DETERMINANTS OF HEALTH CARE USE AMONG RURAL, LOW-INCOME
MOTHERS AND CHILDREN: A SIMULTANEOUS SYSTEMS APPROACH TO
NEGATIVE BINOMIAL REGRESSION MODELING

A Thesis Presented

by

SWETHA VALLURI

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Approved as to style and content by:

_____
Sheila Mammen, Chair

_____
Daniel Lass, Member

_____
Julie Caswell, Chair
Resource Economics

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ABSTRACT

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SWETHA VALLURI, UNIVERSITY OF MASSACHUSETTS AMHERST

M.S., UNIVERSITY OF MASSACHUSETTS AMHERST

Directed by: Professor Sheila Mammen

The determinants of health care use among rural, low-income mothers and their children were assessed using a multi-state, longitudinal data set, *Rural Families Speak*. The results indicate that rural mothers' decisions regarding health care utilization for themselves and for their child can be best modeled using a simultaneous systems approach to negative binomial regression. Mothers' visits to a health care provider increased with higher self-assessed depression scores, increased number of child's doctor visits, greater numbers of total children in the household, greater numbers of chronic conditions, need for prenatal or post-partum care, development of a new medical condition, and having health insurance (Medicaid/equivalent and HMO/private). Child's visits to a health care provider, on the other hand, increased with greater numbers of chronic conditions, development of a new medical condition, and increased mothers' visits to a doctor. Child's utilization of pediatric health care services decreased with higher levels of maternal depression, greater numbers of total children in the household, if the mother had HMO/private health care coverage, if the mother was pregnant, and if the mother was Latina/African American. Mother's use of health care services decreased with her age, increased number of child's chronic conditions, income as a percent of the federal poverty line, and if child had HMO/private health care insurance. The study expands the econometric techniques available for assessing maternal and pediatric health care use and the results contribute to an understanding of how rural, low-income mothers choose the level of health care services use for themselves and for their child.

Additionally, the results would assist in formulating policies to reorient the type of health care services provided to this vulnerable population.

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CHAPTER 1

RURAL RESIDENTS AND HEALTH CARE

1.1 Introduction

Rural residents are disproportionately disadvantaged at obtaining health insurance
and procuring medical services. Residents of rural areas have lower incomes, are more
likely to report higher unmet medical needs, and less likely to access preventive health
care services than urban residents. Estimates indicate that rural adults between the ages of
18 and 64 years are 24% more likely to be uninsured than those living in urban areas, and
that they are more likely to go longer periods without health insurance (Kaiser Family
Foundation, 2003). The disparities in accessing health care insurance extend to children
as well; rural children are at a greater risk of being uninsured than are urban children
(Coburn, McBride, & Ziller, 2002). Estimates suggest that rural children are between
10% and 50% more likely to be uninsured than their urban counterparts (Coburn et al.,
2002).

The risk of being uninsured is greater for individuals from low-income families.
Approximately one-third of the uninsured adults in remote rural areas come from families
with incomes below 200% of the federal poverty line (FPL) (Kaiser Family Foundation,
2003). About 72% of all uninsured children come from families with incomes below
200% of the FPL (Kaiser Family Foundation, 2011a).

Despite the federal government's efforts to expand the eligibility criteria for
Medicaid and State Children's Health Insurance Plan (SCHIP), many still remain
uninsured and report difficulties accessing care. For instance, of the 8.3 million total

uninsured children, 5 million are uninsured despite being eligible for Medicaid or SCHIP (Kaiser Family Founndation, 2011a). This lends credence to the notion that merely increasing coverage options does not address the full scope of the problem. There is increasing evidence as well to suggest that universal health insurance for children would do little to address the problem of pediatric care access and utilization (Halfon, Inkelas, & Wood, 1995). The issue is probably even more complex for rural adults for whom health care access may be affected by a variety of factors, including lack of public transportation. Studies have found that rural adults are 50% more likely than urban residents to have Medicaid coverage, but report poorer health (Ziller, Coburn, Loux, Hoffman, & McBride, 2003).

Janicke and Finney (2000) report that a child's health status does not explain all the variance in health care use among different population groups. For both adults and children, health care utilization is a function of myriad factors, including distance to and availability of medical services, caregiver's income level, and other administrative hassles that continue to impede access to health care services (DeVoe, Krois, & Stenger, 2008; Dubay & Kenney, 2001). Other factors such as not having a regular source of care and the health care user's attitudes and beliefs also act to prevent health care access. Studies suggest that rural adults forgo preventive medical care services either because they believe such care is unnecessary and/or because of a shortage of appropriate medical care services in the area (Slifkin, 2002; Ziller et al., 2003).

The difficulties that rural residents face in accessing health care services are compounded by the well-documented shortage of physicians, specialists, and mental health care providers that exists at all levels of the rural health care system. Rural

community health centers, for example, have difficulties recruiting new physicians (Rosenblatt, Andrilla, Holly, Curtin, & Hart, 2006). The need for physicians and dentists is further exacerbated in rural regions designated Health Provider Shortage Areas (HPSA) (Knapp & Hardwick, 2000).

Adult and pediatric health care consumption is therefore a complex, multidimensional phenomenon that requires further examination. The issue has gained new importance today when budget cuts are being contemplated for the SCHIP and Medicaid programs. Understanding the nuances behind rural pediatric and adult care use can direct policy creation and legislative efforts to restructure the health care budget at both the state and federal levels. The volume of health care services consumed, which varies greatly among individuals, can also act as a nucleus for future health care regulation. Longitudinal studies have demonstrated the relative fixedness of extreme pediatric care usage patterns across time (Janicke & Finney, 2000), permitting targeted policy formulation about health care costs.

1.1.Objective

Pediatric health care use is unique since the caregiver, usually the mother, determines the type and frequency of health care services accessed. Caregivers living in rural regions contend with a constellation of environmental, social, economic, and personal factors that act together to affect the level of pediatric care utilization. The caregiver, however, is also deciding the volume of health care services she consumes for herself. She acts within a similar set of external and internal influences to optimize her own health care use. Health care utilization at both the pediatric and adult levels may

therefore stem from a nonlinear decision making process in which the caregiver simultaneously chooses levels of adult and pediatric health care use.

The purpose of this thesis is to address two issues specific to rural, low-income mothers with children. First, data from a multi-state, longitudinal project on rural, low-income mothers with children are used to analyze the determinants of visits to health care providers. The focus of this study is to assess the factors that influence the frequency of visits to health care personnel made by the mother as well as her child. An analytical model that measures the separate levels of consumption by the mother and child are developed and presented. Anderson and Aday's (1978) conceptualization of the health behavior model is the theoretical model used in this study.

Second, the thesis will present an econometric model that accounts for the simultaneous decision making process that the caregiver encounters when choosing level of care for herself and for her child. Analytical methods that do not treat the health care use process as a simultaneous system produce parameter estimates that may be biased and unreliable. This thesis applies a 2-stage negative binomial regression approach that corrects for biases inherent to models that do not account for the presence of simultaneity. The data and the analytical models of the mother's and child's visits are discussed within the context of simultaneous systems. The results from the 2-stage technique are provided and policy implications are discussed.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1 Determinants of Health Care Utilization

Although differences in utilization levels exist between children with private and public health insurance (Dubay & Kenney, 2001; Janicke & Finney, 2000; King, Holmes, & Slifkin, 2010), having health insurance is probably the single most enabling resource for pediatric care consumption. Health insurance is also important in determining adult use of medical services. Kasper, Giovannini and Hoffman (2000) found that adults who had insurance after a period without insurance experienced greater access to health care services while those who lost their health insurance reported a reduction in access to medical services. Simmons, Anderson, and Braun (2008) found that having insurance increased the number of physician visits. Likewise, Leclere, Jensen, and Biddelcom (1994) found that having insurance, specifically Medicaid insurance, increased the number of contacts the participant had with a physician. Mueller, Patil, and Boilesen (1998) have found that those with insurance are twice as likely to utilize health care resources. In a more recent study, Finkelstein et al., (2011) found that low-income adults with Medicaid had higher primary and preventive care use and more hospitalizations than their control group of low-income adults without health care insurance.

Transportation availability, travel distance to care facilities, possession of a driver's license and a car also determine an individual's ability to access health care. A negative relationship between distance to a health care facility and number of chronic and regular care visits for adults has been found (Arcury et al., 2005a). Greater distances have also been shown to deter use of pediatric health care services (Slifkin, 2002). In addition

to distance, the source of the transportation influences the type of care accessed and number of visits made to a health care provider (Arcury et al., 2005a).

Existing literature has also focused on racial and ethnic disparities as a possible covariate of differential access to medical services and utilization. They have found that being of racial or ethnic minority lowers an individual's health care utilization (Lillie-Blanton, Parsons, Gayle, & Dievler, 1996; Mayberry, Mili, & Ofili, 2000; Mueller, Ortega, Parker, & Patil, 1999). The results also suggest that socioeconomic variations motivate the persistence of the differences in health care use by individuals of racial/ethnic minorities; the utilization gap becomes less evident when the data are stratified by social class and position (Lillie-Blanton et al., 1996).

Children of ethnic minority parents face greater difficulty in accessing and utilizing care (Flores, Abreu, Olivar, & Kastner, 1998; Flores, Olson, & Tomany-Korman, 2005; Mayberry, et al., 2000). Studies suggest that compared to white children, Asian American, Hispanic, and African American children were less likely to have a usual source of care (USC) or have visited a doctor, health care provider, or dentist in the past year (Shi & Stevens, 2005). Hahn (1995) found that disparities in health care use extend to prescription medications as well, with African American and Hispanic children being prescribed fewer prescription medications and taking fewer medications. In contrast to children of other races and ethnicities, African American children were also more likely to visit the emergency room for treatment. White children, on the other hand, have higher frequency of pediatric care use (Janicke & Finney, 2000).

Minority parents reported that health care providers over-discussed certain topics with their children, such as community violence, signifying unconscious racial/ethnic

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profiling (Flores et al., 2005). Focus group participants from a California school system reported language barriers, immigration documentation requirements, not having health insurance, out-of-pocket costs, and difficulty navigating the medical care system as impediments to accessing care (Sobo, Seid, & Gelhard, 2006).

Nonwhite rural adults face comparable levels of discrimination when accessing and utilizing health care services. Rural minorities experience higher disease incidence rates and report greater barriers to their access of medical services (Mayberry et al., 2000; Mueller et al., 1999). African American and Hispanic rural residents have also been shown to underutilize a variety of services including mental health and dental services (Mueller et al., 1999). These factors gain additional importance in rural regions which suffer from a shortage of minority health care providers. The literature also suggests that Hispanics are less likely to have a USC than whites (Weinick, Zuvekas, & Cohen, 2000). In general, studies indicate that rural minorities' access to health care is worse than that of urban minorities (Mueller et al. 1999).

Income levels play an equally important role in access and use, with families with lower income consuming fewer health services (Arcury et al., 2005; Weinick et al., 2000; Woods et al., 2003). Parents with lower incomes cited high out-of-pocket costs and problems with the health insurance plan for not purchasing all the specialized health services and/or prescription medication their child needed (Porterfield & McBride, 2007). Low economic status has also been linked to lower levels of primary care and higher levels of emergency room use (Janicke & Finney, 2000). Moreover, research suggests that low-income women have poorer health than women from higher income levels (Williams, 2002).

The influence of education on adult and pediatric medical service use is less conclusive. Higher education levels were associated with greater parental awareness of need for specialized pediatric care, but parents with lower educational attainment were more likely to access specialist services for their children (Porterfield & McBride, 2007). Research also suggests that lower parental educational levels predicted longer periods without health insurance for children (Coburn et al., 2002). At the adult level, it remains difficult to discern the direction of influence even in cases where education was statistically significant as both negative and positive relationships have been found (G.E.M de Boer, Wijker, & C.J.M de Haes, 1997). Arcury, Preisser, Gesler and Powers (2005b) found that adults with more education had more physician visits for chronic care management. Baker et al. (1997) found that adults with low reading skills were more likely to report poor health status than those with adequate reading skills.

The findings on the role of other demographic variables, such as the child's and mother's age and the child's gender, on pediatric and adult health care utilization are equally split (Janicke & Finney, 2000; Weinick et al., 2000). Age and having a physician in the community have been found to lower the frequency of physician visits made by rural, low-income women (Simmons et al., 2008). Studies focusing solely on chronic illnesses and physician visits are ambiguous about the influence of age. A few found that younger patients are higher users of hospitals and others that older patients are higher users (G.E.M de Boer et al., 1997). In general, however, women tend to seek and receive more medical care services, such as ambulatory, physician visits, preventive care services etc., than do men (Viera, Thorpe, & Garrett, 2006).

The mother's self-perceived physical and mental health determine volume of pediatric and adult health care consumption. The majority of studies have positively related perceived health needs and lower reported levels of activities of daily life with greater hospital use (Al-Windi, Dag, & Kurt, 2002; Weinick et al., 2000). Simmons et al. (2008) found that individuals who reported poor health had more physician visits. Slifkin (2002) cites multiple studies that have linked perceived need for services to the caregiver's physical limitations on everyday activities.

High and low consumption of pediatric services can be explained, in part, by the caregiver's knowledge of health and health services and the caregiver's perceived health needs and beliefs. Mothers who believed their own health was fair or poor were more likely to rate their child's health the same (McGauhey & Starfield, 1993). Children with mothers who perceived their health to be in poor condition had more visits for acute illnesses (Becker, 1977). Studies also suggest that self-reported negative moods, psychological distress, and psychological well-being are associated with, or are predictors of, higher pediatric use (Janicke & Finney, 2000). Depressed patients, in general, are more often hospitalized and had more physician visits than their non-depressed counterparts (Weinick et al., 2000).

Family health also influences the number of physician visits that the mother and child make. Additionally, the mother's physical health and mental health positively influence the number of visits she makes to the doctor (Fylkesnes, 1993). Disease severity increased the mother's number of hospitalizations and duration of stay while symptom severity had the opposite effect. Parents who were limited in their physical

activity were more likely to claim their child needed specialized care and health services (Coburn et al., 2002).

Research has also explored the psychosocial factors that drive medical care utilization by focusing on family and social support, the mother's attitudes towards health care, and the mother's health care practices. Propensity to consume more pediatric services could be a manifestation of the amount of parental and partner support present in the mother's life. There is no consensus in the literature on the role of social support as it could be argued that a higher degree of parental support helps the mother cope with stress in her life, leading to lower pediatric care utilization. On the other hand, higher degree of parental and social support may facilitate better child care options, prompting the mother to access pediatric care more easily (Janicke & Finney, 2000). The impact of parental support remains ambiguous since some authors predicted higher pediatric care use when the caregiver experiences high levels of support in conjunction with decreased satisfaction with the support received (Janicke & Finney, 2000). Other authors found that greater support is negatively correlated with pediatric care consumption.

Within the context of adult use of health care services, there is a negative relationship between low levels of social support and physical health, including heart disease (Shumaker & Hill, 1991). Being divorced, separated, or widowed has also been linked to more physician visits (Simmons et al., 2008). Al-Windi et al. (2002) measured the study subject's degree of satisfaction with their family situation as a component of social well-being. They found that low satisfaction scores with family situation were predictors of higher use of adult health care services.

Family size is also important; small families with fewer numbers of children have been linked to greater pediatric utilization as parents may be more attentive towards their children (Janicke & Finney, 2000). The relationship has been borne out in analyses of volume of pediatric care utilization and use vs. nonuse of pediatric health care services.

Moreover, the child's and mother's number of visits to the physician were positively associated with each other (Hemard, Monroe, Atkinson, & Blalock, 1999; Janicke & Finney, 2000; Janicke, Finney, & Riley, 2001; Minkovitz, O'Campo, Chen, & Grason, 2002). The number of contacts the mother has with a physician increases with the number of physician contacts the child has and vice-versa. In a literature review of the determinants of pediatric care utilization, Janicke and Finney (2000) found that maternal health care consumption was a statistically significant predictor of child health care use in many investigations on the subject. The association has been shown to be present between the mother's doctor visits and the child's doctor/nurse, doctor, emergency room, hospitalizations, and mental health services (Minkovitz et al., 2002). Riley et al. (1993) studied the psychosocial factors that influence pediatric care utilization, and found that the mother's total health care visits were significant in multiple regression analyses with the child's health care use as the dependent variable. Newacheck and Halfon (1986) used the mother's physician visits as a proxy for her health beliefs, and found that maternal visits predicted more pediatric health care visits.

Finally, environmental and health system variables act as determinants of health care access and use. The findings, however, are mixed with a few supporting increased hospitalization and physician visits in more rural areas and others presenting contradictory results (Weinick et al., 2000). Residents of more rural areas typically tend

to have fewer visits to a specialist and a USC, and are more likely to report having an unmet medical need (Sibley & Weiner, 2011). Laditka, Laditka, and Probst (2009) present findings which suggest that use of services rises as the region of residence becomes more rural. Number of primary care providers in the participant's community and surroundings decreased the number of acute care visits, but had no statistical impact on regular or chronic health care vists (Arcury et al., 2005b).

2.2 Unique Contributions of this Study

The caregiver assumes a dual responsibility for deciding the level of health care services received for both herself and her child. In addition, an individual's tendency to seek care increases with the amount of contact she has with a health care provider, i.e., the number of contacts that the mother has with a health care provider increases as she takes her child more often to a physician. The pediatric care consumption process is, in turn, affected by the number of visits the mother makes to the doctor.

This mechanism of decisions is not linear, but rather serves to highlight that the caregiver operates within a system in which one decision influences another. This thesis will add to the existing body of literature by analyzing the determinants of visits to a health care provider by accounting for the simultaneity that is in play. This examination will be conducted within the broader context of other considerations that influence the complete health care consumption process.

The thesis focuses exclusively on low-income families who reside in rural America. It includes variables unique to this data set such as a measure for the degree of emotional support. The Andersen and Aday (1978) Behavioral Model of Health Services

Use (BMHSU) serves as the conceptual framework. This paper accounts for the

simultaneity of the health care consumption process by applying a 2-stage least squares

approach to the negative binomial regression model, a significant contribution to the field

of health care utilization.

CHAPTER 3

CONCEPTUAL MODEL

3.1 The Behavioral Model of Health Services Use

This paper adapts the behavioral model of health services utilization (BHMSU) developed by Andersen (1968, 1995), Andersen and Aday (1978), and Andersen and Newman (1973). The model juxtaposes actual use of health services against some illness level to assess individual health behavior and health service utilization. In its original version, Andersen presented a framework in which health care use is influenced by the individual's propensity to seek services, factors that promote use, and the need for medical care. Later versions of the model were expanded to include environmental factors (Andersen, 1995).

The dependent variables of interest are different dimensions of health care utilization and consumer satisfaction with health care use. The health behavior model defines actual use of health care services as the dependent variable or health outcome. The dependent variable could measure the type of service sought, site at which service was conducted, purpose of visit, and time interval since last visit (Andersen, 1995). In later models, the health outcome variables incorporated consumer satisfaction, included as "explicit outcome of health services utilization" (Andersen, 2008). This dimension was intended to capture concern about the rising health care costs and the subsequent need to justify the continuing existence of certain health service centers. Convenience, availability of services, financing options, provider characteristics, and quality of services were treated as indicators of consumer satisfaction (Andersen, 1995).

Many studies have assessed health care utilization as the number of visits to the primary care provider while others included inpatient hospitalization days, emergency department use, and total health care use (Janicke & Finney, 2000). Analytical results therefore depend on the type of utilization examined and vary across studies. Berdahl, Kirby, and Stone (2007) included variables for both potential access, measured through having a usual source of care (USC), and realized access, measured by number of visits. Difficulty obtaining the necessary care, not having a visit to a health care professional in the last year, not having a dental visit in the last year, and parental satisfaction with the pediatric care received have also been used as measures of health care utilization (Shi & Stevens, 2005). Volume of visits to a health care provider have been further delineated by type of care sought (regular check-up, chronic care visits, and acute care visits) as well (Arcury et al., 2005).

The determinants of health care utilization can be classified into three overarching categories: environmental (e.g. health care system and external environment), individual characteristics (e.g. predisposing characteristics and enabling resources) and need factors (perceived and evaluated need). These individual, need, and environmental characteristics, the independent variables in the operational BMHSU, act together to influence the individual's decision to seek medical care, choice of services accessed, and amount of services consumed (Figure 1).

Environmental Factors	*Individual Characteristics*	*Need Factors*

1. External environment
2. Health care system
	1. Predisposing
	  ▪ Demographic
	  ▪ Social Structure
	  ▪ Health beliefs and behavior
	2. Enabling resources
		1. Perceived need
		2. Evaluated need

Health Outcome
1. Use of health services
2. Consumer satisfaction

Figure 1: Behavior Model of Health Services Use (BMHSU)

Environmental Factors: This category recognizes the influence of socioeconomic and political considerations on individual health care behavior. The nature of the health care system, external environment, health policy, and population health indices all fall under this subheading. Previous literature has included availability of and access to health care personnel and facilities as macro-level indices that symbolize the presence of community-level resources (Janicke & Finney, 2000). The reasoning is relatively straightforward: health care personnel and facilities need to be present for individuals to access and utilize them. Others have included number of specialist physicians, general practitioners, federally qualified health centers, and number of hospital beds (Berdahl et al., 2007).

Individual Factors: The second overarching category, individual characteristics, is comprised of predisposing characteristics and enabling resources, but at the micro rather than macro level. Predisposing characteristics are further decomposed into demographic, social structure, and health beliefs (Andersen, 1995). Demographic factors such as age

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and gender could capture underlying biological processes (Andersen, 1995), and could act as risk factors for certain types of health care consumption behavior. Prior studies on pediatric care utilization have included the mother's and child's age and the child's gender (DeVoe et al., 2008; Janicke & Finney, 2000; Porterfield & McBride, 2007).

Some examples of social structure variables that symbolize the individual's status in her community are race/ethnicity, occupation, educational attainment, marital status, family size, religion, and residential mobility (Andersen & Newman, 1973). Berdahl et al. (2007) included proficiency with the English language and immigration status in their study of health care access for the Latino population. Number of children has also been included as a covariate under this category (Akresh, 2009).

Health beliefs and behavior symbolize the individual's attitudes towards health services, values about health and illnesses, and knowledge of health and health services. The variables in this category affect the individual's health care utilization. Akresh (2009) used proxy measures of family origin to reflect health beliefs. Past investigations on the pediatric care literature have sometimes included parental confidence as an indicator of health beliefs that inform the caregiver's pediatric care utilization. Newacheck and Taylor (1992) included mother's visits to a physician as a proxy for health beliefs and health attitudes.

Enabling resources, another subcategory of individual factors, include personal and family characteristics that facilitate access to care and use of services (Andersen, 1995). Enabling resources have consisted of the educational attainment of the mother (Shi & Stevens, 2005) as well as English proficiency, and time spent in the United States (Akresh, 2009). Urbanity of family's residence, transportation availability, having health

insurance, and degree of poverty/income level have been included in this subcategory (Arcury et al., 2005b; Shi & Stevens, 2005).

Need Factors: At the micro level, both perceived and evaluated need drive an individual's propensity to seek medical attention (Andersen, 1995). Perceived need is indicative of need arising from symptoms, diagnoses, general state of health, and disabilities that influence an individual's desire to seek care. Evaluated need, on the other hand, is indicative of a diagnosis given by a medical care provider. It could also reflect the type of treatment provided to the patient. These factors explicitly recognize the importance of the interaction between the individual's health practices such as diet and exercise with health care utilization (Andersen, 2008). Need factors have been measured as self-reported health status, medical condition diagnosed by a health care provider, and as conditions that limit usual activities (Arcury et al., 2005b; Shi & Stevens, 2005; Berdahl et al., 2007).

3.2 Policy Applications

Andersen incorporates the idea of equitable access to identify disparities in medical care utilization among population subgroups. Access is considered equitable so long as individual, rather than societal, variables drive volume and type of use. On the other hand, differences in health care access and utilization due to area of residence would be considered inequitable.

The independent variables of environmental, individual, and need factors are also classified along a continuum of "mutability" to indicate the ease with which they can be altered. Characteristics difficult to change, such as race or age, rank lower on the

continuum while educational level ranks higher. The concept of "mutability" facilitates the promotion of equitable access, and can therefore serve as the nexus for targeted policy creation and implementation.

CHAPTER 4

DATA AND VARIABLES

4.1 Data

Data for this research came from the USDA-funded multi-state longitudinal project, NC223/NC1011, "Rural Low-Income Families: Tracking Their Well-Being and Functioning in the Context of Welfare Reform,"[1] also referred to as Rural Families Speak (RFS). Data were collected over three years, i.e. three waves, from August 1999 to July 2002. For the purpose of this study, quantitative data from interviews in the third year (wave 3) along with some select data from the first and second years (waves 1 and 2 respectively) were used. The mothers in the sample were chosen because they participated in all three waves. The additional stipulation that information about their child be available for all three waves resulted in a sample of 163 rural, low-income mothers with children. They came from rural counties in 13 states: California, Indiana, Kentucky, Louisiana, Massachusetts, Maryland, Michigan, Minnesota, Nebraska, New Hampshire, New York, Ohio, and Oregon.

The mothers had to have incomes at or below 200% of the federal poverty line (FPL) and at least one child under the age of 13 years at the time of the first interview. The mothers were recruited through programs that serve low-income families, including the Food Stamp Program (SNAP), Supplemental Program for Women, Infants and

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Children (WIC), food pantries, survival centers, housing authority programs, and welfare-to-work programs.

Mothers were chosen to represent the diversity in types of families with children who were considered low-income, with Hispanic mothers being over-sampled in the study. Trained interviewers collected in-depth qualitative and quantitative data from the mothers during face-to-face interviews at a site of the respondents' choice. The semi-structured protocol included questions on a variety of domains including socio-demographics, employment, and subjective as well as objective measures of social support. Interviews were conducted in Spanish where necessary.

Although the purposive sampling limits the ability to generalize the results, the findings and analytical methods employed will provide a greater understanding of factors that affect health care consumption in rural America. In the sections below, specific variables consistent with the conceptual model presented in Chapter 3 are discussed. The health outcomes assess the frequency of health care service use and are used as the dependent variable. The independent variables reflect the different dimensions of the BMHSU discussed in Chapter 3.

4.2 Health Outcome Variables

The dependent variables in this study measured the amount of health care use in the past year, which was the interval between wave 2 and wave 3. The mothers were asked: "About how many times have you seen a doctor or other health care provider since the last interview?" She was asked for similar information about her child: "About how many times has your child been to a doctor or other health care provider since the last

interview?" These responses are used as measures of the mother's and child's health care consumption process, and they are discrete dependent variables. The time between wave 3 and wave 2 interviews was approximately a year for each of the mothers in the sample.

4.3 Independent Variables

Variables that measured environmental factors, individual characteristics, and need factors were identified within the RFS data set and added as covariates to the model. To make the model more robust, measures of the external environment were taken from outside data sets, such as Waldorph's (2007) Index of Relative Rurality and data from the U.S. Department of Health and Human Services.

Environmental Factors: Rural regions are heterogeneous in their degree of rurality and the health care services they are able to offer. The Health Resources and Services Administration branch of the U.S. Department of Health and Human Services designates some counties as a partial or full Health Professional Shortage Areas (HPSA) for primary care physicians and mental health care providers. Binary indicator variables were created for primary care and mental care HPSAs. Each county in the sample was coded as positive (unity) HPSA for primary and for mental care if it experienced either a positive or full shortage of medical personnel. An Index of Relative Rurality (IRR) is also used in the model as a comprehensive, continuous, multidimensional measure of the county's degree of rurality (Waldorf, 2007). The index ranges between 0 (most rural) to 1 (most urban) and is constructed using population size, density, percentage of urban residents, and distance to the closest metropolitan region.

Individual Characteristics: Specific variables that measured individual

characteristics included income as a percent of the FPL, and binary indicators for having

a car, and having medical insurance. Binary variables were constructed to indicate the

mother's health insurance coverage as no insurance, Health Maintenance Organization

(HMO)/private, Medicaid/equivalent, and other insurance type, with unity representing

possession of that insurance kind. Binary variables were coded as unity if the child had

no health insurance, HMO/private, SCHIP/equivalent, and other insurance type.

Several predisposing variables were also added to the model. Demographic

variables included the mother's and child's ages at interview and the child's gender

(female or male). The mother's employment status at interview (employed or

unemployed) and her educational attainment obtained at wave 1 (less than high school,

high school or GED, and more than high school[2]) were used as well. Parent's

race/ethnicity was classified in three groups as non-Hispanic white, Hispanic Latina and

African American, and other non-white. Race and ethnic groups were combined to ensure

enough non-zero observations in each group. Two household structure measures were

identified within RFS data set: the total number of children in the household and a binary

indicator coded for unity if the mother had a partner.

A social support dimension was used as a predictor in the model. Each respondent

in the sample indicated her level of satisfaction (always satisfied, almost always satisfied,

satisfied some of the time, and never satisfied) with the amount of emotional support she

received from her family. An aggregate level of satisfaction was assessed based on the

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[2] The category "more than high school" included mothers with some technical, business, or vocational training after college and those with some college or an AA degree. This category also included those who were a college or university graduate or had one or more years beyond college.

mother's satisfaction with: (a) "the way my family talks over things with me and shares problems with me;" (b) "the way my family expresses affection and responds to my emotions, such as anger, sorrow, or love;" (c) "the way my family and I share time together;" (d) "my family accepts and supports my wishes to take on new activities or directions;" and (e) "I can turn to my family for help when something is troubling me." The scale ranged from 0 to 20; scores below 12 were coded to signify no satisfaction (zero) and scores 13 and greater were coded to signify satisfaction (unity) (Figure 2).

OUTCOME VARIABLES
    1.   Number of visits that child makes to a health care provider
    2.   Number of visits that mother makes to a health care provider
INDEPENDENT VARIABLES
Environmental Factors
    ▪ Index of Relative Rurality (IRR)
    ▪ Mental health care and primary care Health Professional Shortage Area (HPSA) designation
Individual Characteristics
1. Predisposing
    a. Demographic
        ▪ Mother's age and child's age
        ▪ Child's gender
    b. Social Structure and Social Networks
        ▪ Mother's educational level
        ▪ Employment status
        ▪ Mother's ethnicity
        ▪ Total number of children in household
        ▪ Partner status
        ▪ Satisfaction with family support
    c. Health Beliefs and Attitudes
        ▪ Number of visits that child makes to a health care provider
        ▪ Number of visits that mother makes to a health care provider
2. Enabling
        ▪ Income as a percent of federal poverty line (FPL)
        ▪ Having a car
        ▪ Type of medical insurance coverage for mother and child
Need Factors
        ▪ Development of medical condition or illness, injury, or serious surgeries since last interview in child and mother
        ▪ Number of chronic illness in mother and child
        ▪ Maternal depression score based on Center for Epidemiologic Studies-Depression (CES-D)
        ▪ Need for prenatal and/or post-partum care

Figure 2: Dependent and Independent Variables Considered for Model

Number of visits made to a health care provider was included under health behaviors, the final dimension of predisposing variables (Figure 2). The mother's visits were used as a covariate in the model of the child's medical service consumption. The number of visits the child had was used as a predictor variable in the model of the mother's health care utilization. The dual use of these two particular variables as an independent predictor and as the outcome variable drives the need for an analytical model that accommodates the simultaneous choice issue.

Need Factors: The RFS survey instrument in wave 3 included questions on the development of injuries, surgeries, or serious illnesses since the wave 2 interview. A covariate that assessed the development of any new medical condition (yes or no) in the mother and another that measured the same for the child were incorporated into the model (Figure 2).

In wave 2, the mothers were asked to list any medical conditions that they and their child have developed since the wave 1 interview. These responses from these were used to generate a list of chronic conditions in the mother and child. Chronic childhood and adult diseases were defined as health problems or medical conditions that require long term management and care (Mokkink et al., 2008; Perrin et al., 1993).

Newacheck and Taylor's (1992) list of chronic conditions and impairments in children guided the criteria used in this study. These included anemia, asthma, chronic pain, diabetes, hepatitis, seizure disorders, skeletal problems, migraines/headaches, and permanent disability. Strum and Wells' (2001) classification of adult chronic conditions was used to populate a list of chronic illnesses in the mothers. The list totaled 15 different conditions: asthma, diabetes, heart problems, high blood pressure, cancer, liver problems,

seizure disorder, hepatitis, thyroid problems, kidney problems, chronic pain, permanent

disability, reproductive problems, and migraines/headaches.

Maternal depression levels in wave 3 were measured using the Center for

Epidemiologic Studies Depression (CES-D) scale, which predicts depression risk among

adults. The self-reported score ranges between 0 and 60, with a score of 16 or above

indicating a risk for clinical depression. The mother's need for prenatal and/or post-

partum care since wave 2 interview was also controlled for in the model.

4.4 Descriptive Statistics

The sample statistics demonstrate that the mothers averaged almost twice as many

visits to the doctor compared to their child—10.755 visits and 5.472 visits respectively.

Figure 3 is a histogram of the mother's visits, which range from 0 to 100.

Figure 3: Number of Mother's Visits to a Health Care Professional

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A histogram of the child's visits shows an equally wide range for the visits, which range from 0 to 60 within the past year (Figure 4).

Figure 4: Number of Child's Visits to a Health Care Provider

The large numbers can be explained, in part by, the survey instrument which asked for a tally of visits to any health care provider, including emergency room use, psychologist and psychiatrists, specialists, general physicians, primary care physicians, and health counselors.

The environmental factors reveal that an overwhelming majority of counties in which the families resided were designated as a HPSA (Table 1). Approximately 83.3% of the counties suffered from a lack of primary care providers and 53.3% of the rural counties experienced a shortage of mental health care providers.

Table 1: Descriptive Statistics

Variable	Definition	Mean	Std. Dev.
Health Outcomes			
MotherVisits	Number of times the mother visited a doctor or other health care provider since last interview	10.755	15.884
ChildVisits	Number of times child visited a doctor or other health care provider since last interview	5.472	7.399
Environmental Variables			
IRR	Index of Relative Rurality; 0 (most rural) to 1 (most urban)	0.475	0.116
HPSAPrimary	1 if county designated as Health Professional Shortage Area for primary care providers and services; 0 otherwise	0.834	0.373
HPSAMental	1 if county designated as Health Professional Shortage Area for mental health care providers and services; 0 otherwise	0.528	0.501
Demographic Variables			
MotherAge	Mother's age in years	30.857	6.261
ChildAge	Child's age in years	8.881	3.914
ChildGender	1 if child is female; 0 otherwise	0.515	0.501
Social Structure & Social Network Variables			
<HS	1 if mother's education level was some high school or less; 0 otherwise	0.221	0.416
HS	1 if mother has a high school diploma or GED; 0 otherwise	0.344	0.476
>HS	1 if mother has some technical, business, or vocational training after high school; some college including AA; or if she is a college or university graduate, has one or more years beyond college, or a graduate degree; 0 otherwise	0.436	0.497
Employment	1 if mother is employed; 0 otherwise	0.583	0.495
Latina_AA	1 if mother is Hispanic/Latina or African American; 0 otherwise	0.233	0.424
Other_NonWhite	1 if mother is Native American, Asian American, multi-racial, or other; 0 otherwise	0.067	0.252
White	1 if mother is Non-Hispanic White; 0 otherwise	0.693	0.463
TotalChildren	Total number of children in household	2.528	1.297
PartnerStatus	1 if mother has a partner; 0 otherwise	0.663	0.474
SupportSatisfaction	1 if mother is satisfied with family support; 0 otherwise	0.755	0.431
Health Beliefs/Attitudes			
MotherVisits	Number of times the mother visited a doctor or other health care provider since last interview	10.755	15.884
ChildVisits	Number of times child visited a doctor or other health care provider since last interview	5.472	7.399
Enabling Resources			
Child_NoIns	1 if child has no health insurance; 0 otherwise	0.110	0.314
Child_HMO	1 if child has private insurance/HMO; 0 otherwise	0.258	0.439
Child_Medicaid	1 if child has Medicaid/SCHIP; 0 otherwise	0.460	0.500

Variable	Definition	Mean	Std. Dev.
Child_OtherIns	1 if child has other insurance plan; 0 otherwise	0.172	0.378
Mother_NoIns	1 if mother has no health insurance; 0 otherwise	0.258	0.439
Mother_HMO	1 if mother has private insurance/HMO; 0 otherwise	0.350	0.478
Mother_Medicaid	1 if mother has Medicaid/equivalent coverage; 0 otherwise	0.307	0.463
Mother_OtherIns	1 if mother has other insurance plan; 0 otherwise	0.086	0.281
Car	1 if mother has a car; 0 otherwise	0.933	0.252
%FPL	Income as percent of the federal poverty line (FPL)	130.775	92.897
Need Factors			
ChildChronic	Number of chronic conditions in child	0.362	0.683
ChildNewMed	1 if child developed any new medical conditions or had any injuries, surgeries, or serious illness since last interview; 0 otherwise	0.454	0.499
MotherChronic	Number of chronic conditions in mother	1.172	1.345
MotherNewMed	1 if mother developed any new medical conditions or had any injury, surgery, or serious illness since last interview; 0 otherwise	0.509	0.502
CES-D	Mother's self-assessed depression score based on the Center for Epidemiologic Studies-Depression Index	13.675	11.452
Pregnant	1 if mother required prenatal and/or post-partum care since last interview; 0 otherwise	0.172	0.378

The demographic variables (Table 1) show that the mean age of the mothers was around 31 years and that of the children was approximately 9 years. With respect to the social structure and social network variables, only 22.1% of the mothers did not have a high school (HS) diploma or a GED while 43.6% of the mothers had attained education beyond HS, which includes technical, vocational, business training as well as any level of college education. Approximately 70% of the mothers were non-Hispanic and 23.3% were Latina or African American. In addition, 66.3% of the women had a partner, and 75.5% of them were satisfied with the support their family gave them.

An overwhelming majority (93.3%) of the mothers also had a car, with only 6.75% reporting no access to a car. The other enabling resource variables show that almost 89% of the children in the sample had health care insurance, with a little less than half (46%) having Medicaid/SCHIP. In contrast to the children, fewer mothers (74.2%)

had medical insurance. Of those insured, more women had HMO/private (35.0%) than Medicaid/equivalent (30.7%).

With respect to the need factors, the mean number of chronic physical conditions for the mothers was higher at 1.178 while the mean for the children was lower at 0.361. In one year, 45.6% of the children and 50.3% of the mothers developed a new medical condition. Again, a slightly larger portion of the mothers developed a new illness in contrast to the children. Of the 163 mothers, approximately 17% of them also required prenatal and/or post-partum care. The mean CES-D score was 13.675, almost two points lower than 16, the cut-off for clinical depression.

CHAPTER 5

COUNT DATA MODELS

5.1 Count Variables

MotherVisits and *ChildVisits* are both count data: they take discrete, positive values and are not normally distributed (Figure 3 and Figure 4). Ordinary least squares regression is inappropriate in this situation, and an alternative model that accommodates the properties of count data is required. Poisson and negative binomial (NegBin) regression models, two common approaches to count data, are presented here.

5.2 Poisson Regression Model

The Poisson model, the most basic of all count models, is a distribution of the number of times an event occurs in a given time interval. Suppose that Y_i is the number of event occurrences for the ith individual, $i = 1, 2, …, N$, in time period $(t, t + dt)$. Let y_i be the number of events observed in the time interval specified. We use a single year of data here, so the time subscript is dropped. The density function of the Poisson count variable, number of event occurrences, is

$$\Pr[Y_i = y_i] = e^{-\lambda_i}\lambda_i^{y_i}/y_i! , \quad y_i = 0, 1, 2, … ; \quad \lambda_i > 0$$

where λ_i is the rate or intensity parameter, and the presence of the subscript i on λ and y extends the Poisson distribution to non-independently and identically distributed data (non-iid). The first and second moments of the Poisson distribution are:

$$E[Y_i] = Var[Y_i] = \lambda_i$$

The equality between the mean and variance implies that the Poisson distribution is inherently heteroskedastic. Only λ_i requires estimation here since the scale parameter is fixed in estimations of the Poisson distribution and assumed to be unity.

The rate parameter, which is also the mean and the variance here, is often denoted as μ_i in the literature, giving rise to the second representation of the Poisson distribution

$$\Pr[Y_i = y_i] = \mu_i^{y_i} e^{-\mu_i}/y_i\,!$$

where

$$y_i = 0, 1, 2, \dots;\ \mu_i > 0$$

This second formulation is more widely applied in generalized linear models (Hilbe, 2011).

The Poisson distribution is transformed into the Poisson regression model through a parameterization between the mean μ_i, model covariates X_i, and the parameters β. An exponential parameterization is commonly assumed between the mean, covariates, and the parameters such that $\mu_i = \exp(X_i\beta)$, with the vector X_i containing k linearly independent variables, including a constant.

Parameter estimates can be obtained through maximum likelihood (ML) procedures, which produce a vector of estimates $\hat{\beta}$, the solution to the k nonlinear equations that result from the first order ML conditions. The estimates are unique since the log-likelihood function used in ML is globally concave. A Gauss-Newton or Newton-Raphson iterative procedure can be used to find the unique vector of parameter estimates.

5.2.1 Limitations of the Poisson Distribution

The Poisson distribution requires that the conditional mean of Y_i is approximately equal to its variance. This assumption, which is known as equi-dispersion, fails to hold in most applications of the Poisson. Rather the data are either over-dispersed (variance exceeds the mean) or under-dispersed (mean exceeds the variance).

The Poisson distribution also assumes independence of event occurrences over time. That is, the probability of y events occurring in time period A should have no effect on the probability of w events occurring in time period B. The assumption of equi-dispersion may fail to hold in multiple situations, including when there is dynamic dependence between successive event occurrences (Cameron & Trivedi, 1986). The number of event occurrences in a prior time period could have bearing on the number of events counted in the next time period. The events could also happen as "spells" with different spells operating by similar probability rules (Cameron & Trivedi, 1986). For example, periods of being uninsured could be different from periods of being insured, therefore acting as two different spells. Thus, the assumption may fail to hold for panel count data.

Failures of either of the two assumptions could lead to over-dispersion in the model. If real, rather than apparent, over-dispersion is present in the data, then an alternative count model needs to be applied. Score tests, Wald tests, and Lagrange multiplier test have all been developed to check for the presence of real over-dispersion. For instance, Dean and Lawless (1989) developed a z-test that assesses whether there is sufficient over-dispersion in the data to violate the assumption of equi-dispersion. Cameron and Trivedi (1998) proposed a Lagrange multiplier test, commonly referred to

as a score test, which requires estimation of the model only under the null hypothesis that the restriction holds.

5.3 Negative Binomial (NegBin) Regression Model

The NegBin model is appropriate when the tests of over-dispersion provide sufficient evidence in support of real rather than apparent over-dispersion. The NegBin model does not impose equi-dispersion or independence of event occurrences. Instead it allows for correlated count data and can be modified to accommodate either over- or under-dispersion, offering greater flexibility than the Poisson distribution.

The NegBin distribution can be motivated in multiple ways, but the underlying assumption is that there is some random, unobserved inter-person heterogeneity in the model that prevents one from observing a single true mean common to all individuals in the data set. The NegBin distribution accommodates this underlying assumption of a stochastic process by allowing the rate parameter λ_i to vary between individuals according to some probability law. That is, an individual unobserved effect is introduced to the conditional mean of the Poisson such that

$$\ln \mu_i = X_i'\beta + \varepsilon_i,$$

and ε_i is a specification error found in ordinary least squares regression or heterogeneity of cross-sectional data (Greene, 2007). Then, the density of the count variable y_i conditioned on the Poisson mean and variance and the unobserved heterogeneity is

$$f(y_i; u_i, \lambda_i) = (\lambda_i u_i)^{y_i} e^{-\lambda_i u_i}/y_i! \quad \text{where } y_i = 0, 1, 2, \dots$$

The conditional mean of y_i is now $E[Y_i] = u_i \lambda_i$, where u_i is the unobserved heterogeneity, a transformation of the stochastic term ε_i. Therefore, the density function

assumed for u_i, i.e. the underlying stochastic process, determines the form of the NegBin

model. If we assume a gamma distribution for $u_i = \exp(\varepsilon_i)$ with mean 1 and μ_i is the

Poisson mean and variance as expressed above, then it follows that the rate parameter λ_i

has a gamma distribution with mean 1 as well (Cameron & Trivedi, 1986; Hilbe, 2011;

Cameron & Trivedi, 1998; Greene, 2007). The unconditional distribution of y_i under this

particular specification is

$$f(y_i; u_i, x_i) = \int_0^{\infty} \{[e^{-\lambda_i u_i}(\lambda_i u_i)^{y_i} v^v]/y_i! \; \Gamma(v)\} \, u_i^{v-1} \, e^{-v u_i} du_i$$

where v is the gamma scale parameter. The NegBin distribution can take many forms

even if it is developed as a Poisson-gamma mixture model. Such differences arise when

the distribution is parameterized into the NegBin regression model. Various link

functions, such as a log or a lognormal, can be used to link the parameters μ_i and v_i

generated from the underlying λ_i distribution and the vector of exogenous variables X_i.

Typically, a log link is used to parameterize the NegBin model since it facilitates better

comparison between the NegBin and Poisson regression models.

Cameron and Trivedi (1986) derived a more general version of the NegBin model

using an index parameterization of the gamma distribution with density function of $\lambda_i \sim$

Gamma (μ_i, v_i) where μ_i is the mean and v_i is the precision or the gamma index

parameter. They show that, for y_i the number of event occurrences observed,

$$\Pr(Y_i = y_i) \quad = \int \Pr(Y_i = y_i | \lambda_i) f(\lambda_i) d\lambda_i$$

$$= [(\Gamma(y_i + v_i)/\Gamma(y_i + 1)\Gamma v_i)] \, [v_i/(v_i + \mu_i)]^{v_i} [(\mu_i)/(v_i + \mu_i]^{y_i}$$

The first and second moments are

$$E[Y_i] = \mu_i$$

and

$$Var[Y_i] = \mu_i + \frac{1}{v_i}\mu_i^2$$

Non-negativity in the mean is ensured by letting $E[Y_i] = \mu_i = \exp(X_i'\beta)$. The NegBin model therefore specifies a relationship between the expected counts occurring for the ith individual and the set of explanatory variables X_i. It is also evident that this particular formulation of the variance accounts for overdispersion in the data since $Var[Y_i] > \mu_i > 0$.

The precision parameter can be defined in terms of the NegBin over-dispersion or heterogeneity parameter $\alpha > 0$ and k, an arbitrary constant, so that $v_i = (1/\alpha)(E[Y_i])^k$. This gives an alternative form of the variance:

$$Var[Y_i] = E[Y_i] + \alpha(E[Y_i])^{2-k}$$

Setting $k = 0$ yields the variance of the NegBin2 model with $Var[Y_i] = E[Y_i](1 + \alpha E[Y_i]) = \mu_i + \alpha\mu_i^2$. The NegBin2 model reduces to the Poisson when $\alpha = 0$ since $Var[Y_i] = \mu_i$. The variance of NegBin2 model specifies a direct relationship between the mean and scale parameter and ensures that the variance-mean ratio is linear in the mean. The NegBin2 model is applied to the data used in this paper.

As in the Poisson, maximum likelihood estimation using either Gauss-Newton or Newton-Raphson algorithms produce unique parameter estimates of the $\hat{\beta}$ vector. Standard errors are calculated as the square root of the diagonal entries of the variance-covariance matrix, which is the inverse of the information matrix. The observed and expected information matrices do not equal each other, however, in the NegBin2 model (Hilbe, 2011). Standard errors calculated on observed information criteria are asymptotically less biased than those calculated using the expected information matrix.

Consequently, most statistical software programs generate standard errors based on the observed information matrix.

5.4 Parameter Interpretation, Marginal Effects, and Incidence Rate Ratios

Parameters in the NegBin2 and Poisson model are analogously interpreted in terms of log and log difference units. Suppose x_{ik} is a continuous variable and y_i is still the dependent variable. The effect of x_{ik} on y_i can be interpreted as the increase (or decrease) in the expected log-count of y_i given a unit increase in x_{ik}. The effect could also be interpreted as: "Given a unit increase in x_{ik}, the difference in the log of the expected y_i increases (or decreases) by a factor of $\widehat{\beta_k}$."

Logs and log-differences are seldom easy to understand, necessitating a more direct means of interpretation. Marginal effects (MEs) and elasticities, which are again the same in the NegBin and Poisson models, circumvent the challenges posed by log units.

A ME measures the change in the expectation of y_i given a unit change in the independent variable x_{ik}. For x_{ik} a continuous independent variable, the marginal effects are calculated as

$$\frac{\partial E[y_i; x_i]}{\partial x_{ik}} = E[y_i; x_i]\beta_k = \exp(x_i\beta_k)\beta_k$$

where x_i' is a vector of independent variables. MEs can be found for any level of x_{ik} for a continuous variable, but are commonly calculated at the means. Average MEs, another frequent measure, is found as $\widehat{\beta_k}\bar{y}$ where $\bar{y}$ is the mean count. The ME at the mean is interpreted as: "At the sample mean of the predictors in the model, i.e., the mean values

of the independent variables in the model, y_i increases by $\widehat{\beta_k}$ for every one unit increase

in x_{ik}." Alternatively, marginal effects could be predicted at every vector x_i' and then

averaged. The corresponding effect of average ME is interpreted as: "For each additional

unit of x_{ik}, there is an average of $\widehat{\beta_k}\bar{y}$ additional units of y_i." If $\widehat{\beta_k}\bar{y}$ is negative, then

there are an average of $\widehat{\beta_k}\bar{y}$ fewer y_i units.

An elasticity or percent change offers another interpretation of an effect of a

predictor variable on the dependent count variable. The formula for finding the elasticity

is $ME \times x/y$ where ME is still the marginal effect, x the predictor variable, and y the

dependent variable. Suppose the ME was calculated at the mean. Now, let the values at

the mean be denoted x_m, and y_m be the fitted value at x_m. Then, a 1% increase in x_k

corresponds to a $\widehat{\beta_k}$% change (positive or negative) in y_m.

Now, let x_{ik} be a binary variable that takes value 1 or 0, and y_i be the dependent

variable. The parameter effect is: the difference in the log of the expected value of y is

estimated to be $\widehat{\beta_k}$ log units higher (or lower if $\widehat{\beta_k}$ is negative) for $x_{ik} = 1$ than for $x_{ik} =$

0, with all else held constant. Estimated parameter effects for binary variables are still

expressed in terms of log units. Consider the discrete change or finite differences for

binary or categorical predictors:

$$\Delta E\ [y_i; (\tilde{x}_i';\ x_{ik} = 1; x_{ik} = 0)]/\Delta x_{ik},$$

where $\tilde{x}_i'$ is the vector of all predictors excluding the binary variable x_{ik}. The above

formula determines the change in the expected value of the dependent variable as the

independent variable, x_{ik} shifts from 0 to 1. The expected values at $x_{ik} = 1$ and $x_{ik} = 0$

are

$$E[y_i|\ \tilde{x}_i';\ x_{ik} = 1] = \exp\left(\tilde{x}_i'\tilde{\beta} + x_{ik} * \beta_k\right)$$

$$E[y_i| \tilde{x}_i'; x_{ik} = 0] = \exp(\tilde{x}_i'\beta)$$

The log difference in expectations of y_i when $x_{ik} = 1$ and $x_{ik} = 0$ result in:

$$\ln E[y_i; \tilde{x}_i'; x_{ik} = 1] - \ln E[y_i; \tilde{x}_i'; x_{ik} = 0] = (x_{ik} * \beta_k) = \beta_k.$$

Interpretation as a log-difference is not very convenient. We note that the expression is equivalently:

$$\ln \frac{E[y_i| \tilde{x}_i'; x_{ik}=1]}{E[y_i| \tilde{x}_i'; x_{ik}=0]} = \beta_k,$$

and that

$$\frac{E[y_i| \tilde{x}_i'; x_{ik}=1]}{E[y_i| \tilde{x}_i'; x_{ik}=0]} = \exp(\beta_k)$$

Thus, exponentiating the estimated coefficients of the binary variables gives a ratio of expected values (or expected counts) for *y*. For this study, the dependent variable *y* will measure visits. Because visits really constitute a rate (the number of visits per year), we can interpret exponents of estimated binary variable coefficients as the rate ratios. Suppose exponentiating an estimated coefficient results in a rate ratio of 1.5. Then, when the binary variable is unity, the individual would visit 1.5 times more than an individual with a value of zero for the binary variable. These can also be interpreted as the percentage increase (or decrease) in visits as follows:

$$\left(\frac{E[y_i| \tilde{x}_i'; x_{ik}=1] - E[y_i| \tilde{x}_i'; x_{ik}=0]}{E[y_i| \tilde{x}_i'; x_{ik}=0]} \right) \times 100 = (\exp(\beta_k) - 1) \times 100.$$

If, following the example above, the exponentiation of an estimated coefficient yields a rate ratio of 1.5, then the rate when $x_{ik} = 1$ will be 50% greater than the rate when $x_{ik} = 0$.

5.5 Modeling in SAS

SAS offers multiple procedures for modeling the NegBin2 and Poisson regressions. PROC GENMOD, which applies to the family of generalized estimating equations, is the most flexible of them all. This SAS procedure offers the option to conduct a formal test for over-dispersion. It also produces robust covariance-variance matrix estimates with the application of the REPEATED statement, which enables a subject-level specification. Although the REPEATED statement has been designed for analysis of cluster data, treating each individual as a distinct level and specifying one observation per cluster generates robust covariance estimates (Zou, 2004). SAS produces quasi-maximum likelihood estimates and relies on large-sample properties when the REPEATED statement is used. The individual parameter tests are consequently critical z-values rather than the traditional t-values.

The SAS syntax used to generate a test for over-dispersion and robust covariance estimates is:

```
PROC GENMOD <options>;
CLASS variables;
MODEL response = < effects > / DIST=NEGBIN LINK=LOG SCALE=0
     NOSCALE;
REPEATED SUBJECT = subject-effect;
RUN;
```

Specifying DIST=NEGBIN fits the NegBin2 distribution and estimates the NegBin2 variance $Var(Y) = \mu + \alpha\mu^2$. The NOSCALE option holds the over-dispersion parameter α fixed since it would otherwise be estimated through maximum likelihood. The SCALE=0 and NOSCALE together test if the NegBin2 dispersion parameter is 0.

The SAS command sequence above produces the results of a Lagrange multiplier test specified by Cameron and Trivedi (1998) for the NegBin2 model. The SAS program

prints χ^2 statistics for the hypothesis $H_o: \alpha = 0$ and $H_A: \alpha > 0$. The results of the over-dispersion tests for the sample of mother and child visits are given in Table 2.

Table 2: Test for Over-dispersion in Poisson Regression

	Lagrange Multiplier Statistics		
Model	**Parameter**	χ^2 **test Statistic**	**Pr>** χ^2 **(p-value)**
Model 1 (*MotherVisits*)	Dispersion	166.7479	<0.0001
Model 2 *(ChildVisits)*	Dispersion	75.3728	<0.0001

The χ^2 statistics indicate that the null hypothesis of no over-dispersion is rejected at a significance level of 0.01% or better. A Poisson regression model is inappropriate for these data since there is sufficient evidence of real rather than just apparent over-dispersion in the model. Consequently, the NegBin2 model is applied to *MotherVisits* and *ChildVisits*.

SAS commands to generate NegBin2 model with robust standard error estimates are similar to those used for the Poisson regression:

```
PROC GENMOD <options>;
CLASS variables;
MODEL response = < effects > / DIST=NEGBIN LINK=LOG;
REPEATED SUBJECT = subject-effect;
RUN;
```

A log-link function is specified and the over-dispersion parameter is allowed to vary and be estimated during the ML procedure. The REPEATED statement is again used to ensure that the standard errors are robust. Consequently, only large sample properties apply. The results shown in the next few sections are those obtained from performing a robust NegBin2 estimation.

CHAPTER 6

RESULTS

6.1. Introduction

The estimates from the NegBin model for *MotherVisits* and *ChildVisits* are presented in the next two sections. The limitations of the model and the advantages of a 2-stage NegBin approach are then discussed. This chapter concludes with the results of the 2-stage approach and a comparison of both the baseline (single equation) and 2-stage approach. For consistency, all results are considered at the 10% level of significance or better[3].

Average MEs are given for the continuous variables that were statistically significant. Average MEs, however, may not always apply for binary variables, making interpretation of partial effects for binary variables difficult. Percent changes calculated using incidence rate ratios circumvent this issue and facilitate easier interpretation. Consequently, percent changes for binary variables found to be statistically significant are provided.

6.2 Results: *MotherVisits*

Table 3 presents the estimations from the NegBin model of *MotherVisits*. Demographic and environmental variables are not statistically significant to the model. However, the coefficient signs on the environmental variables are interesting. They show

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[3] Some of the variables were found to be significant at the 5% and 1% levels. The exact p-values are given the appropriate tables.

that increasing rurality causes the mother to seek more treatment, while a shortage of

primary care physicians and mental health care providers has the opposite effect.

Table 3: Results of a Single Equation *MotherVisits* Negative Binomial Regression

Variable	Estimate	S.E	Z	P-value	Avg ME/ Percent Change
Intercept	0.385	1.841	0.52	0.604	
IRR	0.858	2.541	1.00	0.318	
HPSAPrimary	-0.067	0.343	-0.32	0.750	
HPSAMental	-0.210	0.170	-1.08	0.278	
MotherAge	-0.026	0.009	-1.47	0.142	
ChildAge	0.036	0.111	0.94	0.346	
ChildGender	0.200	0.533	1.18	0.237	
HS	-0.073	0.421	-0.29	0.773	
>HS	0.229	0.722	0.91	0.364	
Employment	-0.091	0.255	-0.51	0.607	
Latina_AA	0.285	0.854	0.98	0.327	
Other_NonWhite	0.222	0.785	0.77	0.440	
TotalChildren	0.122	0.298	1.35	0.177	
PartnerStatus	0.308	0.677	1.63	0.102	
SupportSatisfaction	0.107	0.385	0.76	0.449	
Child_HMO	-0.541*	0.096	-1.67	0.096	-41.783%
Child_Medicaid	-0.052	0.535	-0.17	0.863	
Child_OtherIns	0.135	0.687	0.48	0.632	
Mother_HMO	0.628***	1.084	2.7	0.007	87.386%
Mother_Medicaid	0.554**	1.007	2.4	0.017	74.020%
Mother_OtherIns	0.199	0.759	0.7	0.487	
Car	-0.033	0.639	-0.1	0.924	
%FPL	-0.002*	0.000	-1.84	0.065	-0.016
ChildChronic	-0.202*	0.021	-1.78	0.075	-2.174
ChildNewMed	0.201	0.475	1.43	0.152	
MotherChronic	0.156**	0.280	2.48	0.013	1.679
MotherNewMed	0.615***	0.946	3.65	0.000	84.966%
CES-D	0.017**	0.030	2.56	0.011	0.180
Pregnant	0.593***	0.950	3.25	0.001	80.941%
ChildVisits	0.043***	0.061	4.68	<0.0001	0.460

*significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

With respect to enabling factors, the coefficients estimates of *Mother_HMO* and

Mother_Medicaid are both positive and significant at the 5% level of significance or

better. The mothers had 87.386% more visits than those with no insurance, holding all else constant. These mothers are estimated to increase their visit rate by a factor approximately 74% more visits, per year if they switch from having no health insurance to having Medicaid/equivalent coverage.

Of the enabling factors added to the model, *%FPL* which denotes income as a percent of the federal poverty line, was significant and negative. The statistical significance of *%FPL* highlights that the degree of poverty is a predictor of health care use among rural, low-income mothers with children. However, while statistically important, mothers whose income was at a higher percent of FPL made only 0.016 fewer visits on average. The child's health insurance also acted as a predictor of rural mothers' health service use. They are expected to have about 42% fewer visits if their child has HMO/private health insurance.

The set of need variables, which assessed both actual and perceived need for medical care, was important to the model. Mothers made approximately 1.70 more visits on average for each new chronic illness diagnosed. Those who developed a new medical condition or required surgery in the past year are expected average about 85% more visits than those who did not report a new medical illness. The coefficient estimate of *Pregnant* was significant and positive, with mothers expected to make 81% more visits than those who did not require prenatal or post-partum care. Mental health was also a predictor of frequency of health care consults. But, while statistically important, rural mothers consume only 0.180 more health care services, on average, with each increment in their CES-D scores.

Variables that pertain to the child's level of actual need for medical care were significant. *ChildChronic* was statistically significant and had a negative impact on the mother's health care consumption. On average, mothers made almost two fewer visits for themselves for every new chronic condition diagnosed in their child.

The health behavior variable, *ChildVisits*, was statistically important as well. The parameter estimate has a positive sign, indicating that the mean number of visits the mother makes increases with each additional visit that the child has. However, the average ME itself is relatively small at less than half an extra visit on average in the past year.

6.3 Results: *ChildVisits*

Table 4 shows that the social structure variable *TotalChildren* is significant to the number of visits made by a child. Rural low-income mothers took their child to the doctor 1.23 fewer times on average for each additional child in the household.

Table 4: Results of Single Equation *ChildVisits* Negative Binomial Regression

Variable	Estimate	S.E	Z	P-value	Avg ME/ Percent Change
Intercept	1.574*	0.934	1.69	0.092	
IRR	-0.612	0.678	-0.90	0.367	
HPSAPrimary	-0.082	0.223	-0.37	0.713	
HPSAMental	0.092	0.203	0.45	0.650	
MotherAge	0.013	0.015	0.87	0.387	
ChildAge	-0.004	0.044	-0.08	0.937	
ChildGender	0.101	0.168	0.6	0.548	
HS	-0.078	0.270	-0.29	0.774	
>HS	-0.264	0.248	-1.07	0.287	
Employment	-0.033	0.253	-0.13	0.897	
Latina_AA	-0.281	0.186	-1.51	0.130	
Other_NonWhite	-0.224	0.502	-0.45	0.655	
TotalChildren	-0.225**	0.110	-2.06	0.040	-1.232
PartnerStatus	-0.005	0.221	-0.02	0.984	

Variable	Estimate	S.E	Z	P-value	Avg ME/ Percent Change
SupportSatisfaction	0.150	0.200	0.75	0.452	
Child_HMO	0.592	0.414	1.43	0.153	
Child_Medicaid	0.252	0.401	0.63	0.530	
Child_Other	0.589	0.394	1.49	0.135	
Mother_HMO	-0.364	0.260	-1.4	0.162	
Mother_Medicaid	0.094	0.242	0.39	0.699	
Mother_OtherIns	-0.202	0.429	-0.47	0.639	
Car	0.081	0.260	0.31	0.756	
%FPL	-0.001	0.001	-0.47	0.639	
ChildChronic	0.176*	0.105	1.68	0.092	0.964
ChildNewMed	0.551***	0.168	3.29	0.001	73.499%
MotherChronic	0.030	0.059	0.51	0.609	
MotherNewMed	-0.168	0.185	-0.91	0.364	
CES-D	0.222	0.282	0.79	0.431	
Pregnant	-0.012***	0.007	-1.71	0.087	-1.193%
MotherVisits	0.015***	0.006	2.71	0.007	0.083

*significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Need variables were again important determinants in the model. Diagnosis of an additional chronic condition resulted in the child frequenting the doctor approximately one more time on average. The development of a new medical condition in the past year had positive and significant effect in the model. Each rural child is expected to have approximately 74% more visits in a year if they developed a new medical illness than if they did not. The mother's need for prenatal and/or post-partum care was important in the model as the negative and statistically significant (at the 10% level) parameter estimate on *Pregnant* indicates. The percent change calculations show that a pregnant mother is expected to make 1.2% fewer visits than mothers who did not require prenatal or post-partum care.

Finally, the health behavior variable, *MotherVisits*, was statistically important in the model. Rural, low-income mothers in the sample consumed an average of 0.083 more pediatric care services for each additional visit she made to the health care professional.

6.4 Limitations of the Analytical Approach

The results demonstrate that *MotherVisits* was an important determinant of the dependent variable *ChildVisits* and that *ChildVisits* was significant to the regression model that used *MotherVisits* as the outcome. Models 1 and 2 can be presented as:

$$\text{Model 1A: } y_{i1} = X_i'\beta_1 + y_{i2}\delta_1 + u_{i1}$$

$$\text{Model 2A: } y_{i2} = X_i'\beta_2 + y_{i1}\delta_2 + u_{i2}$$

The variable y_{i1} is still *MotherVisits*, y_{i2} is *ChildVisits*, and X_i' is the vector of independent variables which includes the environmental, predisposing, and health behavior factors. Models 1A and 2A demonstrate that *MotherVisits* and *ChildVisits* are not truly exogenous. In fact, they are endogenous to the models since they also act as dependent variables determined by the X_i' vector. Consequently, the analytical approach needs to correct for endogeneity.

6.4.1 The Endogeneity Problem and Simultaneous Systems

The NegBin model, similar to other ordinary least squares regression models, assumes that the independent variables are uncorrelated with the disturbance term. That is, the covariates in the model are assumed to be exogenous. Endogeneity arises when an independent variable is not truly exogenous, but is in fact correlated to the error term in the model. An analytical approach that treats all the covariates as truly independent of the

error term will produce biased and unreliable estimates since the endogenous variable is jointly estimated with the dependent variable.

Endogeneity can arise when dealing with an omitted variable problem or in a simultaneous system. In the latter, a predictor in one model is also the dependent variable in another. For example, *ChildVisits* is a predictor in Model 1A but the outcome variable in Model 2A while *MotherVisits* acts as the predictor in Model 2A and as the dependent in Model 1A. Both *MotherVisits* and *ChildVisits* are therefore endogenous. Consequently, the analytical approach should correct for the presence of endogeneity appearing due to simultaneity.

6.4.2 The 2-stage Negative Binomial Estimation

Multiple techniques, such as an instrumental variables approach, generalized method of moments, structural models, etc., have been developed to address endogeneity. A 2-stage estimator approach is used to correct for the endogeneity that arises from the simultaneous health care utilization decision that the mother made.

To ensure that the simultaneous system can be estimated, the parameters need to be identified. In this case, there are more exogenous variables than there are endogenous variables, suggesting that models 1A and 2A are over identified. Moreover, the structural parameters specified in this paper can be identified using a 2-stage estimation process, resulting in consistent and unique estimators (Griffiths, Hill, & Judge, 1993). This particular approach has the advantage of not requiring explicit structural parameters solutions to be found in terms of the reduced form parameters. Moreover, a 2-stage procedure is preferred to an instrumental variable approach since the latter does not make

use of all the information in the system and does not yield unique estimates of the

unknown structural parameters.

The model under consideration in this study is again:

$$\text{Model 1A: } y_{i1} = X_i'\beta_1 + y_{i2}\delta_1 + u_{i1}$$

$$\text{Model 2A: } y_{i2} = X_i'\beta_2 + y_{i1}\delta_2 + u_{i2}$$

The endogenous variables are y_{i1} and y_{i2}, X_i' is a matrix of the reduced form

exogenous parameters, and u_{i1} and u_{i2} are the disturbances. Endogeneity in this model

manifests because there is correlation between y_{i1} and u_{i1} and between y_{i2} and u_{i2}. We

assume that the model is already in reduced form. Assume also that the variables y_{i1} and

y_{i2} have the form:

$$\text{Model 1B: } y_{i1} = X_i'\beta_1 + v_{i1}$$

$$\text{Model 2B: } y_{i2} = X_i'\beta_2 + v_{i2}$$

where $v_{i1} = y_{i1} - X_i'\beta_1$ and $v_{i2} = y_{i2} - X_i'\beta_2$ are a vector of reduced form

disturbances. Finally, suppose that the disturbances u_{i1} and u_{i2} can be written as $u_{i1} =$

$v_{i1}\rho_1 + e_{i1}$ and $u_{i2} = v_{i2}\rho_2 + e_{i2}$, $j = 1, 2$, where the disturbances v_{ij} and e_{ij} are

uncorrelated. The additional assumptions that $E[e_{ij}] = 1$, $j = 1, 2$ and that u_{ij} and v_{ij}

are normally distributed are also made (Wooldridge, 2002). These provide the framework

for the new set of equations:

$$\text{Model } 1_{2s}: y_{i1} = X_i'\beta_1 + y_{i2}\delta_1 + v_{i1}\rho_1 + e_{i1}$$

$$\text{Model } 2_{2s}: y_{i2} = X_i'\beta_2 + y_{i1}\delta_2 + v_{i2}\rho_2 + e_{i2}$$

The model as it stands, however, cannot be implemented since v_{ij}, $j = 1, 2$ is

unobserved. The model can be made operational by using estimates of v_{ij}. The

substitution of $\widehat{v_{ij}}$ in the models and subsequent re-estimation gives rise to the two step estimation procedure.

In the first stage, a reduced form of the model is estimated (Maciejewski, Hebert, Conrad, & Sullivan, 2005; Wooldridge, 2002), which in this case are models 1B and 2B. The predicted values and residuals derived from those models are stored for use in the second stage:

$$\text{Model } 1_{2s}: y_{i1} = X_i'\beta_1 + \widehat{y_{i2}}\delta_1 + \widehat{v_{i2}}\rho_1 + e_{i1}$$

$$\text{Model } 2_{2s}: y_{i2} = X_i'\beta_2 + \widehat{y_{i1}}\delta_2 + \widehat{v_{i1}}\rho_2 + e_{i2}$$

The resulting estimates $\widehat{\beta_i}$, $\widehat{\delta_i}$, and $\widehat{\rho_i}$ are consistent under the assumptions made if robust covariance-variance estimates are also used in both the first and second stages (Wooldridge, 2002). It is relatively straightforward to test if endogeneity is actually present and if the 2-stage method is necessary. The simplest technique is test whether the residuals included are significant using the null $H_0: \rho = 0$ and the alternative $H_A: \rho \neq 0$. The variable is endogenous if and only if the null is rejected. The hypothesis test on ρ relies on large sample properties.

Most statistical software packages print individual tests on the parameter estimate, including on ρ. These are typically t-tests, which rely on small sample properties. Using robust covariance estimates in SAS however requires use of large sample properties, making it possible to use the individual z-statistic that SAS provides to test for endogeneity.

The results of the baseline models 1 and 2, i.e., without a 2-stage estimation, show that the *MotherVisits* and *ChildVisits* are both important to the model. Under the present construction, models 1B and 2B, which do not make use of the information provided by

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MotherVisits and *ChildVisits*, are regressed in the first stage. The exclusion of this information however leads to an omitted variables problem. The first stage estimates would consequently be biased and the residuals would act as catch-all for the information that has been excluded. The residuals would also be biased and would produce similarly invalid parameter estimates in the regressions of Model 1_{2s} and Model 2_{2s}. Using the residuals from Model 1 and Model 2, which include the endogenous variables, is not a viable option since they would produce equally biased residuals. One possible solution is to utilize errors in the second stage estimations (Model 1_{2s} and Model 2_{2s}) from a regression model that includes the information contained in the endogenous variables without making direct use of them.

An instrumental variables approach is a possible technique where a variable that most closely reflects the information provided in the endogenous variables is used in place of the actual endogenous variable, but is uncorrelated with the disturbance. Number of visits the mother made between wave 1 and wave 2 (*MotherVisits_Wave2*) and the number of visits made by the child between wave 1 and wave 2 interviews (*ChildVisits_Wave2*) were used in the first stage to instrument *MotherVisits* and *ChildVisits*. The instrumental variables *MotherVisits_Wave2* and *ChildVisits_Wave2* are both truly exogenous to the model and therefore do not cause any additional endogeneity problems. Their mean and standard deviation are presented in Table 5.

Table 5: Descriptive Statistics of Instrumental Variables

Variable	Definition	Mean	Std. Dev.
MotherVisits_Wave2	Number of times the mother visited the doctor or other health care provider since the wave 1 interview	7.147	10.685
ChildVisits_Wave2	Number of times the child visited the doctor or other health care provider since the wave 1 interview	6.389	8.829

The results of the 2-stage NegBin model—the simultaneous systems approach—are presented and discussed in the next section. The variables *ChildResidual* and *MotherResidual* are the errors from the first stage regression. They have coefficients ρ_i, $i = 1, 2$, so that a test of endogeneity is a large sample property test (z-test) on the coefficients of *ChildResidual* and *MotherResidual*. The predicted values that are generated in the first stage and used in the second stage have been denoted *ChildVisits_Pred* and *MotherVisits_Pred*.

6.3.3 Results of 2-Stage Model: *MotherVisits*

Of immediate concern is the coefficient on the *ChildResidual*, which is highly significant as seen in Table 6. The large sample property test implies sufficient evidence of unobserved randomness in the decision process that influences the number of trips made. The positive sign on the coefficient indicates that the relationship between the unobserved randomness and the mother's visits to the doctor is increasing. Moreover, the health behavior variable *ChildVisits_Pred* is also highly significant at the 1% level or better. It had a positive effect on the outcome variable, with mothers having approximately 0.70 more trips to the doctor on average for each extra trip their child makes[4].

With respect to social structure variables, we can see that the coefficient *TotalChildren* is significant at the 10% level. The mothers consumed 3.64 more health care consultations as the number of children in the household increased.

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[4] Section 6.3 presents comparisons between the results from single equation and 2-stage NegBin regressions for both *MotherVisits* and *ChildVisits* models.

Table 6: Results of 2-Stage *MotherVisits* NegBin Regression

Variable	Estimate	S.E	Z	P-value	Avg ME /Percent Change
Intercept	0.624	0.744	0.84	0.402	
IRR	0.964	0.854	1.13	0.259	
HPSAPrimary	-0.084	0.207	-0.4	0.686	
HPSAMental	-0.193	0.193	-1	0.318	
MotherAge	-0.033*	0.018	-1.9	0.058	-0.357
ChildAge	0.036	0.038	0.95	0.342	
ChildGender	0.164	0.170	0.97	0.333	
HS	-0.117	0.252	-0.46	0.643	
>HS	0.235	0.249	0.94	0.346	
Employment	-0.084	0.175	-0.48	0.632	
Latina_AA	0.334	0.286	1.17	0.244	
Other_NonWhite	0.259	0.285	0.91	0.363	
TotalChildren	0.150*	0.091	1.65	0.100	3.637
PartnerStatus	0.268	0.187	1.44	0.151	
SupportSatisfaction	0.038	0.140	0.27	0.788	
Child_HMO	-0.596*	0.328	-1.81	0.070	-44.899%
Child_Medicaid	-0.085	0.298	-0.28	0.776	
Child_OtherIns	0.052	0.280	0.19	0.853	
Mother_HMO	0.687***	0.235	2.92	0.004	98.774%
Mother_Medicaid	0.506**	0.230	2.2	0.028	65.864%
Mother_OtherIns	0.241	0.287	0.84	0.400	
Car	-0.093	0.341	-0.27	0.786	
%FPL	-0.001*	0.001	-1.67	0.096	-0.015
ChildChronic	-0.209*	0.113	-1.85	0.065	-2.248
ChildNewMed	0.101	0.144	0.7	0.484	
MotherChronic	0.136**	0.064	2.11	0.035	1.462
MotherNewMed	0.632***	0.169	3.74	0.000	88.137%
CES-D	0.566***	0.184	3.08	0.002	6.086
Pregnant	0.015**	0.006	2.32	0.020	1. 511%
ChildVisits_Pred	0.063***	0.012	5.51	<.0.0001	0.680
ChildResidual	0.042***	0.009	4.52	<0.0001	0.453

*significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Of the enabling variables included in the model, having insurance was found to be

significant. The parameters *Mother_HMO* and *Mother_HMO* both have significant

coefficient estimates that orient health care use in a positive direction. As the insurance

coverage type moves from no insurance to HMO/private, mothers are expected to make 90% more visits per year than those who have no insurance. Mothers who gained Medicaid/equivalent coverage are expected to consult with health care personnel nearly 66% more times than mothers without insurance. The other enabling variable that was statistically significant was *%FPL*, whose coefficient sign indicates that lower levels of poverty decreased medical care consumption. The average ME is close to zero, however, at negative 0.015.

With respect to need variables, *MotherChronic* causes the mother to consult a health care provider 1.462 more times on average for every additional chronic condition. *MotherNewMed* also influences expected use in the same direction, causing the mother to make nearly 88% more visits in a year if she developed a new medical condition or required surgery. The need for prenatal and post-partum care also had a positive effect. Being pregnant is expected to increase the expected number of visits made by the mother by 1.5%. The mother's self-reported depression is significant and positive. An incremental increase in the CES-D score caused the mother to make approximately six more visits on average.

Variables that describe factors that facilitate pediatric care consumption were also found to predict the mother's health care utilization. Particularly, *ChildChronic* and *Child_HMO* act to reduce the visits the mother makes. A diagnosis of an additional chronic sickness in the children causes the mother to make an average of 2.25 fewer visits, and the child having HMO/private insurance reduces the mother's expected number of visits by about 45%.

6.4.4 Results of 2-Stage Model: *ChildVisits*

Table 7 demonstrates that there is sufficient evidence of unobserved randomness in the decision process that influences the trips the child made. The positive sign on the coefficient *MotherResidual* suggests that the relationship between the unobserved randomness and *ChildVisits* is increasing. *MotherVisits_Pred* is also statistically significant to the model. Each child makes an average of 0.223 more visits as the trips the mother takes increases.

Table 7: Results of 2-Stage *ChildVisits* NegBin Regression

Variable	Estimate	S.E	Z	P-value	Avg ME/ Percent Change
Intercept	1.835**	0.921	1.99	0.046	10.044
IRR	-0.821	0.660	-1.24	0.214	
HPSAPrimary	0.016	0.194	0.08	0.935	
HPSAMental	0.218	0.184	1.18	0.236	
MotherAge	0.013	0.014	0.87	0.383	
ChildAge	-0.014	0.043	-0.32	0.750	
ChildGender	-0.009	0.182	-0.05	0.959	
HS	-0.060	0.260	-0.23	0.819	
>HS	-0.315	0.245	-1.28	0.200	
Employment	0.066	0.220	0.3	0.764	
Latina_AA	-0.365**	0.184	-1.98	0.048	-30.580%
Other_NonWhite	-0.200	0.499	-0.4	0.690	
TotalChildren	-0.229**	0.108	-2.12	0.034	-1.252
PartnerStatus	-0.082	0.207	-0.39	0.694	
SupportSatisfaction	0.103	0.189	0.55	0.586	
Child_HMO	0.643	0.405	1.59	0.112	
Child_Medicaid	0.233	0.385	0.61	0.545	
Child_OtherIns	0.480	0.381	1.26	0.208	
Mother_HMO	-0.483*	0.283	-1.7	0.089	-38.307%
Mother_Medicaid	-0.059	0.248	-0.24	0.812	
Mother_OtherIns	-0.419	0.347	-1.21	0.227	
Car	-0.033	0.237	-0.14	0.889	
%FPL	0.000	0.001	0.24	0.809	
ChildChronic	0.212**	0.104	2.05	0.041	1.162
ChildNewMed	0.531***	0.160	3.32	0.001	70.063%
MotherChronic	-0.077	0.076	-1.02	0.308	
MotherNewMed	-0.320*	0.186	-1.72	0.086	-27.385%
CES-D	-0.015**	0.007	-2.07	0.038	0.084
Pregnant	-0.034	0.267	-0.13	0.899	
MotherVisits_Pred	0.044***	0.013	3.48	0.001	0.241
MotherResidual	0.011**	0.005	2.02	0.043	0.059

*significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

The regression results also show that the social structure predictor *TotalChildren* is significant, negative, and decreasing. The child is expected to have 1.36 fewer trips to the doctor for each new child added to the household. *Latina_AA*, a demographic variable controlling for race/ethnicity, had a negative effect on the visits made. Mothers identified as either Latina or African American had an expected number of visits that was 31% fewer visits than that of rural, non-Hispanic white mothers.

With respect to enabling resources, the child's insurance types were not important to the model, although the signs on the coefficients all suggest positive effects on health care use. However, the mother's insurance type was found to be an important predictor of health care consumption. Specifically, *Mother_HMO* was significant at the 10% level or higher. It had a negative impact on the pediatric care consumption. Mothers with HMO/private insurance are expected to take their child an average of 38% times less than mothers who have no health insurance coverage. *Mother_Medicaid* and *Mother_OtherIns* were not found to be significant to the model, and signs on their parameter estimates also imply a negative relationship with *ChildVisits*.

Need factors are also important to the model. Coefficient estimates for the covariates concerning the child's actual need for medical services are both positive. The development of a new medical condition in the past year is expected to increase the average number of trips made by about 70%. Having a chronic condition also has a positive impact on frequency of health care use. Rural low-income mothers, on average, take their child an additional 1.13 times to a health care provider with each additional chronic condition. With respect to the mother's need for care, the negative, statistically

significant coefficient on *CES-D* suggests that the child averaged 0.08 fewer visits as the

mother's CES-D score increased.

6.5 Comparing Single Equation and 2-Stage Estimation Results

   At first glance, the coefficient estimates and standard errors from *MotherVisits*

seem remarkably similar in magnitude and sign (Table 8). However, *MotherAge* and

TotalChildren, two variables that were insignificant in baseline model gained

significance in the simultaneous systems approach[5].

Table 8: Comparing Single Equation and 2-Stage Models of *MotherVisits*

| Variable | Single Equation Model | | 2-Stage Model | |
	Estimate (Std. Dev.)	Avg ME/ Rate Percent Change	Estimate (Std. Dev.)	Avg ME/ Percent Change
MotherAge	-0.026 (NS)	-0.275	-0.033* (0.018)	-0.357
TotalChildren	0.122 (NS)	3.097	0.150* (0.091)	3.637
Child_HMO	-0.541* (0.096)	-41.783%	-0.596* (0.328)	-44.899%
Mother_HMO	0.628*** (1.084)	87.386%	0.687*** (0.235)	98.774%
Mother_Medicaid	0.554** (1.007)	74.020%	0.506* (0.230)	65.864%
%FPL	-0.002* (0.0001)	-0.016	-0.001* (0.001)	-0.015
ChildChronic	-0.202* (0.021)	-2.174	-0.209* (0.113)	-2.248
MotherChronic	0.156** (0.280)	1.679	0.136** (0.064)	1.462
MotherNewMed	0.615*** (0.946)	84.966%	0.632*** (0.169)	88.137%
CES-D	0.017** (0.030)	0.180	0.566*** (0.184)	6.086
Pregnant	0.593*** (0.950)	80.941%	0.015** (0.006)	1.511%
ChildVisits	0.043*** (0.061)	0.460	-	-
ChildVisits_Pred	-	-	0.063*** (0.012)	0.680
ChildResidual	-	-	0.042*** (0.009)	0.453

*significant at the 10% level; **significant at the 5% level; ***significant at the 1% level; NS not significant

   The average MEs and percent changes demonstrate that the magnitude of the

parameter effect is incorrectly estimated for all the variables. This is especially evident in

the average MEs of *CES-D*. In the single equation model, the mother's depression score

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[5] For ease of comparison, only variables that were statistically significant are presented and discussed in this section.

has very little effect. However, the true parameter estimates and subsequent marginal

effects indicate that *CES-D* increased average doctor visits by almost 6 in the past year.

The single equation model, therefore, underestimates the true impact on the mothers'

health care consumption. Similarly, the baseline model overestimates the impact of

Pregnant while the percent changes from the simultaneous model is much smaller.

The results of the 2-stage model validate the simultaneous systems approach for

both *MotherVisits* and *ChildVisits*, rendering the parameter estimates from the single

equation regressions unreliable. Table 9 highlights the differences between the two

econometric approaches by comparing estimates from the single equation and 2-stage

models of *ChildVisits*.

Table 9: Comparing Single Equation and 2-Stage Models of *ChildVisits*

| Variable | Single Equation Model | | 2-Stage Model | |
	Estimate (Std. Dev.)	Avg ME/ Percent Change	Estimate (Std. Dev.)	Avg ME/ Percent Change
Intercept	1.574* (0.934)	8.616	1.85** (0.921)	10.044
Latina_AA	-0.281 (NS)	-24.497%	-0.365** (0.184)	30.580%
TotalChildren	-0.225** (0.110)	-1.232	-0.229*** (0.108)	-1.252
Mother_HMO	-0.364 (NS)	-30.511%	-0.483* (0.283)	-38.307%
ChildChronic	0.176* (0.105)	0.964	0.212** (0.104)	1.162
ChildNewMed	0.551*** (0.168)	73.499%	0.531*** (0.160)	70.063%
MotherNewMed	-0.168 (NS)	-15.465%	-0.320 (0.186)	-27.385%
CES-D	0.222 (NS)	-0.668	-0.015** (0.007)	-0.084
Pregnant	-0.012* (0.007)	-1.193%	-0.034 (NS)	-3.343%
MotherVisits	0.015*** (0.006)	0.083	-	-
MotherVisits_Pred	-	-	0.044*** (0.013)	0.241
MotherResidual	-	-	0.011** (0.005)	0.059

*significant at the 10% level; **significant at the 5% level; ***significant at the 1% level; NS not significant

Latina_AA, *Mother_HMO*, *MotherNewMed*, and *CES-D* gained significance in

the 2-stage model estimations while *Pregnant* lost its significance. The parameter

estimates are biased when endogeneity is present but uncorrected for, as evident through

the average ME. Of the parameters that remained statistically important to both models,

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the magnitude of parameter effect on the child's pediatric care utilization has been

underestimated for *TotalChildren* and overestimated for *ChildNewMed* in the single

equation model.

CHAPTER 7

DISCUSSION, POLICY IMPLICATIONS, AND CONCLUSION

7.1 Discussion

Rural low-income mothers and their children face considerable difficulties in accessing and using health care services (Arcury et al., 2005a; DeVoe et al., 2008; Mueller et al., 1999). This study adds to the understanding of factors that drive rural, low-income mothers with children to consult with health care personnel. The health care consumption process was modeled as a joint system, and the results indicate that the mothers face simultaneous choices during the year for child health care visits and their own health care visits. In keeping with past literature (Hemard, Monroe, Atkinson, & Blalock, 1999), this study found that the number of visits the child makes influences the frequency of mother's visits and vice-versa. But, this study found that modeling the choices as simultaneous decisions has an impact on the estimates of the percent changes, calculated using incidence rate ratios, and partial effects.

It also adds to the understanding of determinants that facilitate higher frequency of pediatric health care use among rural, low-income women with children. We expected that numerous environmental, demographic, health belief/attitude, enabling resource, and need factor variables would provide the best predictive model of health care use. This was not the case, however, as the results shows. Only maternal and child health factors, income as percent of the federal poverty level (FPL), family composition variables, health beliefs, and health insurance coverage were important to the model.

The one demographic variable that was found to affect pediatric care consumption concerned the mother's race/ethnicity. This study showed that children of Latina or African American mothers used fewer pediatric care services when compared to children of non-Hispanic white mothers. The results are congruent with those established in previous research about the negative role of race/ethnicity on pediatric care use (Flores et al., 1998; Flores et al., 2005; Mayberry, et al., 2000).

Total number of children in the household, a variable symbolizing social structure and social networks, was found to affect number of visits the mother made for herself and her child. Previous investigations on the subject have found that pediatric care consumption levels decline with more children (Janicke & Finney, 2000). The results of the study likewise showed that rural mothers took their children to the doctor fewer times as the total number of children increased. Such behavior on the mother's part may be attributed to her ability to be more attentive towards her child when there are fewer children in the household. The rural, low-income mothers may also have less discretionary income available to spend on their children as household size increases.

The work done on the effect of the number of children in the household on the mother's health care consumption is less conclusive about the direction of effect. Leclere, Jensenm and Biddlecom (1994) found that the number of household members under 18 years of age reduces total physician contacts that the adult had. Cairney and Wade (2011) used the total number of children in the household as a control variable and found that it was statistically significant and positive in their models. This study also found that the total number of children in the household positively affects the number of visits the mother makes to a health care provider. A possible explanation is that rural mothers feel

higher levels of stress with more children. It has been previously established that minor

parental hassles and lack of confidence in parenting skills contribute to stress (Crnic &

Greenberg, 1990; Erdwins, Buffardi, Casper, & O'Brien, 2001). The study findings could

reflect the mothers' propensity to seek more health care services due to increases in her

stress levels and the associated psychological and physiological effects on the human

body. Moreover, the dependent variable, number of visits, does not distinguish between

the types of care accessed. Emergency room visits, general check-ups, specialist

consultations, and mental health care services are all included under the number of visits

made. The study findings could reflect the higher use of mental health care services due

to greater stress levels.

Two enabling factors (mother has HMO/private and mother has

Medicaid/equivalent insurance coverage) were found to be significant in the mother's

model of health service use. It is reasonable to expect that the presence of health

insurance will allow easier access to health care personnel and facilities (Kasper,

Giovannini, & Hoffman , 2000; Simmons et al., 2008). Congruent with past results,

having Medicaid/equivalent and having HMO/private insurance both predicted greater

numbers of visits by the mothers.

The variable, income as a percent of FPL, influenced health care utilization

among the mothers of this study. Previous work has shown that less annual household

incomes is related to higher numbers of acute care visits and lower numbers of regular

care visits among residents of rural Appalachia (Arcury et al., 2005a). The mothers in this

study made fewer visits as their income increased as a percent of the FPL. One possible

explanation is that the sample consisted of both welfare-reliant (41.7%) and work-reliant

mothers (58.3%). More of the working mothers, i.e. working poor, had incomes that were

a higher percent of the FPL (Table 10).

Table 10: Cross tabulation of Mother's Employment Status with Income as Percent of FPL

	0% ≤ FPL < 50%	50% < FPL ≤ 100%	100% < FPL ≤ 150%	15% < FPL ≤ 200%	FPL > 200%
Employed	4.92%	11.66%	19.63%	10.43%	11.66%
Unemployed	10.43%	15.95%	9.20%	1.23%	4.91%

Of the mothers who were employed, approximately 28% of them had

HMO/private health insurance while about 13% had no medical insurance (Table 11).

These numbers suggest that the working poor may have had to contend with high out-of-

pocket health insurance costs. Moreover, even those who have Medicaid (14%) may have

high co-payments. This could be true for these mothers since Medicaid provides only

limited coverage for the poor unless they are very poor with dependent children, or are

pregnant or disabled (Kaiser, 2009). Among low-income individuals, coverage levels of

Medicaid and HMO/private health insurance are comparable (Kaiser, 2009). The inverse

relation between income as a percent of FPL and mother's doctor visits may, therefore,

be a reflection of higher levels of out-of-pocket expenses.

Table 11: Cross tabulation of Mother's Health Insurance with Employment Status

	Mother_Medicaid	Mother_HMO	Mother_OthIns	Mother_NoIns
Employed	14.11%	27.61%	3.68%	12.88%
Unemployed	16.56%	7.36%	4.91%	12.88%

With respect to enabling factors, presence and type of health insurance coverage

was found to influence number of visits made by the mother and her child. Many studies

have included presence and type of insurance coverage as covariates in their model, and

have found that having health insurance positively influences the volume of care accessed

(Akresh, 2009; Arcury et al., 2005b; Porterfield & McBride, 2007; Simmons et al., 2008; Shi & Stevens, 2005). Like the subjects of past studies, the mothers in the sample made more visits if they had medical insurance (HMO/private or Medicaid/equivalent) than when had they no coverage.

However, these past studies about adults' use of health care services included presence and type of coverage the adults had, but did not consider the child's type of coverage (Arcury et al., 2005b; Berdahl et al., 2007). Similarly, investigations into the factors that influence pediatric care use included the child's insurance type but not the mothers' (Dubay & Kenney, 2001; King et al., 2010; Shi & Stevens, 2005). The simultaneous decision nature that the mother faces motivated the inclusion of the child's health insurance coverage status as a determinant in the mother's model in this study. Similar reasoning led to the addition of the mother's insurance coverage type in the model of the child's visits.

Several influences are possibly at play in the simultaneous decision process. Rural, low-income mothers may be motivated by financial constraints on the type of health care services and personnel they access. That is, the child's insurance may not cover all prescription medications, which may impose high out-of-pocket medical expenses. This is especially true if the child has private health care insurance. Previous investigations have found that low-income parents struggle with financial constraints despite the type of medical insurance their child carries (Porterfield & McBride, 2007). Similarly, the mothers' health insurance may also not include certain prescriptions, medical procedures, or specialist consultations. Moreover, frequency of visits for herself and her child is, in part, determined by the exposure she has to health care providers,

faculties, and literature. Past work has shown a bidirectional relationship between pediatric and adult health care utilization (Hemard, et al., 1999; Janicke & Finney, 2000; Janicke et al., 2001; Minkovitz et al., 2002). Utilization, however, is affected by type of health insurance in addition to other factors. Consequently, the mother's exposure to health care providers is determined by the insurance coverage available for herself and her child.

The results of the 2-stage negative binomial regression suggest that mothers consumed fewer health care services if her child had HMO/private insurance. Likewise, the child visited the doctor fewer times if the mother had HMO/private health insurance. The negative relationship between the child's (mother's) HMO/private insurance and the mother's (child's) visits could reflect financial constraints that the caregiver faces. Weissman et al. (1991) found that adults with private insurance are more likely to delay accessing appropriate health care due to high costs.

Shen and McFeeters (2006) investigated out-of-pocket expenses for low-income families and found that low-income adults with private non-group health insurance had the highest out-of-pocket expenses (Shen & McFeeters, 2006). Estimates also suggest that privately insured rural residents spent more than $1,000 in out-of-pocket medical expenses during the 2001 and 2002 years (Ziller et al., 2006). Low-income adults have been found to delay accessing medical care and obtaining prescription medication due to costs (Shi & Stevens, 2005b). Moreover, low-income parents have cited difficulty accessing proper pediatric care services due to high costs (DeVoe et al., 2007; Porterfield & McBride, 2007; Sobo et al., 2006).

Approximately 22% of rural mothers and their child both had HMO/private insurance. Of the children with HMO/private health coverage, less than 2% of them had mothers with Medicaid/equivalent coverage while almost 2.5% of them had no insurance (Table 12).

Table 12: Cross tabulations of Child's Health Insurance with Mother's Health Insurance

	Mother_HMO	Mother_Medicaid	Mother_OtherIns	Mother_NoIns
Child has HMO/Private insurance	22.09%	1.23%	0%	2.45%
Child does not have HMO/Private insurance	12.88%	29.48%	8.59%	23.31%

Table 13 demonstrates that of the 35% of mothers with HMO/private insurance, less than 5% of them also had a child with Medicaid/SCHIP. In other words, 22.09% of the mothers who had HMO/private coverage also had a child that had HMO/private insurance. Consequently the mothers may have to contend with appreciably higher out-of-pocket medical expenses due to the HMO/private type of health care insurance they carry.

Table 13: Cross tabulations of Mother's Health Insurance with Child's Health Insurance

	Child_HMO	Child_Medicaid	C_OtherIns	C_NoIns
Mother has HMO/Private insurance	22.09%	4.91%	5.52%	2.45%
Mother does not have HMO/Private insurance	3.68%	41.10%	11.66%	8.59%

Child and adult need factors were also found to be significant to the models, but the same variables affected use in markedly different ways in both models. The mother's

pregnancy status affected only her health care use. It is reasonable to expect that being pregnant in the past year would increase the need for medical care. In line with expectations, rural mothers who required prenatal and/or post-partum care frequented the doctor more often.

Of the variables that influenced both pediatric and adult health care utilization, the mothers' self-reported depression score predicted higher frequency of visits for the mother, but fewer visits for the child. Women who are depressed use health care services and facilities more often than women who are not depressed (Weinick et al., 2000). Likewise, maternal depression has been shown to influence pediatric care consumption positively (Janicke & Finney, 2000; Minkovitz et al., 2002; Olfson, Marcus, Druss, Pincus & Weissman, 2003; Riley et al., 1993). The results of this study are not congruent with some previously found. The mothers of this sample consumed fewer pediatric health care services with higher CES-D scores. A plausible explanation could be that the dependent variable, the number of visits, does not distinguish between the kind of service utilized. Minkovitz et al. (2002), for example, found that mothers' mental health visits increased the likelihood of child's mental health visits. Olfson et al. (2003) also investigated the relationship between parental depression and use of pediatric mental health services. Therefore, the positive relationship may be true of certain types of use only. A second possible explanation is that the results are simply an anamoly.

The development of a new medical condition in the past year and number of chronic conditions in the individual positively predicted health care use in their respective models. These results support the findings of past researchers who have shown that an individual's illness positively influences their health care consumption (Akresh, 2009;

Janicke & Finney, 2000; Simmons et al., 2008). This finding persists among those who consult mental health care providers (Cairney & Wade, 2011; Kouzis, 2005) and those who have special health care needs (Porterfield & McBride, 2007). Having acute recurring illnesses have also been shown to influence volume of health care use in a positive manner (Janicke et al., 2001).

Interestingly, the number of chronic conditions in the child adversely impacted the volume of visits by the mother. That is, the mother's consumption of health care facilities and services increased with her number of chronic conditions but not the number of chronic illness in her child. This finding could reflect concern for finances for those with insurance other than Medicaid/SCHIP (Table 14). Approximately 7% of child with HMO/private insurance coverage had one or more chronic conditions while almost 5% of those with other types of insurance had 1 or more chronic illness. The mother may face high out-of-pocket expenses for pediatric health care visits and may therefore reduce her own consumption of health care services.

Table 14: Crosstabulation of *ChildChronic* with Insurance Type

ChildChronic (No. of conditions)	*Child_Medicaid*	*Child_HMO*	*C_OtherIns*	*C_NoIns*
0	31.95%	17.75%	12.43%	11.83%
1	9.47%	5.33%	2.96%	0.00%
2	4.14%	1.18%	1.18%	0.00%
3	0.59%	0.59%	0.59%	0.00%
1 or more	14.20%	7.10%	4.73%	0.00%

The mother's concern for costs could also be influenced by her type of health insurance coverage. The cross tabulations in Table 15 show that 10% of mothers who had HMO/private had a child with one or more chronic conditions. This percentage is only

slightly lower than mothers with Medicaid/equivalent. Almost 5% of mothers who had no health insurance also had a child with a chronic illness. The cross tabulation tables presented here suggest that the mothers could be concerned with out-of-pocket health service fees.

Table 15: Crosstabulation of *ChildChronic* with Mother's Insurance Type

ChildChronic (No. of conditions)	Mother_HMO	Mother_Medicaid	Mother_OtherIns	Mother_ NoIns
0	23.67%	21.89%	5.92%	22.49%
1	7.10%	6.51%	1.18%	2.96%
2	2.37%	1.78%	1.18%	1.18%
3	0.59%	0.59%	0.59%	0.00%
1 or more	10.06%	8.88%	2.95%	4.14%

An alternative explanation is that chronic conditions require constant care and attention. Mothers may be limited in the time available to them, transportation facilities, and child care facilities, restricting the total number of visits that the family makes over the course of a year.

The 2-stage negative binomial approach taken in this paper has shown that mothers evaluate health care consumption for themselves and their child jointly. The simultaneous decision making process has shown that certain factors that enable use of health services by the mother deter pediatric care consumption. Variables that prompt greater frequency of pediatric health care utilization lower the mother's visits to a physician. The policy implications arising from dual effect of the variables are discussed in the next section. The chapter then concludes with model strengths and limitations.

7.2 Policy Implications

The results suggest several directions for future legislation. First, the study showed that the mothers assess tradeoffs between their own health care consumption and their child's health care utilization. Specifically, the mothers make fewer visits when their child has chronic illnesses. A possible explanation is that the mothers are limited in the time available to them to care for themselves, i.e. the mothers may be more focused on providing care for their child than for themselves. Such results are concerning from a public health perspective since the mothers are forgoing care that may be medically necessary. This is especially troublesome in light of past results which suggest that rural adults are also likely to receive certain preventive health care services (Casey, Thiede, & Klingner, 2001; Slifkin, 2002).

Policy makers should focus efforts on expanding health education provided to rural, low-income mothers. Specifically, expanding collaborative care efforts between patients and health care professionals could improve health and well-being of rural residents. Additionally, supplementing patient's education on achieving certain clinical goals with programs that teach patients self-management skills has been found to be effective (Bodenheimer, Lorig, Holman, & Grumbach, 2002).

Increasing health education of mothers, especially in the context of chronic care management, is particularly relevant in the current sociopolitical environment when budget cuts are being contemplated for many of the federal and state funded health care programs. Patient self-management care programs could help lower costs for adults with certain conditions such as arthritis and asthma (Bodenheimer et al., 2002). These cost reductions could act to contain Medicaid expenses since approximately 5% of all

Medicaid enrollees are the recipients of almost 54% of Medicaid spending and typically have long-term care needs (Kaiser, 2011).

The second policy implication concerns mental health care services. The results of the study suggest that mental health had a larger economic impact than did any of the other variables included in the model. Previous investigations indicate that women, in general, have higher rates of depression than men do (Weissman & Olfson, 1995). Studies have also found that people with mental disorders do not receive adequate levels of care, and that those with low-incomes, without insurance, and from rural regions are especially worse off (Wang et al., 2005). It is important to continue offering mental health services to this particular population group, especially since depression influences the rural mothers' labor force participation decisions as well as other aspects of their daily life (Mammen, Lass, & Seiling, 2008).

Rural residents face multiple barriers when accessing mental health care facilities and providers. First, rural health care facilities are typically understaffed and face difficulties recruiting psychiatrists. Estimates indicate that more than 20% of funded mental health care provider positions at clinics are currently vacant with rural community health centers reporting difficulty hiring and retaining appropriate personnel (Rosenblatt, Andrilla, Holly, Curtin, & Hart, 2006). Additionally, compared to other funded positions, such as family physicians, fewer amounts are set aside for psychiatrists (Rosenblatt et al., 2006), aggravating the situation. Consequently, rural residents have fewer options for accessing mental health care providers than their urban counterparts.

Secondly, insurance coverage for mental health care services can impose significant out-of-pocket medical costs. Until recently, insurance companies could apply

numerous regulations, such as different co-payments, deductibles, and restrictions on number of visits to a health care provider. The Mental Health Parity and Addiction Equity Act, which went into effect in 2010, equalized coverage between mental health care and care for physical ailments (Andrews, 2010). The law, however, does not require insurance plans to cover mental health care services and gives them the ability to determine which disorders will be covered. The law applies to Medicaid managed plans as well. Legislation of this kind can orient future policy in the direction of expanding mental health care services. It is, therefore, necessary to understand the effect that this law could have on rural, low-income mothers with children.

It is also important to expand, or at the very least, maintain current mental health care facilities to rural, low-income mothers. The results indicate that rural low-income mothers assess various pros and cons when choosing level of health care service consumption for themselves and for their child. These mothers face significant financial constraints and may be forgoing certain types of essential medical services in favor of providing better care for their children. Current cutbacks on funding to health centers and Medicaid/SCHIP programs may only aggravate the problem, especially in regions that have already been designated as a medical shortage area. It is important to continue making appropriate levels of mental health and chronic care services available to this particular population so as to ensure their well-being.

Finally, the study has methodological implications for future research and policy. The results suggest that rural, low-incomes choose number of health care visits for themselves and for their child simultaneously. As such, it is possible to introduce legislation that takes advantage of this duality. For instance, the site of pediatric health

care facilities could be used to direct mothers to appropriate adult primary care providers. Past research has shown that mothers would be receptive to such use of pediatric health care in referring and screening mothers as appropriate (Kahn et al., 1999). The goal of providing such triage facilities should be to improve the care given to these mothers and their children, which could lower health care costs.

7.3 Conclusions

The study hypothesized a simultaneous health care consumption process for rural, low-income mothers with children. A 2-stage negative binomial regression model was applied to account for the simultaneity that is in play, and the results validated the analytical employed. They indicated that the mothers face a joint decision when choosing amount of health care use for themselves and for their children.

Having health insurance, being depressed, having a need for medical care, household structure, and number of visits the child made to a doctor acted to increase the number of visits the mother made. Presence of chronic conditions in the child and the child having HMO/private insurance, on the other hand, deterred the mother's health care utilization. With respect to the child's use of health care use, having health insurance and having a need for medical attention, and total number of mother's visits to a health care provider all acted to increase pediatric health care consumption. Household structure and the mother's self-assessed depression lowered pediatric care utilization in the sample.

The study underscores the importance of providing chronic self-management education to patients and making mental health care service available and affordable to the rural, low-income mothers. There are several caveats, however. The first concerns the

dependent variable used. The number of visits to a health care provider did not

distinguish between the types of health care services that the mothers and their children

accessed. Future research should attempt a more nuanced study in understanding how the

simultaneity affects use of preventive care services versus emergency room services, etc.

Second, the results of the study are may provide insights on other low-income

mothers even if only rural, low-income mothers were included in the study. Third, it is

possible the mothers underestimated the number of visits to a health care provider made

by themselves and their child. It has been shown that individuals underreport self-

reported ambulatory physician visits for periods greater than two weeks (Roberts,

Bergstralh, Schmidt, & Jacobsen, 1996). The bias is particularly true for higher number

of visits. Consequently, the study results may underestimate the true impact of the

predictors on the number of visits made to a health care provider. Despite these

limitations, the study makes a significant contribution to the field of health care

utilization by approaching the health care consumption process as a joint decision and

using a 2-stage negative binomial approach to account for this simultaneity.

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