and Malever 2000; Zito et al. 1998). Existing research, however, suffers from a variety of limitations. For example, most studies have an insufficient sample of Hispanics or are unable to identify Hispanic ethnicity. Few studies include key determinants of youth's health services use such as caregiver education, family income, as well as any comorbidities that the youth may have. Minority status is correlated with lower socioeconomic status which in turn is associated with lower use of health services. Thus, excluding determinants of treatment may bias our estimates of racial variation. Moreover, most studies are based upon samples from relatively small geographic areas. Since treatment patterns vary widely from place to place (so-called "small area variation"), studies from one region may not generalize to youth residing in different regions of the country (Wennberg 1999; Wennberg, Barnes, and al 1982).

In contrast, the current analyses focus on youth receiving treatment for mental health services in public systems across the nation. The sample includes a large number of Hispanic, black and white youth. Moreover, the data include many family and child characteristics. Furthermore, because all children are treated in the public mental health sector, all children have roughly equivalent access to services in their community. As a result, we avoid some confounding of race and ethnicity with service availability.

Data are analyzed using multilevel logistic regression. This method allows for the facts that children are nested within communities and that the levels of medication use can vary from one community to the next.

PRIOR RESEARCH

Two lines of research form the background for the current study. First, we examine existing research on racial and ethnic differences in the use of psychostimulants. We then briefly review a conceptual model for the use of psychostimulants. This model identifies additional determinants of medication use which could otherwise be confounded with that of race and ethnicity, the focus of our study.

Prior research on racial disparities

A series of studies has identified racial patterns in the use of stimulant medication across a range of communities and populations. These populations include children aged 5-14 enrolled in Maryland's Medicaid program in 1991 (Zito et al. 1998) ; first through fifth graders in Johnston North Carolina during the 1997/1998 and 1998/1999 school years (Rowland et al. 2002b); second through fifth graders from two cities in southeastern Virginia in the 1995/1996 school year (LeFever et al. 2003); Maryland public school students in 1998 (Safer, and Malever 2000); and youth aged 6-17 receiving mental health, alcohol/drug services, child welfare, juvenile justice, or special education in San Diego County, CA in 1996-1997 (Leslie et al. 2003). Across these studies, white youth were 1.4-3 times more likely than nonwhite youth to receive stimulant medication.

It is worth noting that these studies generally are not limited to youth identified with attention problems. For that reason, racial comparisons reflect differences in both the prevalence of the disorder as well as the treatment provided for the disordered. It may be that race affects the two mechanisms differently. Given that race is confounded with economic status (e.g., (McLeod, and Owens 2004)), the rate of disorder may be higher among black children in the study. In that case, the lower rates of medication use are even more striking.

Limitations of Previous Research

To date, studies of racial variation in medication use among youth with ADD have examined boys and girls together and have only allowed for gender differences in the level of medication use (Leslie et al. 2003; Zito et al. 1998). None have considered gender differences in the processes shaping medication use, including racial disparities. Mounting evidence, however, suggests that the prevalence, the etiology and the treatment patterns for youth with ADD differ by gender. For instance, ADD is about three times more common among boys than girls (Cuffe et al. 2001; Guevara et al. 2001; Rowland et al. 2002b). The symptoms of ADD differ between boys and girls as well (Newcorn et al. 2001). Girls with ADD have higher levels of intellectual impairment, lower rates of hyperactivity and externalizing behaviors (Gaub, and Carlson 1997).

Few studies have examined stimulant use among Hispanic youth. For example, the studies by Safer and Malever (2000), LeFever et. al. (1999) and Zito et. al. (1998) compared white and black youth but excluded Hispanic youth.

A third limitation of ADD treatment research is that studies are typically based on samples from small geographic regions. For instance, the studies by Zito et al (1998) and Safer and Malever (2000), although the largest of the studies described here, were each based on the experiences of youth from within a single state, Maryland. Comparing across studies, one can see both wide variation in medication use as well as substantial regional variation in treatment (Morrow, Morrow, and Haislip. 1998; Rawal et al. 2004).

A fourth limitation of these studies is that they typically omit important determinants of health services utilization. For instance, the studies by Rowland et. al. (2003), Lefever et. al. (1999) and Safer and Malever (2000) used data collected in schools. The data did not include information such as family income, caregiver education and child's insurance status. Yet race is confounded with each of these (DeNavas-Walt, Proctor, and Mills 2004; Stoops 2004). Similarly, the studies by Safer and Malever (2000) and Zito et al. (1998) did not control for the presence of attention problems. Thus they could not distinguish between selection into receiving any care for attention problems and not receiving care among those with attention problems.

Conceptual Framework

The current research focuses on sources of variation in receipt of health services. A common model for studying determinants of health services use is the Andersen/Aday Behavioral Model of Health Services Use. This model suggests that one's use of health services is a function of their predisposition to use services, factors that enable or impede use, their need for care and availability of services (Andersen 1995).

Predisposing factors found to affect use of mental health services for youth include: (a) child's age, gender, race/ethnicity and (b) the caregiver's education (Bussing, Zima, and Belin 1998; Elster et al. 2003; Zahner, and Daskalakis 1997). According to data from the 1996 Medical Expenditure Panel Survey, youth under the age of 6 are less likely than youth aged 6-18 to receive medication for attention problems (Olfson 2002).

Enabling factors include economic resources such as family income and health insurance that reduce the financial barrier to care (Padgett et al. 1993). Other enabling factors relate to the family's capacity to care for the child including family structure and the number of children in the family (Tuckman, and Regan 1967). Among youth with attention problems who were enrolled in special education, higher socioeconomic youth were more likely to receive medication (Bussing et al. 1998). Uninsured youth were less likely than privately or publicly insured youth to receive medication for attention problems (Olfson et al. 2003).

Need is typically the strongest predictor of health services. In general, sicker youth are more likely to receive treatment. For example, in a sample of youth at risk for developing ADD, youth with oppositional defiant disorder, were more likely than youth without oppositional defiant disorder to seek treatment (Bussing et al. 2003b).

Youth with ADHD were also more likely to have substance abuse problems than similarly aged youth without ADHD (3.6% vs 1.0%) (Guevara et al. 2001). According to the AACP (2002), having a substance abuse disorder is a contraindication for stimulant medication.

Special education also indicates the youth's need. Almost 30 percent of youth treated for ADHD receive special education services (Olfson et al. 2003). Special education students are 5.6 times more likely to be medicated for attention problems than youth in general education (Safer, and Malever 2000). This disparity may reflect several mechanisms. Being evaluated for special education involves psychological assessment which may lead to treatment. In addition, attention disorder may be more severe for youth in special education. Finally, involvement in special education may reflect family persistence in seeking treatment, and that persistence may affect mental health services use.

Contextual factors may affect which youth receive services. Safer and Malever (2000) found a three fold difference in medication rates for attention problems across regions. Schools in counties with high minority enrollment rates (85-87% minority) had the lowest rates of medication for attention problems (1.2%). Meanwhile, schools in counties with the low percent of minority (.7%) had relatively high rates of medication (4%). Three large clinics in Maryland treat youth with ADD. Youth who lived in these clinics' counties received more medication for ADD.

Zito et al. (1998) also found that the effect of race on the probability of receiving stimulant medication varied by geography. The relative odds of receiving medication between whites to blacks ranged from 1.23 to 2.60 depending upon where the youth lived.

In the study by LeFever (1999), higher levels of neighborhood household income was associated with an increased probability of medication for attention problems for white youth but not for black youth.

Rappley et al (1995) examined use of methylphenidate (Ritalin) among youth aged 0-19 from Michigan who received treatment during 1992. The proportion of youth receiving this medication varied 11 fold across counties (from 2.5 per 1000 youth to 28 per 1000 youth).

METHODS

Data

The data for these analyses were collected as part of the evaluation of the Comprehensive Community Mental Health Services for Children and Their Families (CCMHSCF) program (Macro International Inc. 1997). This program provides comprehensive and coordinated services to children with serious emotional disturbance and their families. Federal grants are provided to states, communities, territories, American Indian tribes, and Alaskan Native communities to develop and expand mental health services for these individuals. The Center for Mental Health Services (CCMHS), part of the Substance Abuse Mental Health Services Administration (SAMSHA), is primarily responsible for administering the systems of care across more than 50 sites throughout the country. Data on over 50,000 youth were collected on child's mental health, race, age, gender, special education status, family income and parental education collected through caregiver reports.

These data were supplemented with data collected by the Bureau of Health Professionals , the Area Resource File (ARF) (Health Resources and Services Administration, and Bureau of Health Professions). The ARF contains descriptive information on county resources such as number of health professionals, health facilities, demographic data (e.g number of residents, composition by race, age, gender, morbidity and crime data), and economic data (per capital income, median income, and income distribution).

The CCMHSCF data contain the child's residential zip code. Using Arview GIS, the child's zipcode was used to identify the county in which the child lives. After identifying the child's county, we merged key county level characteristics from the ARF with child characterics from the CCMHSCF.

Analytic Sample

The sample included youth aged 3 to 22 whose caregiver identified attention problems as the reason for seeking treatment during the first wave of the study. The original CCMHSCF dataset had 46 sites. Five sites missing zipcode information for over 40 percent of the sample were excluded from the analyses. The remaining sample includes 4490 youth with attention problems in first wave of data collection. For roughly 1% of the observations key variables were missing, and these individuals were excluded from the analyses. The final sample included 4193 observations.

The dependent variable in these analyses was a dichotomous variable indicating whether or not the youth received behavioral medication.

A categorical variable was included denoting the child's age as 3-8, 9-15, and 16 and older. Race was represented as a categorical variable (white, black, Hispanic, or other).

Gross family income was included as a categorical variable (less than $10,000, $10,000-$19,999, $20,000-34,999, $35,000 and above or income missing). A dichotomous variable indicated whether the child was eligible for Medicaid. Family structure was represented as a categorical variable (two parent family, single parent family, child lives in foster care, adopted, is a state ward, or other). A categorical variable indicated the number of children in the family (less than 3, 3 or more children, number of children missing). Caregiver's educational status was included as a categorical variables (less than high school, high school, some college, college graduate or above or missing).

Three measures of youth's comorbidity status were included based upon caregiver reports of the youth's problem leading to referral for services. Dummy variables were included for whether the youth had an internalizing disorder, externalizing disorder or an alcohol/substance abuse disorder. This study included a categorical variable indicating whether the youth was in special education or special education was missing.

Mental health professionals include psychiatrists, clinical psychologists, clinical social workers, psychiatric nurse specialists, psychiatric nurse specialists, and marriage and family therapists. Designation as a shortage area was based upon on the population to mental health provider ratio adjusted for the level of need in the area.

Four county-level measures of demographics were included in this analysis. The first three were the percent of the population that a) was black, b) was Hispanic and c) lived in an urban area based on 2000 Census data. The fourth county-level measure is the percent of children under age 18 living in poverty. This measure of poverty was based on projections from the 1990 Census.

Statistical Methods

Medication management of youth with attention problems was estimated using a random effects model. Equation 1 expresses the model. $Y_{site,child}$ is the dependent variable (receipt of medication management).

$$Y_{site,\ child} = B_o + \underline{B}\underline{X}_{site,\ child} + \underline{\Gamma}\underline{C}_{site} + \delta_{site} + e_{site,child} \quad \textbf{(1)}$$

X is a matrix of youth specific covariates. Γ is a matrix of covariates describing characteristics of the county in which the youth resides. The random effect, δ_{site}, refers to unmeasured community-level characteristics. The error term, $e_{site,child}$,s unmeasured youth characteristics.

Separate models were estimated for males and females. In addition, within gender, separate models were estimated for blacks, Hispanics and white/other race. To examine whether separate models for boys and girls and for the racial groups within gender were appropriate, we conducted Chow tests (Davidson and Mackinnon, 1996). The Chow test compares the coefficients from two models using a log likelihood ratio test.

For descriptive statistics, differences in gender and race of categorical variables were determined via two-way cross tabs and chi-square statistics. Differences in the means of continuous variables were estimated using t-tests allowing for unequal variances across groups. All analyses presented here were conducted in Stata.

RESULTS

Table 2.1 displays descriptive statistics by race and gender. Roughly two-thirds of our sample received medication. Somewhat surprisingly, levels of use did not differ by gender (68% of boys and 65% of girls). However, a larger proportion of white boys (71%) received medication than black (62%) or Hispanic (64%) boys. Similarly white girls were more likely to receive medication than black or Hispanic girls (70% vs 57% and 61%, respectively.

Table 2.1 Descriptive Statistics by Race and Gender

	All		Black		White/otherrace		Hispanic		Boys vs girls	Within Boys	Within Girls
	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys			
n	1126	3067	301	804	722	1940	103	323			
Child Characteristics		Mean									
Medication	65%	68%	57%	62%	70%	71%	61%	64%		ab	a
Child's Race											
Hispanic	9%	11%					100%	100%			
Black	27%	26%	100%	100%							
Other	7%	8%			11%	12%					
Race missing	4%	3%			6%	5%					
Child's Age											
9-14 years	55%	59%	55%	60%	56%	58%	52%	57%	k		
15 years or older	27%	20%	26%	18%	27%	21%	34%	21%	klmn		
Child's Mental Health	83%	79%									
Internalizing Disorder	30%	24%	22%	16%	32%	28%	41%	25%	klmn	ac	ac
Externalizing Disorder	34%	33%	25%	24%	36%	36%	45%	37%		ac	ac
Substance Abuse Disorder	8%	6%	4%	5%	8%	6%	19%	7%	kmn		abc
Special Education	25%	31%	23%	30%	27%	31%	21%	33%	klmn		
Special Education missing	53%	54%	53%	55%	53%	54%	53%	50%			
Medicaid Eligibility	69%	70%	76%	82%	65%	66%	77%	67%	l	ac	ab
Medicaid Eligibility Missing	1%	1%	1%	1%	1%	1%	2%	2%			
Family Characteristics											
Education of the Caregiver											
High School	30%	32%	29%	36%	32%	31%	19%	26%	l	abc	b
Some College	27%	25%	22%	21%	28%	28%	33%	21%	n	ab	ac
College Graduate	12%	10%	11%	7%	14%	11%	7%	9%	kl	a	b
Caregiver education Missing	8%	9%	10%	11%	7%	9%	6%	8%			
Household Income											
$10,000-$19,999	26%	27%	30%	28%	24%	26%	31%	32%		b	
$20,000-35,000	22%	19%	20%	18%	24%	20%	17%	17%			
More than $35,000	17%	15%	8%	6%	22%	19%	13%	13%		abc	ab
Household Income Missing	10%	12%	11%	14%	10%	11%	9%	10%		a	
Number of children in the family											
More than 3 children in the family	41%	39%	52%	50%	37%	33%	42%	47%		ab	a
Number of children missing	9%	10%	12%	12%	8%	9%	8%	10%		a	a
Family Structure											
Single parent family	47%	49%	52%	57%	43%	45%	53%	53%		ab	a
Foster care, adopted, state w ard	18%	9%	20%	15%	18%	12%	13%	11%	km	a	
Other family situation	10%	13%	13%	13%	8%	8%	8%	7%		ac	a
Contextual Effects											
MHSA	13%	16%	3%	5%	18%	22%	7%	4%	km	ab	ab
Partial MHSA	20%	19%	29%	25%	15%	14%	27%	36%		abc	ab
Mean % of children in Poverty 1999	16.9	17.25	17.9	17.81	16.7	17.30	15.7	15.57	m	bc	abc
Mean % Hispanics	9.0	8.50	9.4	8.43	7.7	7.14	16.7	16.79		abc	abc
Mean % Blacks	12.2	12.43	23.6	24.35	7.8	8.03	9.0	9.21		abc	ac
Mean % Urban	76.1	74.96	89.7	88.05	68.9	67.46	87.0	87.49		ab	ab

Authors' tabulations of the Comprehensive Community Mental Health Services for Children and Their Familes Dataset

Note: Omitted group is w hite, age 3-8 years, not enrolled in special education, less than high school, less than $10,000, Few er than 3 children, tw o parent family, not a mental health provider shortage area (MHSA)

a p<.05 w hite vs black; b p<.05 w hite vs hispanic; c p<.05 hispanic vs black; k p<.05 boys vs girls; l p<.05 black boy vs black girls; m p<.05 w hite/other boys vs w hite/other girls; n p<.05 ; hispanic boys vs hispanic girls

Multivariate findings

We began by estimating the multilevel model described above for the entire sample and for key sub-groups. The pooled models included main effects for race and gender. We then used this information to consider whether the race- and gender-specific models fit the data better than the pooled model. The Chow test revealed important differences in the coefficients across race and gender. Results from the chow test revealed that the coefficients in the pooled model differed significantly for boys and girls (X^2=1.46, df=32, p<.001). Within gender, the coefficients for white and black boys differed (X^2=6.8, df= 28, p<.001) as did the coefficients for white and Hispanic girls (X^2= 14.5, df=28, p<.02).

As a result, tables 2.2 and 3 present the logistic regression results by race for boys and girls respectively. Among boys, minority status was associated with a decreased probability of receiving medication management. Relative to white boys, Hispanic (b= -.62, p<.001), black (b =-.70, p<.001) and other boys (b=-.70, p<.001) were less likely to receive medication after controlling for the child's predisposing and enabling factors, need, and contextual factors. These beta coefficients correspond to large marginal effects on the predicted probability of medication use (13.7%, 14.9% and 15.6%, respectively).

Table 2.2. Multivariate Logit Results of Behavioral Medication Use Among Males, by Race/ethnicity

	All	Black	White	Hispanic
Child Characteristics				
Child's Race				
Hispanic	-0.62***		NA	
Black	-0.70***	NA		NA
Other	-0.70***		-0.66***	
Child's Age				
9-14 years	0.49***	0.35	0.50***	0.7
15 years or older	-0.12	-0.35	-0.05	-0.5
Child's Mental Health				
Internalizing Disorder	0.07	0.29	0.02	0.81
Externalizing Disorder	-0.28*	-0.57	-0.08	-0.24
Substance Abuse Disorder	-0.52*	-0.83	-0.48	-0.06
Special Education	0.71***	0.90***	0.67***	0.96*
Medicaid Eligibility	0.49***	0.26	0.41**	1.72***
Family Characteristics				
Education of the Caregiver				
High School	0.14	0	0.12	0.78*
Some College	0.21	0.17	0.13	0.43
College Graduate	0.14	0.31	0.09	-0.06
Household Income				
$10,000-$19,999	0.12	-0.25	0.36*	0.25
$20,000-35,000	0.34*	-0.04	0.51**	1.25*
More than $35,000	0.64***	-0.14	0.77***	1.93**
Number of children in the family				
More than 3 children in the family	-0.24*	0	-0.32**	-0.42
Family Structure				
Single parent family	0	0.05	-0.02	0
Foster care, adopted, state ward	0.48**	0.95**	0.2	1.82**
Other family situation	-0.08	-0.15	-0.05	0.44
Contextual Effects				
MHSA	-0.23	-0.4	-0.33	1.97
Partial MHSA	-0.15	-0.32	-0.45	0.63
% Children in Poverty	-0.02	-0.07*	-0.01	-0.05
% Hispanics	0.02*	0.04	0.02	0.04
% Blacks	0	0.01	0.01	0
% Urban	0	-0.01	0	-0.01
Model Parameters				
Constant	0.17	1.83	-0.1	-1.82
lnsig2u	-0.39*	-0.85	-0.2	-1.35

Note: Omitted Category: Omitted group is white, age 3-8 years, not enrolled in special education, less than high school, less than $10,000, Fewer than 3 children, two parent family, not a mental health provider shortage area (MHSA)
legend: * p<0.05; ** p<0.01; *** p<0.001

Table 2.3. Multivariate Logit Results of Behavioral Medication Use Among Females, by Race/ethnicity

	All	Black	White	Hispanic
Child Characteristics				
Child's Race				
Hispanic	-0.3	NA	NA	NA
Black	-0.51*			
Other	-0.57		-0.54	
Child's Age				
9-14 years	0.12	0.37	0.11	-0.14
15 years or older	-0.04	-0.75	0.31	-0.06
Child's Mental Health				
Internalizing Disorder	0.3	0.2	0.25	0.28
Externalizing Disorder	-0.14	0.18	-0.08	1.29
Substance Abuse Disorder	-0.06	0.63	-0.08	-0.86
Special Education	0.64**	0.19	0.56*	1.67
Medicaid Eligibility	0.37*	0.94*	0.13	0.79
Family Characteristics				
Education of the Caregiver				
High School	0.03	-0.06	-0.13	1.42
Some College	-0.01	-0.3	-0.16	1.12
College Graduate	0.75*	1.14	0.38	2.19
Household Income				
$10,000-$19,999	0.33	0.4	0.35	-0.77
$20,000-35,000	0.67**	0.66	0.72*	0.81
More than $35,000	0.66*	0.99	0.69*	-0.93
Number of children in the family				
More than 3 children in the family	-0.34*	-0.43	-0.32	-0.16
Family Structure				
Single parent family	0.24	0.22	0.27	-0.36
Foster care, adopted, state ward	0.50*	0.42	0.54	-0.42
Other family situation	0.05	-0.02	0.04	-0.96
Contextual Effects				
MHSA	-0.19	-2.92*	-0.18	0.09
Partial MHSA	-0.39	-0.6	-0.37	-0.74
% of Children in Poverty	-0.02	-0.05	-0.03	-0.07
% Hispanic	0.02	0.02	0.04	0.06
% Blacks	0.01	-0.01	0.03	0.02
% Urban	0	-0.07*	-0.01	-0.05
Model Parameters				
Constant	0.47	6.83*	0.62	3.16
lnsig2u	-0.71	-14	-0.57	-0.2

Omitted group is white, age 3-8 years, not enrolled in special education, less than high school, less than $10,000, Fewer than 3 children, two parent family, not a mental health provider shortage area (MHSA)
legend: * p<0.05; ** p<0.01; *** p<0.001

DISCUSSION

Racial variation in receipt of medication treatment among youth with attention problems is clear. Although this study included a wide range of factors, underlying reasons for differences in treatment by race remain unknown. Neither enabling factors (such as family income and family structure) nor comorbidity status explain the racial and ethnic differences. Moreover, we could not explain racial variation by differences across site or community level characteristics. Although not presented here, we estimated several multilevel models allowing the slope of race to vary across site. However, these analyses failed to find evidence that the racial disparity varied by site.

Relative to prior research, these analyses have several strengths. The sample comprises youth served in the public sector. Because the majority of our sample comes from low-income families, this study avoids problems typically encountered whereby race is associated with a host of factors related to low socioeconomic status such as household income, caregiver education and insurance arrangements. Unlike studies based on claims data, these analyses include measures of mental health status derived from parent reports. Parent reports represent the problems that motivated the parent to seek treatment for their child. Moreover, our analyses are not limited to the study of youth who have been given a formal ADD diagnosis by a medical professional. Because white youth may be more likely to go to the physician and receive a diagnosis, limiting the sample to physician identified ADD may create further selection biases.

Limitations

This study has several limitations. First, our sample includes relatively few Hispanic girls. This limits our ability to examine the effects of the numerous determinants of health services use among this population.

A second limitation is that the data do not contain information on parental preferences for treatment. Yet, racial variation in these preferences may partly explain differences in use of medication. A recent study of parents whose child was on medication for attention problems found that relative to white parents, nonwhite parents were more likely to prefer counseling to medication (dosReis et al. 2003). Similarly, nonwhite parents were more likely than white parents to think that medication use leads to substance abuse. In a study of parents of elementary school parents, black parents were also less concerned than white parents about the consequences of attention problems on school outcomes (Bussing et al. 2003a).

A third limitation of the data is that they do not contain information on parent's perceptions of the effectiveness of medication for attention problems. dos Reis and colleagues (2003) found that relative to white parents, black parents were less satisfied with stimulant medication's ability to improve youth's school performance. Whether this difference is real or just perceived is unknown. However, teacher ratings from the MTA study suggest that treatment benefits whites more than blacks in terms of conduct problems (Arnold et al. 2003).

A fourth limitation of the data is that they do not contain information on which provider treated the youth. Yet, providers play an important role in determining what treatment a youth receives. For instance, in a study that analyzed prescription claims of youth under the age of 19 in Michigan, provider-level effects were very large (Rappley et al. 1995). Of prescriptions for Methylphenidate (Ritalin) medication in Michigan, 5 percent of pediatricians wrote 30 percent of all prescriptions received. If white and minority youth either seek treatment from different doctors or receive different treatment from the same doctors, then this might explain racial variation in use of medication.

Clinical Implications

These possibilities bear further research on the underlying reasons for racial disparities in medication management of youth with attention problems. Research should explore how differences in parental attitudes and preferences toward treatment vary by race. Further work also should consider whether treatment effectiveness varies by race as well as parental attitudes toward treatment. Finally, in order to better understand determinants of treatment as well as racial variation in treatment, researchers need to examine information from all key decision makers (the youth, the youth's caregiver as well as the youth's health care provider).

CHAPTER THREE

Memo: Does the Effect of Race Vary by Site: A Multilevel Approach

This memo is a supplement to chapter 2. In the analyses presented here, we explored whether the effect of race varied across sites. This memo reports the methodology used and the findings derived from those analyses.

Initial analysis suggested that the effect of race/ethnicity on medication use varied at the site level. For each site, we compared the mean difference in medication for whites with a) blacks and b) Hispanics (see Figure 1). Across sites, typically a lower percent of black youth used medication than white youth. This difference appears to vary by site. A test of the equality of variances suggested that the variation in the level of use for blacks and whites differs across sites (p<.001). Similar results were observed for Hispanics (p<.001) .

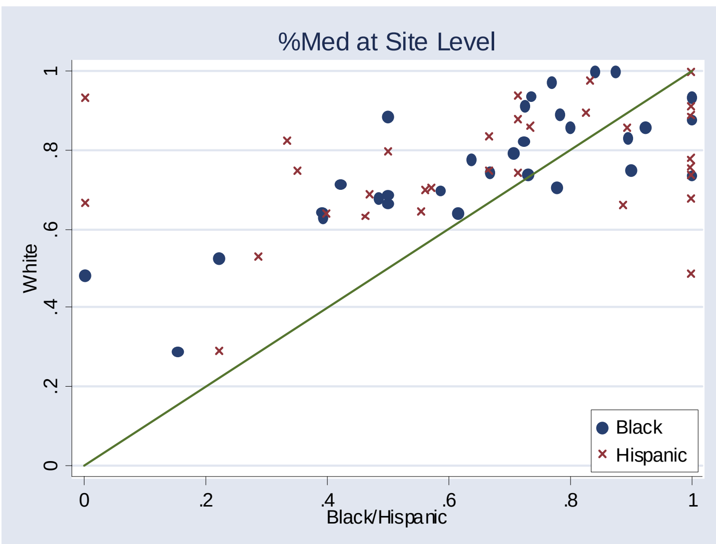

Figure 3.1 Mean % Use of Medication Among Youth with Attention Problems By Race

To examine whether the effect of race varied by site, we estimated a two-level multilevel logistic regression model. The dependent variable was a binary variable that indicated whether or not the youth received medication. Covariates included the youth's race, age, gender, presence of comorbidies, special education status, family structure and family income, the caregiver's education status as well as county-level attributes of the youth's residence such as percent of children living in poverty, percent black, percent Hispanic, and the county's designation as a mental health provider shortage area.

In order to estimate this model, we experimented with several software packages including Sas proc mixed with GLIMMIX, GLAMM (Generalised Linear Latent and Mixed Models) and Xtlogit in Stata, Mlwin, Winbugs and HLM. We explored so many packages due to differences in the advantages and disadvantages of the alternative methodology procedures used in the various packages.

For example, we began with Mlwin. The main advantage of this program is that it can produce full Bayesian estimates. Theoretically, Bayesian estimates have an advantage over maximum likelihood estimates when the number of level two units is small or the data are unbalanced (number of level 1 units differs across the level 2 units) (Raudenbush, and Bryk 2002b). Maximum likelihood estimates of the level-two fixed coefficients and the variance covariance parameters depend upon large sample theory. Inaccurately assuming that the variance terms are normally distributed can have severe consequences for our estimates of the standard errors. In unbalanced designs, the level 1 variance covariance parameters serve as weights for the level 2 fixed coefficients. However, uncertainty in the level 1 variance-covariance parameters will not properly be reflected in the estimates of the level-2 fixed parameters. Thus our confidence intervals will typically be too small increasing the chance of type I error. In contrast, Bayesian estimates of unknown parameters are based on samples drawn from the joint posterior distribution. When limited information is available as to the distribution of the unknown parameters, as is often the case in the social sciences, we can assume a non-informative prior. Thus, we are able to accurately reflect the uncertainty in our estimates.

A second advantage of MlWin is that it has a friendly user interface. The disadvantage of this program was that it repeatedly crashed when we attempted to estimate a model with the full set of covariates.

The second software package that we explored was Winbugs. This naturally followed MlWin as MlWin can output the data and the code in a format that Winbugs can read. With a little work, I was able to adapt the model, the data and the starting values of the parameters within Winbugs. The advantages and disadvantages of this program are similar to that of Mlwin. Like Mlwin, Winbugs can produce full Bayesian estimates. Also like MlWin, Winbugs crashed when the full set of covariates were included in the model. One advantage of Winbugs over Mlwin is that the programming language for Winbugs is similar to that of R whereas the programming language for Mlwin is unlike other commonly used packages.

The third software package that we used was proc mixed in SAS with the GLIMMIX macro. This program has several practical advantages. In particular, relative to MlWin and Winbugs, GLIMMIX allowed a larger number of covariates to be estimated. Moreover, time until convergence was almost immediate whereas convergence was roughly 5 minutes in Winbugs and 20 minutes Mlwin. The disadvantage of this program is that it uses first order marginalized and penalized quasilikelihood techniques to estimate the model. Estimates produced using these techniques are sometimes biased (Skondral, and Rabe-Hesketh 2004).

The fourth program that we used was GLAMM in Stata. One major advantage of GLAMM is that it is a subroutine that can be executed from within STATA, the program that was used to perform all data manipulation. The main disadvantage of GLAMM is that it took hours to converge. In fact, we did not estimate a random slope model in this program because convergence was so slow in a simple two-level model.

The fifth program used was the Xtlogit command for random effects in Stata. The Xt commands in were primarily developed by economists for use with cross-sectional time-series data. Unlike the other programs considered here, Xtlogit can not estimate random slopes. However, Xtlogit can estimate random effects for nested data, converges within seconds and is a procedure within Stata. Because Xtlogt uses a gauss hermite quadrature procedure which might produce biased estimates we bootstrapped the random effect of race. We took 5000 draws from the posterior distribution. The estimate from this bootstrap was slightly different than that from the Xtlogit. While Xtlogit produced b= -.64, se .11, the mean from the bootstrap sample was -.61 sd .13.

MODEL SPECIFICATION

NOTE: A complete description of the data and methods are provided in the paper. Although we limit the discussion to the variation in the effect of black race across sites, we also examined whether the effect of Hispanic varied across site.

Use of medication among youth with ADHD is estimated as a two-level model with individuals (i) nested within sites (s). Covariates for the model are more fully described in the attached paper. Briefly they include a matrix of child (gender, age, comordities, special education status) and family characteristics (X), a matrix of community characteristics (Γ) and a vector that describes whether the child is black or not (r). Because we are interested in the whether the effect of black varies by site, we allow the slope of black (r) to vary across site. Thus, the equation includes two random effects, one for the effect of race (U_r) and one at the site level

(U_s). The intercept (B_0) is a function medication use across sites plus a site specific random effect (U_s). The slope for black is a function of the effect for black across sites (r) plus a site specific effect of the effect of black (U_r). We are primarily interested in whether the effect of race varies by site. In the models shown below we were interested in whether the effect of black varied by site. Equations representing this model are presented below.

$$Y_{is} = B_0 + BX_i + \Gamma X_s + B_{1R} + e_{is}$$

$$B_0 = a + U_s$$

$$B_{1R} = r + U_r$$

COMPARISON OF ESTIMATES FROM VARIOUS SOFTWARE PACKAGES

Table 3.1 contains estimates produced from Mlwin, Winbugs, Proc Mixed GLIMMIX, Xtlogit in Stata, and GLAMM in STATA packages. The sample used for these estimates includes only sites in which there were at least 5 black youths. Across these packages, the point estimates for the fixed effects are fairly consistent.

The aim of this research was to examine whether the effect of race varies across site. The results in table 3.1 can be used to test the null hypothesis that the effect of “black” is equal across sites. This hypothesis is tested by examining whether the random effect for black (U_r) is statistically different than zero. We could not reject the null hypothesis in any of the packages and concluded that the effect of Black did not vary across site. For example, the results of Mlwin suggest that the random effect for black had mean of .135 and a standard error of .134. Based upon the SAS, the random effect for race is U_r=.12 , p=.19. The results from Winbugs produced similar results to those from Sas proc mixed and Mlwin, Figure 2 is of the posterior distribution of the site-level random effect for black at site 22 after 2000 draws. The mean for the random effect of race across all sites was .005. Figure 3 is the posterior distribution of the precision (the inverse of the variance) of the random effect for race. Although the precision is highly skewed right, the precision is relatively peaked reflecting that the estimate of the random effect is relatively precise.

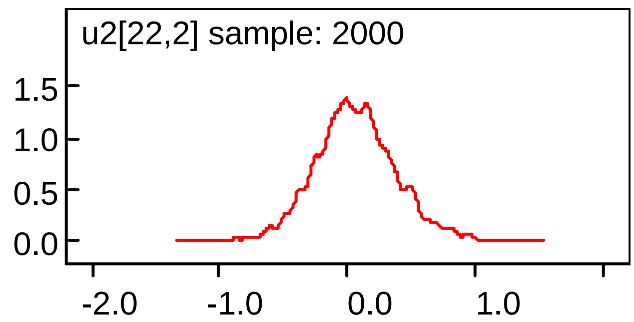

Figure 3.2 Posterior distribution of the random slope for race at site 22 after 2000 simulations

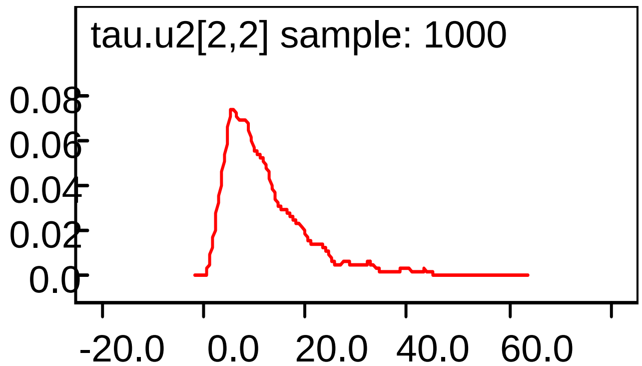

Figure 3.3 Posterior Distribution of the Precision in the random effect for race

Table 3.1 Comparison of Results from Multilevel Modeling Statistical Packages : Two level Model with a Random Effect for Black

	MLWin		Winbugs		ProcMixed		Xtlogit Stata		GLAMM Stata	
	mean	sd	mean	sd	Beta	S.E.	Beta.	S.E.	Beta.	S.E.
Child Characteristics										
Child's Race (reference: White)										
Black	-0.57	0.14	-0.54	0.17	-0.52	0.15	-0.64	0.11	-0.64	0.11
Hispanic	-0.71	0.15	-0.99	0.17	-0.98	0.17	-0.99	0.16	-0.99	0.16
Other	-0.43	0.19	-0.06	0.24	-0.07	0.23	-0.11	0.23	-0.11	0.23
Child's Age (reference: Less than 6 years)										
7-13 years	0.71	0.14	0.74	0.17	0.72	0.17	0.70	0.17	0.70	0.17
14 years or older	0.43	0.15	0.43	0.18	0.40	0.18	0.41	0.18	0.40	0.18
Eligible for Medicaid (reference: Not eligible)	0.56	0.11	0.63	0.12	0.62	0.12	0.63	0.12	0.63	0.12
Not in Special Education (reference: Enrolled in Special Education)	-0.74	0.13	-0.75	0.14	-0.73	0.14	-0.74	0.14	-0.74	0.14
Special Education Missing	-0.77	0.10	-0.71	0.12	-0.70	0.12	-0.73	0.12	-0.73	0.12
Family Characteristics										
Number of children in the family (reference: 0-2 children)										
More than 3 children in the family	-0.37	0.09	-0.28	0.10	-0.28	0.10	-0.28	0.10	-0.29	0.10
Number of children missing	0.13	0.25	-0.08	0.30	-0.11	0.28	-0.09	0.32	-0.13	0.30
Family Structure (reference: Two parent family)										
Single parent family	0.09	0.11	0.06	0.12	0.06	0.12	0.06	0.12	0.06	0.12
Foster care, adopted, state ward	0.59	0.18	0.63	0.21	0.61	0.20	-0.13	0.18	-0.13	0.18
Other family situation	-0.05	0.15	-0.10	0.18	-0.11	0.18	0.61	0.20	0.61	0.20
Household Income(reference: less than $20,000)										
$20,000-35,000	0.41	0.12	0.51	0.14	0.49	0.13	0.53	0.13	0.53	0.13
More than $35,000	0.57	0.19	0.58	0.21	0.56	0.21	0.57	0.21	0.57	0.21
Education of the Caregiver (reference: less than high school)										
High School	0.14	0.11	0.10	0.13	0.09	0.12	0.10	0.12	0.10	0.12
Some College	0.12	0.12	0.12	0.13	0.12	0.13	0.14	0.13	0.14	0.13
College Graduate	0.37	0.17	0.42	0.20	0.41	0.19	0.41	0.19	0.41	0.19
Contextual Effects										
Mental Health Provider Shortage Area (reference: Not a shortage area)	-0.53	0.11	-0.59	0.27	-0.58	0.26	-0.64	0.23	-0.64	0.23
Partial Mental Health Provider Shortage Area	-0.33	0.34	-0.06	0.38	-0.07	0.37	-0.25	0.13	-0.25	0.13
Intercept	0.58	0.25	0.47	0.32	0.48	0.29	0.37	0.24	0.38	0.24
Model Parameters										
Intercept	1.00	0.33	0.04	0.65	0.45	0.19				
Race (Black/Hispanic)	0.14	0.13	0.00	0.30	0.12	0.14				
/lnsig2u (level 2 variance component)							-0.50	0.20		
sigma_u (standard deviation)							0.78	0.08		
rho (Percent of Site-level variation)							0.16	0.03		
Variance									0.52	-0.11

HLM

It is worth noting that the data used in table 3.1 are consistent across software packages. However, after performing the above analyses, further data analyses revealed several coding errors in the data. These errors were corrected and analyses were conducted in yet another statistical package, HLM, to examine whether the finding that race did not vary by site was still valid. These analyses were conducted over two subsamples. The first subsample included only sites with at least 5 black youth. Using this sample, we examined whether the effect of black varied across site. Second, using a sample that included only sites that had at least five Hispanics, we examined whether the effect of Hispanic varied across site. Table 3.2 show these results.

All evidence from these models suggest that neither the effect of black nor Hispanic varied by site. The reliability estimate is an average across sites of the variance explained by the random effect of interest divided by the total variance. According to Raudenbush (2004), very low reliability (<.10) estimates suggest that the effect of the variable should be considered fixed rather the random. The reliability estimate for both the random effect for black and Hispanic was low (.01 and .16) respectively. The p-value for the random effect of black was greater than .5. For Hispanics the p-value was .23 which is above conventional levels of statistical significance.

Table 3.2 Reliability Estimates for the Random Slope Terms

Random Effect	Standard Deviation	Variance Component	df	Chi-square	P-value	N (level 2 units)	N (level 1 units)	Reliability Estimate
BLACK slope, U1	0.03	0.00	27	26.87	>.500	28	3449	0.01
Hispanic slope, U1	0.25	0.06	20	24.22	0.23	21	2552	0.16

CONCLUSIONS

Our multilevel analyses did not reveal any indication that the effect of race varied by site. However, future research should continue to explore this issue. One possible explanation for our failure to find that the effect of race/ethnicity varied by site could be related to statistical power. Increasing the number of sites used in the analyses may increase both the observed variation in race/ethnicity at the site level as well as the statistical power. Moreover, making use of repeated measures on individuals may improve the precision of our estimates of the fixed effects. Observations from waves 2 and 3 were not included in this study due to severe attrition problems.

CHAPTER FOUR

Memo: Multilevel Modeling in Health Services Research

This memo expands upon some of the issues that I briefly discussed or completely omitted from the NIDA grant proposal due to space limitations. This material ordinarily would have been included in a dissertation proposal. While this memo will not cover these issues in detail, it will provide some of the necessary background for next Monday's discussion.

This document contains three sections. To begin, I discuss the motivation for applying multilevel models in health services research. Second, I provide a brief overview of the current project. Third, I discuss challenges to analyzing administrative data that were designed for billing purposes rather than research purposes.

MOTIVATION FOR USING BAYESIAN MULTILEVEL MODELS TO STUDY YOUTH'S TREATMENT

Multilevel models are an appropriate tool to study services that youth receive; however they have not typically been employed in this body of research. Much of the research focuses on individual level characteristics such as the youth's predisposing (age, race, gender), enabling (income, insurance), and need (severity of illness) characteristics. However, medical providers often have a variety of treatment options even for the same illness. Providers are responsible for balancing factors such as the efficacy of the treatment with its cost and the likelihood that the patient will comply. Even for patients with the same illness, there can be a wide range in the treatment that is received, the outcomes that youth experience, and the cost of these services.

In other areas of health research, there is evidence of substantial provider-level variation in the types of treatment that an individual receives after having sought care. For instance, researchers with the Dartmouth Atlas have found that individuals with the same disease who live in different regions of the country receive vastly different treatments. This geographic clustering is known as a surgical signature. This variation appears to result from the manner in which knowledge passes through the physician community. Physicians are more likely to use procedures that they have always used or that are similar to the procedures used by other physicians around them rather than seek a more distal opinion as to the appropriate treatment. This pattern can be seen for a range of different procedures (ex. Hysterectomy rates, cancer and heart procedures) where one might otherwise expect the treatment to be standard practice.

Provider Profiling

Identifying providers whose care is extreme (good, poor, cost-effective, excessively costly), is an important area of health services research. Within the American health care system, there has been a recent push toward holding providers publicly accountable for their patients' health outcomes as well as the cost of providing care. Methodologically this is challenging because providers do not treat a homogeneous population of patients. Rather the health needs and available resources vary greatly across patients. Yet, appropriately risk adjusting across providers (i.e. measuring and comparing patient severity of illness) from available data sources is nearly impossible. For example, data on providers vary in the information that providers report, how providers interpret and report illness levels and quality of the data. Moreover, we may have substantially more observations for some providers than others. This alters the confidence with which we are able to conclude a provider's behavior is extreme. One can easily imagine that use of inappropriate statistical tools can wrongly identify a provider as an outlier.

Pooling information from multiple units (ex. Sites, studies, providers)

As a second motivating factor for this project, we recognized that Bayesian multilevel models have a great potential for furthering our knowledge of treatment for children with behavioral or emotional problems. Much of this research has been conducted on relatively small samples from numerous geographically distinct sites. Naturally, this research is criticized for not representing the experiences of youth at the national-level. However, these data are valuable because they often represent the only information that we have on treatment for these youth.

Together, incorporating provider-level effects with pooled information across multiple sites, lends itself to employing Bayesian multilevel analyses in the area of children's mental health services. The former because availability of services, practice patterns, state funding mechanisms and individual characteristics each contributes to variation in the treatment that youth receive. The latter, because Bayesian analysis allows the researcher to pool information across larger units (studies, sites or providers). As discussed below, Bayesian analyses can incorporate information from multiple upper level units in which we have a different number of observations. Yet, although multilevel models are common in other areas of research such as education and criminology, they have only begun to be used by health services researchers.

THE CURRENT PROJECT

The current project represents a unique opportunity to examine the care received by a large sample of youth treated in many facilities. We have a population of Medicaid claims from two states. Many previous studies have been based on data from self reports (or parent reports) of service use. These reports are flawed because individuals vary in their ability to recall medical events accurately. Characteristics that appear to be negatively correlated with ability to recall events include, having a large number of children in the family, poorer education, and payment through a third party payer (such as Medicaid) or being enrolled in a managed care plan. In particular individuals tend to telescope (think events occurred more recently than is accurate) and also to inaccurately report information on intensity of care (such as duration of care) (Marrquis et al. 1976, Bean et al. 2002).

As an alternative, the data for this analysis come from an administrative source. Relative to self-report, administrative data are thought to more accurately describe details on service use such as dates of use, duration and cost of use. However, administrative data provide a more limited set of information than is typically available through survey data (for example, they does not provide information on household characteristics or family income). Moreover, providers may have an incentive to report individuals as sicker than they otherwise are (in order to get a larger reimbursement) or healthier than otherwise (so that they can be referred to another provider). Thus administrative data may be less reliable and valid than the researcher would hope.

PROCESSING CLAIMS DATA

There are a host of data management issues surrounding the claims data. The original file from the Medicaid agency contained the claims for all services paid for by Medicaid in each state for the years 1991-2001. Each claim refers to a service or a bundle of services delivered on one or several days. Service or cost per claim is not terribly interesting. It would be a bit like studying history one day at a time. Rather, we need to summarize an individual's experience in the medical system. We can do this in several ways. In some cases, this involves examining the timing of a single service, such an inpatient admission. In other cases, it involves grouping services of multiple types into a larger unit, such as a treatment episode. For example, a treatment episode for one patient might include a short inpatient length of stay followed by weekly outpatient care in a different service setting. Identifying treatment episodes is challenging-- requiring the analyst to identify when one episode ends and the next begins. The analyst has limited information to determine whether the individual has an ongoing illness or had not fully recovered and has now relapsed.

In order to provide a sense of what was involved in determining length of stay, I describe some of the relevant steps. The claims file does not explicitly have a code for date of admission or date or discharge. Moreover, while the patient is in care, multiple services may be provided, creating multiple claims within an episode of care. To determine length of stay we sorted the data by person and service date. Then we looked across records to identify the first (admission) and last (discharge) date that an individual was in the hospital (or other inpatient facility) within a sequence of dates. In addition, we were able to identify really short episodes of discharge and readmission, one or two days, which we assume were weekend home visits rather than actual discharges. These short LOS were combined to form one longer length of stay. Finally, we created a file that was one record per admission, rather than one record per claim.

CHAPTER FIVE

Understanding provider influences on inpatient length of stay among children with mental health, substance abuse and comorbid disorders: A Bayesian Cross-classified approach

ABSTRACT

OBJECTIVE: Previous research on inpatient care for children and adolescents with emotional or behavioral problems indicates that patient-level factors predict length of stay (LOS) poorly. This analysis examines whether patient-level factors are poor predictors of LOS because LOS is primarily determined by facilities rather patients. These analyses also demonstrate a method for profiling healthcare facilities whose patients on average have exceptionally long or short LOS.

STUDY DESIGN: This study uses Tennessee Medicaid claims data from 1996 to 2001. The data include information on 16,217 observations related to 9,4183 patients (aged 12-21) from 197 facilities. We estimate LOS using a Bayesian cross-classified model. Covariates include patient characteristics (age, gender, race, qualification for Medicaid, diagnosis) and facility characteristics (facility type and primary specialty of the facility).

PRINCIPLE FINDINGS: Our results suggest that about 4 percent of the variation in LOS is explained at the patient-level while 42 percent is explained at the facility-level. These analyses also demonstrate that having a cross-classified data structure rather than a completely nested data structure improve the precision of our patient-level variance estimate by 84 percent. By presenting shrinkage estimates of the residuals, we demonstrate a method for pooling information across patients and facilities to identify facilities whose average LOS is truly exceptionally long or short.

CONCLUSIONS: About 40 percent of the variation in LOS is explained at the facility-level. Given the vulnerable nature of youth who are in need of inpatient psychiatric care, it may be particularly important to monitor provider-level processes and outcomes. Measuring facility or provider level quality is complicated because of difficulties in adjusting for case-mix severity across providers. The methodology presented here represents a general framework that can be widely used in health services research. Potential applications include broadening models of utilization to simultaneously include patient, provider, geographic and community level variation as well as provider profiling.

The use of health services is determined by the choices of multiple actors, including the patient, his or her family, the provider and potentially others (such as a case manager). These choices represent the outcome of intersecting processes operating at different levels. While patients have their own preferences regarding their medical care, they typically lack the expert knowledge that the physician possesses. As such, the physician makes decision on behalf of the patient, taking into account the patient characteristics such as illness severity, financial resources as well as the patient's preferences. At the same time, factors external to the patient, such as reimbursement policies and regulatory considerations, also influence the physicians decisions about patient care (Buchanan 1988; Dranove, and White 1987; Robinson 1993, 2001; Ross 1973).

The relative influence of each actor and level may differ across services types or dimensions of service use. While patient and family characteristics may influence whether an individual enters services, provider characteristics may determine the amount of services an individual receives.

Researchers, policymakers and clinicians each have a stake in understanding how each level or process influences the use of health services. For instance, economists are often interested in the degree to which individual characteristics predict service use and expenditures. This information can be used for risk-adjustment purposes. At the same time, clinicians and care managers may want to identify individuals who are likely to exit treatment soon after initiating care (Foster 2003).

Moreover, many decisions about patient care are made at the provider level. Concerns about cost, quality and access to medical care have prompted initiatives to monitor the practices and outcomes of health care providers (Tucker 2000). These initiatives include developing practice guidelines as well as monitoring care that physicians and practices provide. Interest in public accountability through health plan report cards and provider profiling has grown substantially (Scanlon, Chernew, and Lave 1997; Scanlon et al. 2001). The goal of these initiatives is to identify physicians or health plans whose performance on specific measures related to quality of care is exceptionally high or low. Numerous measures have been used to monitor providers' performance such as mortality rates, incidence of pressure sores and inpatient length of stay (Austin, Naylor, and Tu 2001; Berlowitz et al. 2002; Ross, Johnson, and Castronova 2000). Past research suggests that physicians' treatment decisions are affected by organizational management practices such as utilization review and performance reports (Ross, Johnson and Castronova 2000).

This multi-process perspective naturally leads to hierarchical models, which explicitly recognize that an outcome of interest is determined at multiple levels. These models allow one to partition the variance in an outcome across levels and examine variation in the effect of a factor at one level across higher-level units. For example, as in the illustration below, one might examine length of stay and specify three levels–the specific admission, the patient, and the facility. Such a model leads to a natural hierarchy. Individuals may have multiple admissions, and facilities have multiple patients.

While common in many fields (Congdon 2003), statistical models that reflect this hierarchical structure are fairly rare in health services research. This article illustrates the application of hierarchical modeling in health services research and examines the multi-level determinants of inpatient psychiatric care. This application is particularly well suited because–as discussed below–diagnosis and other individual characteristics have generally been quite poor in predicting inpatient care. A fundamental issue is whether previous models of LOS have been insufficient because variation in LOS occurs at the facility level rather than the individual level. This leads to a related issue–if variation in service use is determined at the facility-level, is it possible to identify particular facilities whose outcomes are extreme?

This article considers three questions. First, to what degree is variation in length of stay a characteristic of patients or of the facilities that treat them? Second, from a methodological standpoint, do different data structures vary in the amount of information they contain? Third, if a substantial proportion of variation in LOS is determined at the facility level, can facilities with excessively long or short lengths of stay reliably be identified?

This article examines the experiences of a large sample of patients in a statewide database. The analyses estimate the degree to which length of stay is determined at the admission, individual or facility level. A key feature of the sample is that a substantial proportion was hospitalized multiple times and in different facilities. This data structure is known as "cross-classified". As will be discussed, this feature of the data complicates the statistical model considerably–the model has three levels (admissions, individuals and facilities), but the top two levels are not nested within each other. The parameters of such models, however, can be estimated using Markov Chain Monte Carlo (MCMC) techniques, which we employ here. While computationally complex, the cross-classified structure offers advantages for answering the questions of interest. The fact that some individuals are observed in multiple facilities allows us to distinguish between person-level and facility-level variation.

This article contains six sections. The first section reviews the literature on length of stay for children and adolescents with emotional and/or behavioral problems. The second section considers different methods that have been used to profile providers. In the third section, the cross-classified model is discussed and MCMC techniques are briefly introduced. The fourth section provides a description of the data used for these analyses. In the fifth section the results are presented. The last section discusses how the tools presented here relate to quality monitoring and provider profiling. The results from these analyses suggest that only about 4 percent of the variation in LOS is explained at the patient-level while 42 percent is explained at the facility level. In addition these results suggest that having a cross-classified data structure rather than a completely nested data structure improves the precision of the individual-level variance estimate by 84 percent. As demonstrated in these analyses, Bayesian hierarchical modeling is a potentially valuable method for profiling providers. This method recognizes that the precision with which providers can be characterized varies. Some providers, for example treat a very small number of patients and so it is difficult to measure a mean for such providers with much accuracy. Bayesian methods allow this precision to vary. As will be discussed below, this allows the researcher to pool information from providers who treat different numbers of patients.

PRIOR RESEARCH

Previous Research on Predictors of Length of Stay

Prior research suggests that individual level factors predictor LOS poorly. For example, several studies report that diagnoses or diagnostic related groups explain only 5 to 10 percent of the variation in LOS (English et al. 1986; Frank, and Lave 1986). Incorporating a broader array of patient demographics such as age, gender, race, marital status, employment status and rurality does improve prediction (Kiesler, Simpkins, and Morton 1990; Stern, Merwin, and Holt 2001). For instance, Foster (1999) predicts length of stay with a comprehensive list of over 20 individual and family characteristics. This model encompassed a rich set of covariates including diagnosis, multiple measures of health status such as functioning and symptomatology, as well as demographic characteristics and measures of previous service use. Nonetheless, these characteristics still explain less than 40% of the overall variance.

Relatively few studies of treatment for children and youth with substance abuse and or mental health problems have examined the effect of provider-level characteristics on service utilization. The few that have were based on small samples and have not simultaneously examined patient and provider characteristics (Stiffman et al. 2001). Research that has included patients treated in multiple facilities typically has involved only a few facilities in a given geographic area and/or has not explicitly stated the number of facilities in which study participants received care (e.g., Foster, 1999). Other research includes dummy variables representing each hospital (e.g. (Stern et al. 2001)) or broad characteristics of study facilities. For example, Kiesler, Simpkins and Morton (1990) do find that hospital region/size is a significant predictor of length of stay.

Most research on inpatient care for youth with mental health and substance abuse disorders has not examined the effects of patient-level characteristics while controlling for provider level effects. However, research suggests that provider-level effects may be important determinants of health care use. For instance, in a literature review of the effects of managed care on children's mental health services treatment, Hutchinson and Foster (2002) found that the introduction of managed care was associated with decreases in the use of inpatient care. Similarly, Wickizer (1999) found that the introduction of utilization management was associated with decreases in LOS among children receiving treatment for mental health disorders. Moreover, research in other areas of health services suggests that variation at the provider level can be substantial. For example, physician characteristics such as age and specialty are important determinants in the treatment breast cancer patients receive (Keating et al. 2001; Richardson 2004). Together, this evidence suggests that provider-level effects may have an enormous impact on the treatment a youth with mental health and/or substance abuse disorders receives.

Methodology for Profiling Providers

To date, multilevel models have only been used sparingly in most health services research. However, multilevel models are emerging in the area of provider profiling (e.g. (Burgess et al. 2000a; Burgess, Lourdes, and West 2000b). The United States health care system is heading toward holding providers accountable for treatment costs and outcomes. This research identifies individual providers whose performance stands out in some way and represents the most common application of multilevel models in health services research.

Methodologically, identifying providers whose outcomes are extreme is challenging because providers do not treat a homogeneous population of patients. Rather the health needs and available resources vary greatly across patients. Yet, appropriately risk adjusting across providers (i.e. measuring and comparing patient severity of illness) from available data sources is nearly impossible. For example, data collected from different health care facilities may differ as to what information is collected, how providers interpret and report illness severity as well as the overall quality of the data (Crombie, and Davies 1998). Moreover, we may have substantially more observations for some providers than others. This variation creates further variation in the confidence with which we are able to conclude a provider's behavior is extreme.

A variety of different tools have been used for provider profiling. Provider profiling can involve comparing provider performance to an external threshold, such as a benchmark or comparing providers relative to other providers within a given dataset (Normand, Glickman, and Gatsonis 1997). In fact, using different statistical tools can affect the inferences that are made from the data. For instance, Austin (2001) compared a frequentist approach (predicted probabilities derived from logistic regression) with a Bayesian hierarchical method for profiling hospitals. Using hospital-level 30-day mortality rate following acute myocardial infarction as a dependent variable, this study demonstrated that the two methods differed dramatically in identifying outliers. In general, relative to the frequentist method, the Bayesian approach identified fewer outliers from high and medium risk patient profiles and more outliers for low risk patient profiles.

In a study of mortality rate following acute myocardial infarction (AMI) among Medicare beneficiaries, Normand and colleagues (1997) compared two statistical approaches for determining whether hospital-level mortality rate was exceptionally high. The first method of profiling was modeled after the method used by the Health Care Financing Administration (HCFA). This analysis used data from 3196 Medicare patients treated in 96 hospitals discharged with a primary diagnosis of acute myocardial infarction. HCFA's method involved calculating adjusted probabilities of mortality within each hospital. Outliers were identified through the use of z-scores (standardized expected - observed mortality). The approach taken by HCFA was limited because it failed to adjust for differences in the precision of estimates based on hospital size. In addition, HCFA's method did not distinguish between variation that was attributable to differences in patient case-mix from facility level differences. In contrast, the method taken by Normand et al. (1997) involved examining posterior probabilities derived from hierarchical regression models. The conventional method identified nine hospitals whose performance indicated poor quality whereas the results of the hierarchical analysis suggested that only three hospitals were potentially poor performers.

The U.S. Department of Veteran Affairs (V.A.) has been developing Bayesian hierarchical models for provider profiling (Burgess et al. 2000b). Using ten years of data from 136 V.A. hospitals on tens of thousands of patients, Burgess and colleagues (2000) have demonstrated that hierarchical models can be a valuable tool in identifying changes in outcomes from within a single facility as well as comparing outcomes across facilities.

This article will demonstrate that Bayesian multilevel models presents several advantages for modeling determinants of health services utilization. First, simultaneously examining patient-level and provider-level characteristics helps to control for differences in case-mix severity across providers. Second, because Bayesian hierarchical model assume that all facilities provide the same level of care, information can be pooled across facilities. Third, confidence intervals reflect the greater amount of uncertainty contained in estimates of provider-level effects for which we have fewer observations. This reflection of different degrees of certainty in the estimate is a valuable feature for profiling providers.

METHODS

<u>The cross-classified multi-level model</u>

As described below, the data for these analyses involve admissions of Medicaid enrollees to inpatient facilities in Tennessee. However, in this case, the data are not strictly nested. In particular, individuals may have been treated in more than one inpatient facility. This type of structure is known as "cross-classified" (Rasbash, and Browne 2001). Figure 1 depicts the structure of the data. One can see that length of stay is determined at multiple levels–the admission, the patient (child) and the facility. The structure is not nested–child A received care in facilities 1 and 2.

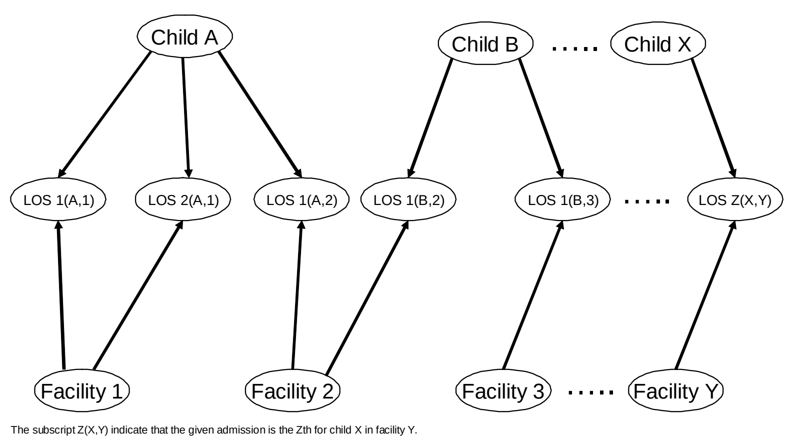

Figure 5.1 Cross-classified Data Structure

While increasing the computational complexity of the estimation procedure (as described below), the cross-classified structure of the data is quite advantageous for examining the question at hand. In a strictly hierarchical structure, individuals would be observed in only a single facility. For that reason, it would be difficult to separate individual-level variation from facility-level variation. However, in these analyses, we observe individuals in multiple facilities, which improves our ability to identify variation that is strictly due to (unmeasured) individual characteristics.

We can represent the structure of the model in figure 1 with the following set of equations:

$$1)\, Y_{i(c,f)} = \mu + \Pi X_{i(c,f)} + \mu_f + \mu_c + \varepsilon_{i(c,f)}$$

$$2)\, \mu_f = \mathrm{B} Z_f + \delta_f$$

$$3)\, \mu_c = \Gamma Z_c + \zeta_c$$

$$4)\, Y_{i(c,f)} = \mu + \Pi X_{i(c,f)} + \mathrm{B} Z_f + \Gamma X_c + \delta_f + \zeta_c + \varepsilon_{i(c,f)}$$

where i indexes admission, c indexes child, and f indexes facility. The subscript $i_{(c,f)}$ identifies the admission as nested jointly within facility f and child c.

Equation 1 specifies that length of stay for a given admission is a function of the facility, child and admission-specific variance (μ_f, μ_c and $\epsilon_{i(c,f)}$, respectively). Equations 2 and 3 provide further detail about the facility and child variance. μ_f is determined by a vector of facility characteristics (Z_f) and a random error component (δ_f). μ_c is determined by a vector of child characteristics (X_c) and a random error component (ζ_f). Equations (1)-(3) can be combined, generating equation (4). *(Note: More elaborate models are possible within this framework. For example, one might allow the effect of a given child covariate to vary across facilities. In this application, we do not allow for random slope coefficients.)* $\epsilon_{i(c,f)}$, $\zeta_{f,}$ and δ_f are all assumed to be normally and independently distributed.

<u>Estimation</u>

The unknown parameters in the cross-classified structure can be estimated in several ways, including iterative generalized least squares, data augmentation, and MCMC to name a few (Rasbash, and Browne 2002). In this analysis MCMC is used to estimate the cross-classified model. Briefly, MCMC simulation is a powerful tool that can produce estimates of the parameters. Each of the unknown parameters (Β, Γ, Π, δ_f, δ_c, ζ, $\epsilon_{i(c,f)}$,) is considered to come from an underlying probability distribution. Through MCMC simulation, the researcher draws repeated samples of the unknown parameters, revealing the conditional sampling distribution of each**.**

The first step in this analysis was to estimate the cross-classified model with no covariates and a random intercept. This model represents a variance components model and is useful for examining the distribution of the variance across each level (Raudenbush, and Bryk 2002a). The second step in the analysis was to examine the effect of individual-level and provider-level covariates by estimating the model with the regressors described above. In the full model, the slope coefficients are assumed to be fixed across facilities and patients.

Our analysis produces estimates of the random effects ($\mu_{i(f),}\ \mu_{i(c)}$). The traditional approach in multilevel analyses is to use the *shrinkage* estimator. This is a Bayesian notion reflecting prior belief that all of the facilities are the same. For each observation, a facility-level residual, r_{cf}, is calculated as $y_{i(c,f)} - \hat{y}_{i(c,f)}$ The raw facility-level residual is just the mean of the residuals from within facility (f), denoted $r_{i(+f)}$. This raw facility-level residual is then multiplied by the shrinkage factor to derive the shrunken facility-level random effect, $\mu_{i(f)}$ **.** The shrinkage factor is $\dfrac{\sigma^2_{i(f)}}{\sigma^2_{i(f)} + (\varsigma^2_{i(c)} + \ \varepsilon_{(c,\,f)}) / n_{i(f)}}$. This multiplier term has several important properties (Rasbash et al. 2000). First, it never exceeds one, thus tends to shrink the raw residual towards zero, the population mean. Second, if there is a lot of random noise, $\epsilon_{i(c,f)}$, individual-level variation (ς^2_{ic}), or if the number of patients seen within the facility is small, then the shrinkage factor is substantially less than one and carries more weight in pulling the residuals toward zero, the population mean.

Two features of the Bayesian cross-classified estimation strategy are considered below. The first is whether having a cross-classified rather than a fully nested data structure improves the precision of the estimates of the variances. In order to compare estimates produced from a cross-classified model with those from a nested model, two subsamples were randomly generated from the full dataset. Each subsample contained 11,780 admissions. Controlling for sample size helped to ensure that differences in the precisions of the estimates were attributable to differences in the estimation strategy and not due to the additional power that is associated with having more observations. Over each the cross-classified and the nested data structures, separate variance components models were estimated.

The second feature of the cross-classified model examined here relates to how Bayesian methods compare to traditional econometric approaches for profiling providers. The facility-level residuals produced from the cross-classified model in MlWin 2.0 were compared with facility-level fixed effects results produced in STATA.

Data

The Tennessee Impact Study provided the data for this study. That study is part of a multi-site investigation of the effect of managed care on the use of health services by children and adolescents. The Impact study is funded by the United States Department of Health and Human Services, Substance Abuse and Mental Health Services Administration. Researchers at Vanderbilt University's Institute for Public Policy Study (VIPPS) obtained and processed the Medicaid claims used in these analyses.

The data provide information on service use from July 1996 until December 2001. Our sample includes all overnight visits where the youth's primary diagnosis was related to mental health or substance abuse. Of the observations that contain complete information there were 16,217 observations related to inpatient visits from 9,183 patients in 197 facilities. Of the individuals in our data 2,460 received care in multiple facilities. Similarly, we had information on multiple observations for 124 of the facilities in our analysis.

Relatively few of our observations had any item nonresponse. We excluded 109 admissions (less than one percent of the total number of admissions) from our analysis do to incomplete information on eligibility for the Medicaid program (n=89) or facility identification number (n=20).

These data provide information on LOS, child's race, gender, how the child qualified for Tenncare, child's diagnosis at the time of inpatient service use, the type of facility in which the service occurred and the primary specialty of the facility.

As noted, the dependent variable for our analysis is length of stay. In order to correct for the right skewness in this variable, a natural log transformation was used. In addition, because a few individuals have very long inpatient stays, LOS was right censored at 100 days[1]. The explanatory variables are described in more detail below.

The Z matrix includes two variables that describe characteristics of the facility. The first is a categorical variable that describes the type of facility (residential facility, detox facility vs inpatient hospital). The second is a categorical variable that describes the treatment generally provided at the facility (community mental health care, other specialty mental health care or other such as general pediatric care). The X matrix consists of two variables that are constant within child. The first is the child's race (white, black, other or unknown). The second is the child's gender. The π matrix contains 4 variables that are specific to the admission but may vary within the child or facility. These include the child's age at discharge, the child's eligibility status within the Tenncare program (SSI, Medically Needy/Spend Down, Foster Care, Temporary Aid for Needy Families (TANF), other state program, other poverty related vs uninsured/uninsurable), and the child's diagnosis during his or her inpatient stay (substance abuse only, substance abuse and mental health vs mental health only) and the year during which the admission occurred.

RESULTS

This section considers three questions. The first question is what is the source of variation in length of stay and how do individual- and facility-level regressors affect LOS. The second question asks whether it is statistically informative to have a cross-classified rather than a fully nested data structure. The third and final question is how do the shrinkage estimates of the facility-level random effects compare with traditional fixed-effects estimates.

Before turning to these questions, we briefly describe our sample. Table 5.1 provides descriptive information on the sample. The majority of sample is white (75.1%) while roughly 22 percent is black. A larger proportion of the sample is male (57.0%) relative to female (43.0%). The age range in the sample is 12 to 21 years, with roughly 40 percent of admissions occurring among individuals aged 15-17. The most common diagnosis for admission was a mental health disorder (83.9%) while 10.6 percent of admissions occurred among youth with a mental health and substance abuse diagnosis and 5.4 percent occurred among youth with a substance abuse diagnosis.

Most of the admissions in this sample occurred in inpatient facilities (87.0%) while 11.4 percent occurred in residential treatment facilities and 1.6 percent occurred in detox facilities. The primary specialty of the facility in which admissions most frequently occurred was community mental health care (82.1%), while 16.1 percent of admissions occurred in other specialty mental health care facilities and 1.8 percent occurred in other types of facilities.

These descriptive statistics are constructed at the admission level. Because individuals with certain characteristics are more likely to use health services, the relative proportion of characteristics changes slightly if we examine the descriptive statistics at the individual-level rather than the admission-level. For example, while 43 percent of admissions occurred among females, 45 percent of individuals in the sample were female. However, the relative proportions are reasonably similar.

Table 5.1 Descriptive Statistics

	Mean	S.D.
Ln(los)	1.92	1.11
	N	Percent
Total	16217	100%
Diagnostic Category (omitted category: Mental health)		
Mental Health and Substance abuse	1,720	10.6%
Substance Abuse	874	5.4%
Eligibility Category (omitted category: Uninsured-Uninsurable)		
SSI	5,004	30.9%
MedNeedy Spend Down	1,573	9.7%
Foster Care Psy 21	2,195	13.5%
AFDC TANF	2,876	17.7%
Other Poverty Related	661	4.1%
Other State Program	188	1.2%
Race/Ethnicity (omitted category: White)		
Black	3,608	22.3%
Otherorunknown	258	1.6%
Gender (omitted category: Male)		
Female	6975	43.0%
age (omitted category:12)		
13	1,659	10.2%
14	2,151	13.3%
15	2,535	15.6%
16	2,488	15.3%
17	1,885	11.6%
18	1,371	8.5%
19	1,116	6.9%
20	987	6.1%
21	772	4.8%
Facility Type (omitted category: Inpatient)		
Detox	262	1.6%
Residential Treatment Facility	1851	11.4%
Primary Specialty (Omitted category: Specialty Mental Health)		
Community Mental Health Care	13,306	82.1%
Other	284	1.8%
Year (Omitted category: 1996)		
1997	2,848	17.6%
1998	2,891	17.8%
1999	3,480	21.5%
2000	3,298	20.3%
2001	2,040	12.6%

Source: Authors' tabulations of the Tennessee Impact Study

A primary goal of this analysis is to examine the key source of variation of LOS. As can be seen in Table 5.2**,** total variation in LnLos is 1.51. According to our model, about 42 percent of the variance is explained at the facility level and only 4 percent is explained at the individual-level while nearly 55 percent of the variation is still unexplained or is specific to the admission.

Table 5.2. Comparison of variance estimates for two cross-classified models: A variance components model vs the full model

	Variance components model			Full-model			Reduction in variance from adding covariates
	Variance	S.E.	% Variance	Variance	S.E.	% Variance	
Facility-level variance	0.63	0.02	41.7%	0.72	0.10	45.8%	11.8%
Person-level variance	0.06	0.02	3.7%	0.05	0.05	3.1%	-14.6%
Admission-level variance	0.82	0.02	54.5%	0.80	0.06	51.0%	-3.5%
Total	1.51			1.56			3.2%

Source: Authors' tabulations of the Tennessee Impact Study

As can be seen in Table 5.3, the individual-level covariates are not strong predictors of LOS. From a frequentist perspective, the majority of the covariates are statistically significant. However, the corresponding slope coefficients are very small in practical terms. This indicates that the individual and facility level characteristics such as race, diagnosis, and facility type are poor predictors of LOS. Table 5.2 compares the variance estimates produced from the full model with the those produced from the variance components model. These results suggest that adding individual level covariates to the model barely changes our variance estimates. Adding the covariates to the model had the largest effect on individual-level variation, decreasing the explained variance by about 14 percent. However, the facility-level and admission-level variance appeared to increase by roughly 12 percent and 4 percent respectively. In fact, contrary to expectations, the total variation LOS appears to increase when the covariates are added. This highlights the fact that the numbers describing the relative proportion of the variances are merely estimates. Although they are a useful guide to understanding what factors best explain sources of variation, they are nonetheless estimates.

Table 5.3. Results from a cross-classified model of Ln(LOS)

	Beta	S.E.	T-score
Diagnostic Category (omitted category: Mental health)			
Mental Health and Substance abuse	0.05	0.03	1.91
Substance Abuse	-0.22	0.05	-4.61
Eligibility Category (omitted category: Uninsured-Uninsurable)			
SSI	0.15	0.02	0.15
MedNeedy Spend Down	-0.05	0.03	-1.69
Foster Care Psy 21	0.02	0.03	0.88
AFDC TANF	-0.02	0.02	-0.65
Other Poverty Related	-0.07	0.04	-1.63
Other State Program	-0.24	0.07	-3.42
Race/Ethnicity (omitted category: White)			
Black	0.01	0.02	0.46
Otherorunknown	0.14	0.07	2.10
Gender (omitted category: Male)			
Female	-0.02	0.02	-1.02
age (omitted category:12)			
13	0.02	0.04	0.53
14	-0.07	0.04	-0.07
15	-0.08	0.04	-2.35
16	-0.11	0.04	-3.22
17	-0.15	0.04	-4.00
18	-0.40	0.05	-8.89
19	-0.34	0.05	-6.90
20	-0.34	0.05	-7.42
21	-0.29	0.05	-6.02
Facility Type (omitted category: Inpatient)			
Detox	-0.07	0.07	-1.12
Residential Treatment Facility	0.12	0.04	3.06
Primary Specialty (Omitted category: Specialty Mental Health)			
Community Mental Health Care	0.35	0.03	12.18
Other	-0.32	0.07	-4.46
Year (Omitted category: 1996)			
1997	-0.33	0.03	-9.57
1998	-0.49	0.04	-12.33
1999	-0.63	0.04	-15.61
2000	-0.68	0.04	-17.34
2001	-0.89	0.04	-21.42
Constant	2.30	0.09	25.58

Source: Authors' tabulations of the Tennessee Impact Study

The second part of this analysis considers the benefits of having a cross-classified data structure relative to a nested data structure. In order to compare the statistical properties of the two data structures, estimates from two variance components models were derived. The first model was estimated using a sample with a cross-classified structure. The second was estimated using a sample of patients whose observations were completely nested within a single facility. That is, the data for the nested sample still contained repeated observations on multiple patients and facilities. However, the data did not include observations on the same patient treated in multiple facilities. As shown in Table 5.4, the variance estimates for each of the levels are approximately equal in both the nested and the cross-classified models. However, the standard errors of the variance estimates for the admission-level(.013 vs .063) and individual-level variances (.010 vs .061) are smaller in the cross-classified than in the nested model.

Table 5.4 Comparison of two variance components models: A cross-classified vs a nested data structure

	Cross classified Model (n=11780)		Nested Model (n=11780)		Reduction in S.E..
	Variance	S.E.	Variance	S.E.	
Facility-level variance	0.79	0.118	0.79	0.116	-2%
Person-level variance	0.12	0.010	0.11	0.061	84%
Admission-level variance	0.76	0.013	0.74	0.063	79%
Total	1.67		1.65		
Source: Authors' tabulations of the Tennessee Impact Study					

Figure 2. demonstrates how Bayesian analysis shrinks the estimates of facility-level residuals differently based upon the number of observations from that facility. In particular, facilities with fewer observation points are shrunk toward the population mean more than facilities with a larger number observations. For illustrative purposes two facilities are highlighted, A and B. The facility-level residual for these two facilities is approximately equal, .22 and.23 respectively. Statistically, facility A is not an outlier because the confidence interval of the residual includes zero. On the other hand, facility B would be categorized as a facility whose length of stay is above average. The major difference between the two facilities is that facility A has only one observation point while facility B has 208 observations. This improves the precision with which the residual for facility B is estimated. Notice also the difference of the effect of the shrinkage multiplier on the facility-level variance. In facility A, the fixed-effects facility-level residual is approximately 0.64 but is shrunk to 0.22, a difference of 66%. However, for facility B, the fixed-effects residual and the shrunken residual are substantially closer, .27 vs. 23, a difference of only 15 percent. This reflects the greater certainty that we have that facility B an outlier (length of stay is typically shorter in facility B relative to the other facilities contained in this sample).

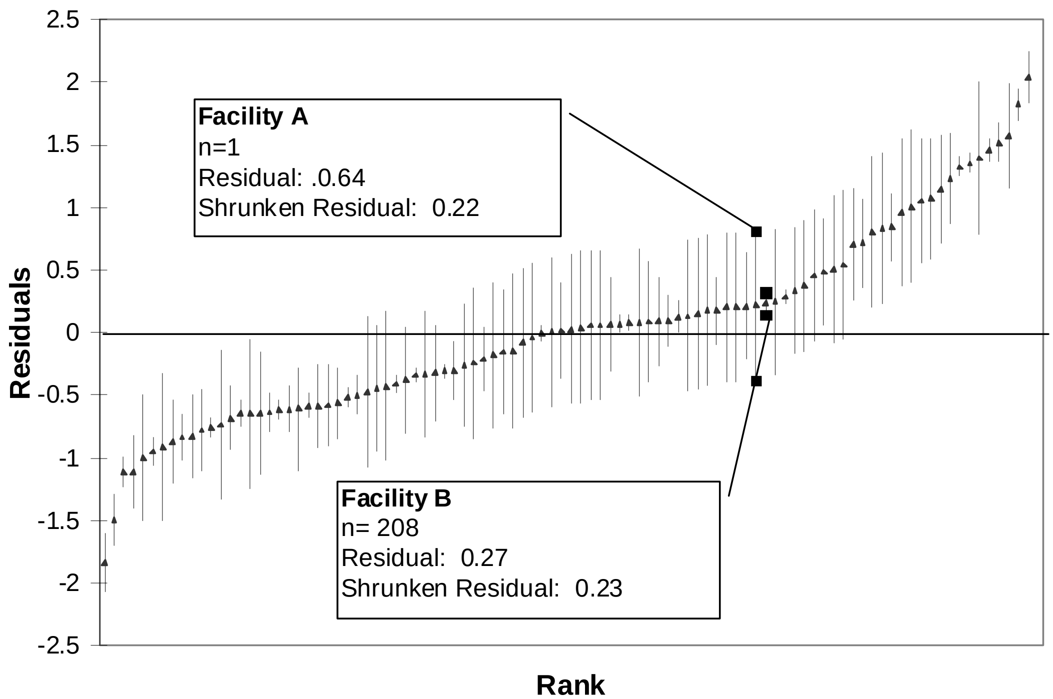

Figure 5.2 Illustration of "Shruken" Residuals

DISCUSSION

This study was primarily designed to address whether individual-level predictors of LOS are poor because variation in LOS is determined at the facility-level. These analyses suggest that once a youth is admitted for a psychiatric and/or substance abuse diagnosis, roughly 40 percent of the variation in LOS is explained at the facility level while less than 5 percent is explained at the individual level. These findings suggest that once a patient is admitted to the hospital, it may be more important to monitor facility practices rather than to use individual incentives to curb costs. Monitoring facility-level practices is particularly important for children with psychiatric diagnoses. For instance, Wickizer et al (1999) found that administratively reducing the number of inpatient days requested by a youth's physician was associated with an increased probability that the youth would be readmitted within 60 days. Concern that inappropriate use of utilization management may negatively impact the quality of patient care suggests the need to monitor the care that youth with mental health and substance abuse problems receive.

A second aim of this study was to demonstrate several methodological advantages of incorporating multilevel modeling in health services research. This research takes advantage of several features of the data such as repeated observations on both individuals and facilities as well as the information on the same individual treated in different facilities. Having repeated observations on individuals and facilities helps to better identify the model and avoid biasing estimates due omitted variables. As demonstrated here, the cross-classified nature of the data improved the precision of the estimates of the variance terms.

Moreover, the Bayesian approach allows the researcher to pool information across facilities. In many traditional approaches, patients treated by providers with small patient bases are excluded from analyses. Pooling information from facilities which treat dramatically different numbers of patients allows the researcher to incorporate observations from smaller providers. Hierarchical modeling takes into account the clustering of patients within providers. In previous research where only one or a few facilities have been included in the sample, the fact that these observations are clustered at the facility level is often ignored. Failure to appropriately account for this clustering violates the assumption that the observations are identically and independently distributed (Goldstein, Browne, and Rasbash 2002).

Multilevel modeling represents a unified frame work for simultaneously examining patient and provider characteristics. This same framework can be extended to incorporate geographic and community level variation in access to care. This feature is potentially important for research that examines determinants of health care. Dramatic geographic variation in the treatment that individuals receive has been long been recognized (e.g.(Keller et al. 1990)). Geographic variation can be observed even for surgical procedures which one might otherwise think there was little room for discretion on the part of either the provider or the patient (ex. Rates of hip fraction repair) (Birkmeyer et al. 1998). As the level of discretion increases, so does the amount of geographic variation in surgical procedures. In the area of child and youth substance abuse and mental health treatment, it is likely that providers can exercise a relatively large degree of discretion. Similarly, community level factors such as social capital and HMO penetration rates have been shown to affect health care utilization (Hendryx et al. 2002). Thus, multilevel models allow researchers to incorporate a broader range of factors in models of health services utilization.

CHAPTER SIX

Provider-level Influences on Receipt of Aftercare Services: A Multilevel Hazard Model

ABSTRACT

Objective: Previous research on determinants of aftercare service use for youth with mental health or substance abuse disorders has focused on patient level characteristics. However, providers can influence whether or not a youth receives such services. This study examines both patient- and provider-level determinants of aftercare services for youth with mental health and substance abuse disorders following inpatient hospitalizations.

Study Design: This study uses Tennessee Medicaid claims data from 1996 to 2001. The data include information on 9,181 youth aged 12-21 discharged from 170 facilities. We estimate the hazard of receiving aftercare services using a multilevel discrete-time event history model. Covariates include patient characteristics (gender, race,), facility characteristics (type, specialty), episode characteristics (length of stay prior to discharge, year, child's qualification for Medicaid, age, and diagnosis) and duration from discharge until receipt of follow-up services.

Results: Twelve percent of youth in our sample received aftercare services within four months of discharge. Relative to youth with mental health problems, the hazard of receiving aftercare services was 26 percent lower for youth with substance abuse problems. Relatively little (9%) the variation in aftercare services was determined at the facility level, and 16 percent was explained by patient and family characteristics.

Conclusion: A relatively small percentage of youth discharged from inpatient facilities received the appropriate level of aftercare services. Further research should examine factors that could improve this low rate. Because relatively little of the variation in aftercare is determined at the facility level, these results call into question the use of aftercare receipt as a measure of quality of care provided by a facility.

The National Committee on Quality Assurance recommends patients receive follow-up care within a week of discharge from an inpatient stay related to a mental health disorder (National Committee for Quality Assurance (NCQA) 2003). Such aftercare provides an opportunity to monitor a patient's progress after discharge; patients who are not faring well can have their medications adjusted or treatment modified.

Research has linked aftercare services to lower readmission rates and better treatment outcomes. For instance, for youth with substance abuse problems, receipt of aftercare services reduces the likelihood of relapse (Kelly, Myers, & Brown, 2000; Kennedy & Minami, 1993; Whitney, Kelly, & Meyers, 2002; Daniel, Goldston, Harris, Kelley, & Palmes, 2004). In turn, substance abuse problems have been linked to problems maintaining employment and premature death (Hu et al. 2001). Thus ensuring youth receive appropriate follow-up services has the potential for great public cost savings.

Nevertheless, only limited research exists as to whether youth leaving inpatient psychiatric institutions receive aftercare services. As discussed below, this research focuses on the role of patient and family characteristics and neglects the role of providers. This gap is surprising given that research in other areas of health services have shown the importance of such factors. For example, Gifford and Foster (2005) find that roughly 40 percent of the variation in length of stay among youth with mental health and substance abuse disorders is determined at the facility level. This compares with only 4 percent of the variation being explained by patient level characteristics.

The role of the provider in ensuring compliance with treatment recommendations such as receipt of aftercare services may be particularly important for youth mental health and substance abuse disorders. The nature of these disorders may impede the individual's ability to seek services. Continuity of care is especially important for chronic conditions, such as mental disorders, where failure to treat the disorder in a timely fashion may lead to more severe episodes of illness.

This article examines determinants of receiving aftercare services following discharge from an overnight medical visit among youth with mental health and/or substance abuse disorders. Data for these analyses were collected as part of the Tennessee Impact Study. This article has five sections. First, we review prior studies of determinants of aftercare service use among youth with mental health and/or substance abuse problems and discuss the limitations of these studies. Then we describe the Tennessee Impact Study data and the sample used in our analyses. Next, we describe the multilevel event history model used to examine differences in the timing of receiving aftercare services and then present the results of our analyses. Finally, the implications of our findings are described.

PRIOR RESEARCH

A recent review of the scientific literature in MEDLINE or Pyschinfo published between January 1992 and August 2003 identified only 21 articles that examined aftercare services for children with mental health or substance abuse disorders (Daniel et al. 2004). Only eight studies examined determinants of aftercare use among youth who have been discharged. Only four of these studies focused on the timing of the initiation of aftercare services (Foster 1998; Goldston

2003; Kelly, Myers, and Brown 2000; Parmelee et al. 1995).

These studies examined receipt of aftercare following discharge from an inpatient facility in a range of populations. Parmelee et al (1995) followed 79 youths for six months after discharge from a state psychiatric facility. Foster (1998) examined 204 youth discharged from psychiatric facilities whose parents were members of the military. These youth were divided between two groups. Youth were followed for 60 days post discharge. Kelly and colleagues (2000) examined 99 youth with substance abuse problems discharged from two private hospitals in San Diego. Attendance at 12-step meetings was monitored for 6 months following discharge. Goldston et al (2003) examined the experiences of 180 adolescents who were discharged from an inpatient psychiatric facility in North Carolina. Youth were followed for up to one year.

Together, this literature identifies a series of individual and family characteristics that predict the use of aftercare. A higher probability of receipt of aftercare service use was associated with younger age (Foster 1998, Goldston 2003), higher caregiver educational attainment (Foster, 1998), lower socioeconomic status (Foster, 1998), presence of a biological parent or grandparent (Golston et al 2003, Parmelee et al 1995, Foster, 1998), substance use severity (Kelly et al 2000), comorbid psychiatric disorder (Goldston et al 2003), higher levels of objective caregiver burden (Foster 1998), lower levels of internalizing or externalizing burden of care (Foster 1998) and higher levels of functioning (Foster, 1998). Prior experience with the health system also was related to the care that youth received. Higher rates of receiving aftercare were observed for youth who had ongoing patient therapy prior to hospitalization (Goldston et al, 1998 and Parmelee 1995), were voluntarily admitted to the hospital (Parmelee et al 1995), were exposed to a coordinated network of providers (Foster, 1998) and who did not have multiple previous hospitalizations (Foster, 1998).

For some characteristics, findings were inconsistent across studies. For instance, Foster (1998) found that minority youth were less likely to receive aftercare services. In contrast, Goldston (2003) found no link between race and service use. Foster (1998) found conduct disorder was associated with an increase in the hazard of receiving aftercare services at the demonstration site. However, Godston et al (2003) did not find a statistically significant association between receipt of aftercare and conduct disorder.

These studies suffered from a variety of limitations. First, and most importantly, none of the studies examined whether provider level factors may encourage or discourage receipt of aftercare services. Each study focused on no more than a handful of facilities or providers. This limits the generalizability of findings from one study. Second, all of the studies were based on small samples with the largest having 204 observations. Small sample size limits the researcher's ability to examine the effects of the large number of factors known to affect the probability of receipt of health services. Moreover, inconsistencies across studies–both in findings and in methodology–make it difficult to synthesize findings across studies.

METHODS

The current study examines determinants of receipt of follow-up services using a multilevel hazard model. This model allows one to model both the nature of the dynamic process shaping the use of aftercare as well as the multilevel determinants of service use. In particular, this study examines the degree to which provider-level factors affect the probability that a youth will receive aftercare services. The sample for these analyses includes a large number of youth who received care from many facilities from a single state. All youth in our sample are insured through the Medicaid program. Receipt of aftercare services is modeled as a function of child's age, gender, race/ethnicity, eligibility for the Medicaid program, diagnosis, length of stay of the most recent discharge, type of facility from which they were discharged, the primary specialty of the facility, and the year that the child entered services.

Data

The Tennessee Impact Study provided the data for these analyses. That study is part of a multi-site investigation of the effect of managed care on the use of health services by children and adolescents and is funded by the United States Department of Health and Human Services, Substance Abuse and Mental Health Services Administration. Researchers at Vanderbilt University's Institute for Public Policy Study (VIPPS) obtained and processed the Medicaid claims used in these analyses.

The data provide information on service use from July 1996 until December 2001 for youth aged 12-21. Our sample includes all discharges from an inpatient stay related to a mental health and/ or substance abuse disorder. For patients who had multiple discharges from multiple facilities, we limited the sample to include only discharges from a single facility. Individuals with mental retardation were excluded from these analyses.

These data contain information on all services that the youth received which were paid for by Medicaid. This includes information such as the dates when the child was admitted, discharged and received subsequent services. The data also provide details such as whether the service was inpatient or outpatient and the child's diagnosis for at the time of service use. Moreover, these data provide information on the child's race, gender, age, and how the child qualified for Tenncare. Another important feature of this data is that they include the ICD-9 diagnosis code for the youth's mental health and substance abuse problem.

Relatively few observations had any item nonresponse. We excluded 109 admissions (less than one percent of the total) from our analyses due to incomplete information on eligibility for the Medicaid program (n=89) or facility identification number (n=20). Of the observations that contain complete information there were 11,884 discharge from 9,181 patients in 170 facilities.

The data contain a facility identifier that can be used to link individuals discharged from the same facility. The data also include information on the type of facility in which the service occurred (detox facility, residential treatment center or inpatient facility) and the primary specialty of the facility (mental health, community mental health center, or other center).

Statistical Model

The hazard of receiving aftercare services was modeled using a multilevel discrete-time event history model to examine whether there were provider level effects on duration until follow-up services (Steele, Goldstein, and Browne 2003). Equation 1 represents the hazard of receiving services. It is a function of facility, child and discharge characteristics. The hazard rate also has a discharge-level variance term, $\varepsilon_{f,c,d}$. Equation 2 indicates that the mean for a facility and child, $\beta_{f,c,}$ is a function of the facility-level mean, β_f and a child-level mean, B_c. Equation 3 implies that the facility mean is a function of observed facility characteristics, X_f, and unobserved characteristics, δ_f. Similarly, Equation 4 implies that the child mean is a function of observed child characteristics, X_c, and an unobservable term, δ_c.

$$h_{f,c,d} = \exp(\beta_{f,c} + \beta X_{f,c,d} + \varepsilon_{f,c,d})$$
$$\beta_{f,c} = \beta_f + \beta_c$$
$$\beta_f = \gamma X_f + \delta_f$$
$$\beta_c = \eta X_c + \delta_c$$

The X_f matrix consists of two variables that describe facility-level characteristics, the type of facility in which the episode occurred (residential facility, detox facility vs inpatient hospital) and the primary specialty of the facility (Community Mental Health Center, other vs mental health).

The X_c matrix consists of two variables that are constant within child, the child's race (white vs nonwhite) and gender.

The $X_{,f,c,,d}$ matrix contains 6 variables are specific to the discharge. These include the child's age at admission, the child's eligibility status within the Tenncare program (SSI, Medically Needy, Foster Care, cash assistance, other state program, other poverty related vs uninsured), and the child's diagnosis during his or her inpatient stay (substance abuse only, substance abuse and mental health vs mental health only), the length of the inpatient visit preceding the discharge and the year during which the admission occurred. The $X_{f,c,d}$ matrix also includes a measure of the amount of time between discharge and follow-up is measured in weeks.

Estimation

The data were organized in a person-day format. Spells were right-censored at 120 days or approximately 4 months. There are both theoretical and practical reasons for censoring. Theoretically, it is difficult to know whether an outpatient visit observed four months post discharge is related to the original episode of care. For practical computational reasons, censoring at some arbitrary cutoff was necessary in order to keep the dataset sufficiently small so that the computer could estimate the model. The resulting sample included 478,729 person days.

The dependent variable was a dichotomous variable indicating whether patient received aftercare services on that day.

One aim of this study was to partition the variance across various levels. Typically researchers calculate what is known as a variance partition coefficient. This coefficient represents the variance explained at the level of interest divided by the total variance. In order to partition the variance, we used the latent variable approach (Browne et al. 2003). This approach assumes that the underlying distribution of the dependent variable is continuous. In the model of receipt of aftercare services we have assumed the dependent variable follows a logistic distribution. The variance of a logistic distribution is a constant ($\pi^2/3$). This value is substituted for the variance of the lowest level, the discharge level ($\varepsilon_{f,c,d}$). The total variance is the sum of $(\pi^2/3)+\delta_f+\delta_{c.}$

It is important to note that the interpretation of coefficients from hazard models differs from those obtained from ordinary least squares regression. The interpretation of the coefficients depends upon the specific type of hazard model used. Hazard ratios were used to interpret the coefficients from the model presented here. A hazard ratio represents the effect of a unit change in the value of X_j on the hazard rate. A hazard ratio can be calculated by exponentiating the coefficient of interest. Models were estimated in MLWin using the iterative generalised least squares algorithm.

RESULTS

Table 6.1 contains descriptive statistics of the sample discharges. Following discharge, 12 percent of patients received aftercare services within 4 months post. The other 88% of discharges were censored at 4 months. The mean and median time from discharge until receipt of aftercare services was 7.1 and 6.3 weeks respectively.

Table 6.1 Descriptive Statistics of Discharge Characteristics

	Median	Mean	SD
Time until aftercare received (in weeks)	6.3	7.1	5.1
Length of stay prior to discharge (in days)	6.0	12.5	19.2
	N	Percent	
Total	11884	100%	
Received follow-up	1,478	12%	
Race/Ethnicity (omitted category: nonWhite)			
White	9,126	77%	
Gender (omitted category: Male)			
Female	5156	43%	
age (omitted category:12-15 years)			
16-18 years	4,231	36%	
19-21 years	1,797	15%	
Diagnostic Category (omitted category: Mental health Only)			
Substance Abuse Only	694	6%	
Comorbidity	1,320	11%	
Eligibility Category (omitted category: Uninsured)			
SSI	3,148	26%	
Medically Needy	1,257	11%	
Foster Care	1,532	13%	
Temporary Aid to Needy Families	2,410	20%	
Poverty Related	536	5%	
Other State Program	174	1%	
Facility Type (omitted category: Inpatient)	10,478	88%	
Detox	219	2%	
Residential Treatment Facility	1,187	10%	
Primary Specialty (Omitted category: Mental Health)			
Community Mental Health Center	9,410	79%	
Other facitlity	261	2%	
Year (Omitted category: 1996)			
1997	2,178	18%	
1998	2,081	18%	
1999	2,443	21%	
2000	2,262	19%	
2001	1,390	12%	
Source: Authors' tabulations of the Tennessee Impact Study			

About three quarters of the sample was white (77%). A slightly smaller proportion of girls had discharges for substance abuse and/or mental health problems (43% vs 57%). The majority of the sample (57%) had a mental health diagnosis at admission. Six percent of the sample had a diagnosis of a substance abuse disorder and 11 percent had a comorbid condition. Youth qualified for the Medicaid program in a variety ways. Roughly a quarter of discharges were made by individuals who qualified for the Supplemental Security Income Program (SSI). Another quarter of the discharges involved individuals who would have been uninsured were they not covered by Medicaid. The remaining individuals qualified via their status in foster care (11%), participation in TANF (20%), other poverty related reasons (5%) or through the state run program (1%). Regarding facility type, 88 percent of discharges were from an inpatient facility. One tenth of discharges were from a residential treatment facility and 2 percent were from a detox facility. The primary specialty for 79 percent of discharges was a community mental health center, a mental health center for 19 percent and 2 percent came from facilities with other specialties.

Table 6.2 contains the hazard ratios from the multilevel discrete-time hazard model. Females were 14 percent more likely than males to receive aftercare services. Relative to youth aged 12-15, the hazard of receiving aftercare services was 35 percent lower for youth aged 16-18 and 51 percent lower for youth aged 19-21. Probability in receiving aftercare services varied by how an individual qualified for the Medicaid program. Relative to other children in the Medicaid program, youth in foster care had a 52 percent lower hazard of receiving aftercare services and youth who qualified for other state programs had an 80 percent lower hazard of receiving aftercare services. Youth discharged from an inpatient facility had 35 percent higher hazard rate of receiving aftercare services than youth discharged from a detox facility. Youth treated in community mental health centers had a 19 percent higher hazard rate for receiving aftercare services than youth treated in a mental health facility. The likelihood of aftercare receipt rose over time: relative to youth admitted in 1996, for those admitted in 1998, 1999 and 2000,the hazard rate for receiving aftercare services was 20, 51 and 44 percent higher respectively.

Estimates from the reduced multilevel discrete time logistic regression model suggest that 9 percent of the variance in the hazard of receiving aftercare is attributable to the facility level and 16 percent is attributable to the individual-level. Because the distribution of estimated variance components is often quite different than the normal distribution, significance levels were determined using the posterior distribution. The posterior mean for the variance of both the facility-level and patient-level random effects were statistically significantly different than zero ($p<.05$).

Table 6.2 Multilevel Logistic Event History of Receipt of Aftercare Services

	Hazard Ratio	T-score	Significance[a]
Weeks following discharge	0.80	-75.33	--
Length of Stay	1.00	-4.00	--
Diagnostic Category			
Substance Abuse	0.74	-3.40	--
Comorbidity	0.93	-1.38	
Race/Ethnicity			
White	1.03	0.63	
Gender			
Female	1.14	4.06	+
age			
16-18 years	0.65	-12.53	--
19-21 years	0.49	-14.18	--
Eligibility Category			
SSI	0.97	-0.70	
Medically Needy	0.86	-2.70	--
Foster Care	0.38	-17.44	--
TANF	0.96	-1.02	
Other Poverty Related	1.01	0.09	
Other State Program	0.20	-10.18	--
Facility Type			
Inpatient	1.35	2.31	-
Residential Treatment Facility	1.15	0.99	
Primary Specialty			
Community Mental Health Center	1.19	3.38	++
Other facility	1.22	1.63	
Year			
1997	1.03	0.58	
1998	1.20	2.86	++
1999	1.51	6.19	++
2000	1.44	5.41	++
2001	1.10	1.21	
Variance Estimates			
Facility			
Variance estimate	0.36	5.37	
% of total (unexplained) variance	8%		
Patient			
Variance estimate	0.69	26.50	
% of total (unexplained) variance	16%		
Discharge			
Variance estimate	3.29	NA	
% of total (unexplained) variance	76%		
N			
Person days at risk	478729		
Number of Failures	1478		

Source: Authors' tabulations of the Tennessee Impact Study
a This column indicates hazard ratios of p<.01 as "++" or "--" and p<.05 as "+" or "-" depending upon whether the corresponding characteristic increases or decreases the hazard of aftercare services.

DISCUSSION

Our results suggest many youth are not receiving the recommended levels of care. Our sample is limited to a Medicaid population where patients do not bear out of pocket expenditures. Since cost of care is often a barrier to care, one might expect compliance to be higher in a Medicaid population than in other low-income populations.

A key question this study asks is whether the hazard of receiving services differs across providers as well as across patients. The random effects for both facility and patients was significantly different than zero suggesting that the hazard rate for receiving aftercare depends on factors at both the facility and individual levels.

However, the facility-level component explained only 9 percent of the total variance. This finding could imply several things. The overall rate of receipt of aftercare services was relatively low in our sample. This could imply that all facilities were generally providing poor quality care or were not using strategies that could improve follow-up rates. Other studies of various populations (low-income pediatric populations, adults with chronic conditions, veterans discharged from substance abuse clinics, etc.) have found that follow-up rates improve if facilities implement strategies such as helping patients schedule appoints and reminding patients of when their appointments are (Bodenheimer, Wagner, and Grumbach. 2002; Lozano et al. 2003; Quattlebaum, Darden, and Sperry 1991; Wagner et al. 2001).

A second explanation as to why facilities had little effect on receipt of aftercare services may be that individual characteristics are stronger determinants than facility level factors. Even if that is the case, then providers may wish to identify individual characteristics that are associated with low compliance with recommended treatment. Better identifying which individuals are least likely to comply with treatment recommendations may help providers target hard to reach populations. This possibility implies that future research could explore whether there is an interaction between provider and individual characteristics.

Limitations

The observed rate of aftercare service use in our study was12 percent. This rate is substantially lower than the rate of about two thirds seen in most studies of aftercare receipt (Daniel et al. 2004). This finding is particularly surprising given that our study followed patients for up to four months post-discharge. One explanation for this is that our data come from one payment source, Medicaid claims data. It is possible that some youth received follow-up services that were paid for by another source such the Drug and Alcohol Treatment Block grant, private insurance or out of pocket payment or another service sector such as the school system or the juvenile court system.

A second limitation of this study is that we lack information on individual and family characteristics known to be related to receipt of aftercare services such as socioeconomic status, family structure, substance use severity, or caregiver characteristics such as burden of care.

Conclusion

This is the largest study to consider the determinants of aftercare services. Unlike previous studies, this study is able to examine post-discharge care from a large sample of individuals who sought care in many different facilities. Although our study did not find large provider-level effects, our results suggest that few youth are receiving appropriate follow-up treatment. Providers have the potential to improve the percent of youth who receive services. Further research could explore which patient level characteristics are most important determinants of receipt of aftercare services and what provider-level strategies improve patient compliance for those who are least likely to comply.

CHAPTER SEVEN

Conclusion

This dissertation presented several uses of multilevel modeling in health services research. In the coming years, it is likely that multilevel models will increasingly be used in this field. In this final chapter I summarize what was demonstrated in each chapter and suggest a few additional uses of multilevel modeling.

The first article demonstrated that multilevel modeling can be used to analyze data collected in a multisite data collection effort. In the area of children's mental health services, data are often collected across multiple sites. This is in large part due to the difficulty in collecting a sufficiently large population-based sample of youth with mental health disorders. Any specific mental disorder has a relatively low prevalence. Thus it is usually necessary to oversample youth with mental health ailments. Yet, identifying youth with a mental health disorder is challenging. It involves administering a long checklist of questions or having health professionals administer a battery of psychometric tests (Achenbach 1991; American Psychiatric Association 1994; Shaffer et al. 2000). Therefore generating an oversample of youth with mental health disorders can be resource intensive. As an artifact of these challenges, many studies of children's mental health and mental health services have been based on samples from within a single community or a few communities (Conduct Problems Prevention Research Group 1992; Costello et al. 1996; Shaffer et al. 1996). Even though the sample for these studies may contain 1,000 subjects, they may not contain sufficient sample sizes to study subpopulations of interest such as African American male adolescents or girls with substance abuse problems.

To examine whether racial variation in receipt of medication varied by site we used Bayesian hierarchical models (see Chapter 3). Many of the sites in this study had only a few black or Hispanic youth with attention problems. However, multilevel models allowed us to pool information across sites to estimate the effect of race/ethnicity on receipt of medication. Moreover, in the multilevel model framework, the slope of race/ethnicity was allowed to vary across sites. This is different than regression techniques such as the fixed or random effects approach in which the effect of race would have been assumed to be fixed (identical) at each site.

The first article also demonstrated how geocoded data could be incorporated into multilevel analyses. By using geographic information systems, the youth's zipcode was linked to attributes of the place where he or she lived such as the county-level poverty rate. Combining geocoded data into multilevel analyses has a broad applicability in much of health services research. For instance, geographic information systems could inform health services researchers about the providers available to the patient. Mapping providers in an area would contribute valuable information such as distance to nearest provider, provider density, or a measure of the different types of providers within a patient's community. A second example of how geographic information systems could compliment multilevel analyses comes from a related field--epidemiology. With geographic information systems, it is possible to look for geographic disease clusters. The causes of these disease clusters can then be analyzed for factors related to both the individuals within a community (ex. poverty) and the community environment (amount of air pollution).

The second article took advantage of a large administrative database. The primary advantage of the administrative database was that it provided information on many patients treated by many providers. In fact some patients were treated by more than one provider in the database. This produced the cross-classified data structure shown in Figure 5.1. As demonstrated in Chapter 5, observing a patient's treatment outcomes across different providers can greatly improve the precision of our variance estimates. Moreover, having a large sample of providers where we observe a large number of patients is helpful for identifying outliers. As the US health care system fights rising health care costs while striving to improve quality, there is increasing interest in holding providers accountable for their outcomes. However, accurately comparing the care provided across practioners is difficult (Austin 2002; Zaslavsky 2001). Bayesian multilevel modeling provides a means by which researchers can pool information across providers and reflect the amount of uncertainty in our estimates of provider performance.

The third article (Chapter 6) also took advantage of data from the same large administrative database. In this article we combined multilevel modeling with event history techniques. Event history methods are useful for understanding variation in duration of events. Health services researchers are often interested in questions related to time. For instance, researchers are interested in whether a treatment adds extra days to ones life, reduces the number of disability days or variation in timing of different services. Thus this article demonstrates a straight forward way of simultaneously incorporating provider-level and patient-level variation into event history models.

FUTURE DIRECTIONS

To date, little research in the area of children's mental health services has focused on partitioning the variance in outcomes across patients, communities and providers. As evidenced by the research presented in this dissertation, some levels may influence the relative amount of variation in the outcome of interest more strongly than other levels. Better understanding sources of variation may help to target research efforts more efficiently. For example, the results from our multilevel models of racial and community level variation in receipt of psychotropic medication suggest that the effect of race does not vary across communities. To better understand why receipt of medication varies across races, future research efforts may need to focus on differences across the races in terms of their health beliefs rather than differences across where individuals live. Similarly, the results from the Bayesian cross-classified model in Chapter 5 suggest that differences in providers rather than individuals are important for understanding variation in length of stay. This suggests that future studies may need to focus their efforts on understanding differences across providers. Finally, the results from our model of aftercare services suggest that we know little about explaining variation in who will receive follow-up services. This might suggest the need to do qualitative research and focus groups to develop better models of determinants of aftercare services.

While this dissertation illustrated several examples of multilevel modeling, there are many possible applications which were not addressed. For instance, multilevel modeling could be used to perform meta analyses and thereby pool information across multiple studies that have asked the same research question. Another application of multilevel model not presented in this dissertation is multiple membership models. These models allow researchers to weight the amount of time that an individual spends within different higher order units. For example, adolescents receiving day treatment services may receive multiple services throughout the day. However, the percentage of time allocated to the various services may vary across adolescents within a facility. This type of data could be analyzed using a multiple membership model. A third example of a multilevel model that was not demonstrated in this dissertation is growth curve analysis. Growth curves analysis is useful for analyzing repeated information across individuals over time. For instance, we may be interested in studying whether a service improves youths' depression. Growth curves would allow researchers to compare changes overtime in depression scores across individuals who did and did not receive the service.

The studies presented in this dissertation used methods that are relatively new in the field of children's mental health services research. This statistical tool, multilevel modeling, has broad applicability in children's health services research since determinants of access, cost and quality of children's health care depend upon the child's family, school, community and medical environment (Andersen 1995). In order to best make use of this tool, future data collection efforts will need to consider hierarchical structures in their sampling plans (Snijders, and Bosker 1999).

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CURRICULUM VITA

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EDUCATION

2005	PhD Joint Degree in Health Policy and Administration & Demography	Penn State University, College of Health and Human Development, State College, PA
2000	M.S. Health Policy and Administration	Penn State University, College of Health and Human Development, State College, PA
1997	B.S. Biology with a minor in Nutrition	Cornell University, College and Agriculture and Life Sciences, Ithaca NY

PUBLICATIONS

Foster, E. M. and Gifford, E. (2005). "The transition to adulthood for youth leaving public systems: Challenges to policies and research"in R. A. Settersten, F. Furstenberg, and R. Rumbaut (Eds), On the Frontier of Adulthood: Theory, Research, and Public Policy. Chicago, IL: University of Chicago Press.

Gifford, E., Weech-Maldonado, R. and Short, P. Encouraging preventive services for low-income children: The effect of expanding Medicaid coverage to parents. *Forthcoming in Health Care Financing Review*.

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SELECT PRESENTATIONS

Gifford, E. and Foster, E.M.. Understanding provider influences on residential length of stay among youth with mental health, substance abuse, and co-occurring disorders: A Bayesian cross-classified approach, was presented at the 24th Biennial Conference of the Society for Multivariate Analysis in Behavioral Sciences at the Friedrich Schiller University Jena, Germany in July 2004 and will be presented at the International Health Economics Conference in Barcelona Spain in July 2005.

Gifford, E. and Foster, E.M. Combining information from multiple informants was presented at Center for Child and Family Policy at Duke University and Chapin Hall Center for Children in June 2004.

Enderlein, T. and Gifford, E. An introduction to Geographic Information System methods and resources, to be presented at Penn State University's Health Policy and Administration Colloquium in January 2004.

Foster, E.M. and Gifford, E. What is the value of Safe Streets? A economic evaluation of the Philadelphia Safe Streets Program, was presented for the Mayor of Philadelphia in April 2003.

Gamm, L, Gifford, E., and Benson, K. Environmental Support for Community Health Partnerships: State Level Organizations' Perspectives on the Value and Sustainability, was presented at "Putting the Public back in Public Health" the 130th Annual Conference of the American Public Health Association in November 2002.

Foster, E. M. and Gifford, E. The transition to adulthood for youth in special populations was presented to the John D. and Catherine T. MacArthur Network on the Transition to Adulthood in Philadelphia in March 2002.

Gifford, E., Weech-Maldonado, R. and Short, P. Encouraging preventive services for low-income children: The effect of expanding Medicaid coverage to parents, was presented at the Academy for Health Services Research Annual Research Meeting in Atlanta, Georgia in June 2001.