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A comprehensive analysis of the determinants of state Medicaid prescription drug expenditures

Sanjoy Roy
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**A COMPREHENSIVE ANALYSIS OF THE DETERMINANTS OF STATE MEDICAID
PRESCRIPTION DRUG EXPENDITURES**

Sanjoy Roy

**Thesis submitted to the
School of Pharmacy
at West Virginia University
in partial fulfillment of the requirements for the degree of**

**Master of Science
in
Pharmaceutical Systems and Policy**

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**Keywords: Medicaid, prescription drugs, per capita payments, determinants, Andersen's
model, structural equation modeling, cluster analysis, panel data regression**

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ABSTRACT

A comprehensive analysis of the determinants of state Medicaid prescription drug expenditures

Sanjoy Roy

Prescription drug payments are the fastest growing and most widely varying expenditures across state Medicaid programs. To aid health policy efforts, this study identified determinants of drug utilization and expenditures using Andersen's Behavior Model of Health Services Utilization. A Structure Equation Model was built using five-year data for 48 states, to test relationships among the latent constructs of policy, access, predisposing characteristics, enabling resources, and need for healthcare; and, their influence on drug utilization. Only predisposing characteristics and enabling resources showed significant effects on drug utilization. Cluster Analysis classified state Medicaid programs into eight groups that differ on federal matching, prior authorization, federal support, access to physicians, high school graduation rate, and disease severity. Finally, panel data regression methods offered a predictive model for estimating changes in per capita drug expenditure using time-adjusted pure effects of federal matching, access to physicians, disease severity, unemployment, and high school graduation rates.

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1 Chapter One: Study background

1.1 Introduction

Prescription drugs are an essential component of today's health care. For millions of Americans, prescription therapies are necessary to fight diseases, to improve health related quality of life, and to maintain their ability to function in society. In fact, almost half (45.3 percent) of the nation's population had at least one prescription drug in any given month in 2002.¹

In 2003, prescription drug expenditure in the United States amounted to \$179.2 billion, comprising 12.4 percent of national health expenditure.² However, although prescription drugs contribute to a relatively small share of the overall healthcare expenditure, spending on these has been growing at a disproportionate rate compared to the Consumer Price Index (CPI), as well as, the costs of other components of health care.³

Although much of the growth in prescription drug expenditures impacts private health insurance (45 percent), and out-of-pockets payments (30 percent), publicly-funded state and Federal government sources are also seriously impacted as they pay for a significant 24 per cent of the national prescription drug expenditure.² Figure 1 shows the split by source of funding for prescription drug expenditure in 2003, the latest year for which national health expenditure data are available at this time.³

Medicaid is the single biggest contributor among the publicly-funded sources, bearing 19 percent of the national drug expenditure.² Hence, prescription drug benefits under the Medicaid program are among the most impacted by continued increases in drug expenditure trends, and hence have been under constant review in the recent years.

Figure 1. National prescription drug expenditure by source of payment, 2003

Source: National Center for Health Statistics. Health, United States, 2005: With chart book on Trends in the Health of Americans, Hyattsville, Maryland: 2005

The Medicaid program

Medicaid, started in 1965, is a federally funded program of national health assistance in the United States that provides health care coverage to certain individuals and families with low incomes and resources, and disabilities. It was enacted under Title XIX of the Social Security Act as companion legislation to Medicare. Medicaid serves many roles in the health care system, providing health coverage and long-term care assistance to people in low-income families, and elderly and disabled people, filling in gaps in Medicare coverage, and supporting safety net providers.⁴

Medicaid was initially formulated as a medical care extension of federally funded programs providing cash income assistance for the poor, with an emphasis on dependent children and their mothers, the disabled, and the elderly. Over the years, however, Medicaid eligibility has been incrementally expanded beyond its original ties with eligibility for cash programs. Legislation in the late 1980s assured Medicaid coverage to an expanded number of low-income pregnant women, poor children, and to some Medicare beneficiaries who are not eligible for any cash assistance program. Legislative changes also focused on increased access, better quality of care, specific benefits, enhanced outreach programs, and fewer limits on services.

The Medicaid program operates on the basis of a division of funding responsibilities between Federal and state governments with the former matching the latter's health care provider reimbursements at an authorized rate. While states have considerable flexibility in framing and implementing their Medicaid program policies, Federal review of all plans and changes are required before matching Federal funds are paid. A state's Medicaid program must offer medical assistance for certain basic services to most categorically needy populations. These services include:⁵

- Inpatient hospital services
- Outpatient hospital services
- Prenatal care
- Vaccines for children
- Physician services
- Nursing facility services for persons aged 21 or older
- Family planning services and supplies
- Rural health clinic services
- Home health care for persons eligible for skilled-nursing services
- Laboratory and x-ray services
- Pediatric and family nurse practitioner services
- Nurse-midwife services
- Federally qualified health-center (FQHC) services, and ambulatory services of an FQHC that would be available in other settings
- Early and periodic screening, diagnostic, and treatment (EPSDT) services for children under age 21

States may also receive Federal matching funds to provide certain optional services like:⁵

- Diagnostic services
- Clinic services
- Intermediate care facilities for the mentally retarded (ICFs/MR)
- Prescribed drugs and prosthetic devices
- Optometrist services and eyeglasses

- Nursing facility services for children under age 21
- Transportation services
- Rehabilitation and physical therapy services
- Home and community-based care to certain persons with chronic impairments

The Federal share of Medicaid expenditure, known as the Federal Medical Assistance Percentage (FMAP), is determined annually by a formula that compares the state's average per capita income level with the national income average. In order to support states appropriately to facilitate delivery of care to the indigent, states with a higher per capita income level are reimbursed a smaller share of their costs. By law, the FMAP cannot be lower than 50 percent or higher than 83 percent.

In fiscal year (FY) 2004, the FMAPs varied from 50 percent in twelve states to 77.08 percent in Mississippi (the highest), and averaged 60.2 percent overall.⁵ For FY 2006, 12 states have matching rates at the statutory floor of 50 percent and 11 states and the District of Columbia have FMAPs of 69-76 percent.

Growth in Medicaid expenditure

In most years since its inception, Medicaid has had very rapid growth in coverage and in total expenditures. Number of persons served per year has increased from 21.6 million in 1980 to 42.8 million in 2000 and is over 52 million today.^{6,7} From a modest beginning of \$1.3 billion (2.9 percent of all national health expenditures) in 1966, Medicaid expenditure has grown to a massive \$224 billion (16 percent of all national health expenditures) in 2001 to about \$300 billion today.^{6,7} The Medicaid program currently accounts for seven percent of the federal outlays and for 17 percent of state general fund spending.^{8,9}

The Centers for Medicare and Medicaid Services (CMS), the Federal Agency that administers this program, identified the following factors for such growth:¹⁰

- The increase in size of the Medicaid-covered populations as a result of Federal mandates, population growth, and economic recessions;
- The expanded coverage and utilization of services;
- The Disproportionate Share Hospital (DSH) payment program that compensates hospitals for providing care to Medicaid eligibles, coupled with its inappropriate use to increase Federal payments to states;
- The increase in the number of very old and disabled persons requiring extensive acute and/or long-term health care and various related services;
- The results of technological advances to keep a greater number of very low-birth-weight babies and other critically ill or severely injured persons alive and in need of continued extensive and very costly care;
- The increase in drug costs and the availability of new expensive drugs; and
- The increase in payment rates to providers of health care services, when compared to general inflation.

Prescription drugs in Medicaid

As noted earlier, prescription drugs are an optional service under the federal rules. However, state Medicaid programs recognize the importance of this benefit and all states cover prescription drugs for at least some categories of Medicaid recipients. Medicaid pays for all prescription drugs that are sold by manufacturers who have agreed on national drug rebates with the Secretary of the Department of Health and Human Services (HHS).

At about \$34 billion, prescription drugs formed 13 percent of the total net Medicaid expenditures in 2003 growing at an annual growth rate of 15 percent – almost three times the total expenditure growth rate of 5.8 percent.^{7,11}

Studies have identified general inflation, population growth, increases in per capita prescription use, and the fact that prescription drug prices exceeded general inflation – as the major factors contributing to the growth in national prescription drug expenditures.^{12,13} For Medicaid in particular, increases in drug expenditures have been associated with growth in the number of drug recipients, increases in prescription drug prices, and economy wide inflation.¹³

Since the majority of state Medicaid programs have unrestricted formularies, clinicians have greater freedom with their prescribing patterns and thus use of prescription drugs in Medicaid is different than in the private sector.¹⁴ A three-year claims-based analysis of one state's Medicaid program found that changing prescribing patterns was the factor most responsible for rising prescription expenditures in this population. The findings further showed that individual drug prices did not increase markedly, but that prescribing patterns dramatically shifted to favor new higher cost medications over the study period.¹⁵

Medicaid Drug Rebates

Apart from the overall Federal matching of expenditures, policy provisions have been made to obtain Medicaid prescription drugs at prices lower than in the private sector. Created by the Omnibus Budget Reconciliation Act of 1990 (OBRA'90), the Medicaid Drug Rebate Program requires a drug manufacturer to enter into and have in effect a national rebate agreement with the Secretary of the Department of Health and Human Services (HHS) for states to receive Federal funding for outpatient drugs dispensed to Medicaid patients. States that wish to pursue Medicaid supplemental rebates in addition to rebates already received under the

national drug rebate agreement have the option to negotiate such rebates with drug manufacturers as specified in Federal law. Currently, 33 states are receiving Medicaid supplemental rebates in addition to those received under the National Rebate Agreement. Approximately 550 pharmaceutical companies currently participate in this program.⁶

However, despite Federal assistance and drug rebates, prescription drugs constitute the second largest and fastest growing state Medicaid expenditures. Such expenditures are often a severe burden – especially for poorer states like Mississippi (19.7 percent of total state budget) and West Virginia (17.5 percent of total state budget).¹¹

Medicaid drug cost control initiatives

States have put various administrative and policy measures in place with varying degrees of strictness to control the high rate of growth of prescription drug costs under Medicaid. Efforts like – a “formulary” or “preferred drug list (PDL)”, “prior authorization (PA)”, “drug utilization reviews (DUR)”, “fail-first” or “step therapy” requirements, “quantity limits”, “generic substitution” and “cost-sharing” – are among the most commonly adopted administrative measures.

In 2005⁴:

- 43 states implemented new pharmacy cost controls;
- 50 states froze or reduced payment rates for at least one group of providers among hospitals, physicians, or nursing homes;
- Eight states imposed new or higher beneficiary co-payments;
- Eight states imposed eligibility restrictions; and
- Seven states restricted or reduced benefits.

However, the futility of such measures have been captured in a recent survey which reports that despite state budget-driven cost containment initiatives, Medicaid spending in the financial year 2004 grew by 9.5 per cent – faster than other state programs.¹⁶ Drug costs have been found to be among major drivers of such an increase.¹⁶

Variations in Medicaid drug expenditures

Medicaid, unlike Medicare, is not essentially uniform across the nation – since the eligibility criteria and services provided differ considerably among states. Thus there are actually 56 different Medicaid programs – one for each state, territory, and the District of Columbia.¹⁷ It is not a surprise, therefore, that increases in prescription drug expenditure is not uniformly distributed across all Medicaid beneficiaries and programs. It varies by population groups and by states.

As with all health insurance programs, most Medicaid beneficiaries incur relatively small average expenditures per person each year, and a relatively small proportion incurs very large costs. Moreover, the average cost varies substantially by type of beneficiary. National data for 2000, for example, indicate that Medicaid payments for prescription drugs for 12.1 million child recipients, who constitute 46 percent of all Medicaid beneficiaries, average about \$170 per child, a relatively small average expenditure per person. Similarly, for 5.5 million adult drug recipients, who comprise 21 percent of beneficiaries, payments average about \$360 per person.¹⁸ On the other hand, certain other groups have much larger per-person drug expenditures. For example, Medicaid payments for prescription drugs for 3.4 million aged, constituting 13 percent of all Medicaid beneficiaries, average about \$1,590 per person.¹⁸

Although Federal assistance and supplemental drug rebate negotiations are directed at reducing program differences among states, individual Medicaid programs are also not

necessarily faced with similar levels of expenditure burden. While the current pattern of federal Medicaid matching payments reduces policy variation to some extent, these effects are found to be rather modest and fiscal incentives provided by matching rates are found to be comparatively weak instruments for national policymakers.¹⁹ Findings of a study indicated that under the current Medicaid matching formula, fewer federal subsidy dollars per poor person go to states with lower per capita incomes and to states with a higher percentage of African-Americans than to states with the opposite characteristics.²⁰

Hence, major differences exist in per capita drug costs across state Medicaid programs. Table 1 presents the range of per capita drug expenditures by Medicaid programs each year over the last few years. Minimum prescription drug payments per recipient increased from \$430 per Medicaid recipient in New Mexico in 1998 to a high of \$765 per recipient in Georgia in 2001. Connecticut has always been the most expensive in terms of drug expenditure and ranged from \$1,722 per recipient in 1998 to \$2,886 in 2002. Mean and median payments per recipients have been growing each year and the range between the minimum and maximum payments has been continuously widening in the 1998 – 2002 time period.

Prior research

Several studies are available in health policy literature that have attempted to explain such variations by understanding the determinants of Medicaid drug expenditures.

Some studies have examined demographic determinants. Johnshrud and Lawson (1995) found tenable relationships between demographic characteristics, and previous and subsequent prescription costs, prescription utilization, and deviation in prescription costs among Medicaid nursing home residents in Texas.²¹

Table 1. Range of per recipient drug expenses across state Medicaid programs*

Year	Minimum per capita drug payments	State	Annual growth	Maximum per capita drug payments	State	Annual growth	Range width for per capita drug payments	Annual growth
1998	\$430	New Mexico		\$1,722	Connecticut		\$1,292	
1999	\$507	Maryland	18%	\$2,029	Connecticut	18%	\$1,522	18%
2000	\$607	Texas	20%	\$2,340	Connecticut	15%	\$1,733	14%
2001	\$765	Georgia	26%	\$2,608	Connecticut	11%	\$1,843	6%
2002	\$696	Georgia	-9%	\$2,886	Connecticut	11%	\$2,190	19%

Source: National Pharmaceutical Council. Pharmaceutical Benefits under state Medical Assistance Programs reports 2000 through 2004

* Does not include data for Arizona and Tennessee since these two states do not have a fee-for-service pharmacy benefit structure

Ash, Ellis, and Pope et. al. (2000) used prospective diagnosis data along with demographic data to conclude that these models predicted drug costs significantly better than ‘demographics only’ models. They distinguish groups of high- and low-cost individuals and also identify a high-cost tail, with small number of very expensive people.²² Fortess et. al. (2001) identified links between specific characteristics of patients, physicians, and treatment settings, and associated changes in utilization of essential medications in a chronically ill, elderly population following New Hampshire Medicaid’s three-prescription monthly reimbursement limit.²³ Using several models combining demographic characteristics with health status measures, Wrobel, Doshi, and Stuart et. al. (2003) managed to explain approximately 23 percent of the variations in drug expenditure – up from only 5 per cent using just demographic variables.²⁴

Several researchers have examined effects of policy (and its changes) on Medicaid drug expenditure. A RAND study for the National Institute on Aging (1999) found that availability of insurance coverage for prescription drugs, including Medicaid, significantly increases the probability of use but not total expenditures.²⁵ Lexchin (2002) reviewed the impacts of several individual or multi-state Medicaid program interventions like – restricted formulary, drug category exclusion, prior authorization, prescription cap and co-pay, drug protocol enforcement, supply restriction etc., and found them to have only had mixed effects at best.²⁶ Soumerai (2003), in a review of stand-alone and comparative studies that analyzed effects of New Hampshire’s 3-drug payment limit or ‘cap’, concluded that while the policy was able to reduce the use of prescription drugs among the elderly and the mentally ill patients – it caused secondary increases in other services utilization showing that such policies may actually experience adverse effects in cost owing to compensatory measures that create more expenses in

other parts of the program.²⁷ Using a simulation model, Domino, Olinick, and Sleath, et. al. (2004) concluded that ‘supply restriction’ from a 100-day to a 34-day limit may actually increase cost of drug therapy in the North Carolina Medicaid program.²⁸

Simmons, Payne and Smith (1986) attempted to explain variations across Medicaid programs by studying cost factors for Medicaid drugs to identify variables that raise or lower drug expenses.²⁹ The authors identified that strategies like supply restrictions, dollar limit on prescriptions, eligibility restrictions, and prescription drug category exclusions tend to lower drug expenditure. On the other hand, larger pharmacist fees, minimum supply requirements, OTC drug category exclusions were found to be associated with higher drug costs.

1.2 Need for the study

Policy initiatives and Medicaid program interventions have not shown convincing effects in controlling drug expenditures in pharmacy benefit programs across states. Variations in the level of drug expenditure across states add another level of complexity in framing policies.

At the heart of such issues lie the basics of why and how care is sought. Studies have shown the reasons that lead a person to visit a physician (and hence get prescriptions) result from a complex interaction of different factors such as demographic, socioeconomic, psychological, morbidity profiles, and health services availability.^{30,31,32,33} Additionally, while these factors would explain utilization and costs in one area, other related areas need to be considered as well since analyses of the health-care system as a whole has also shown that the efforts to constrain spending with budget in one area can lead to higher total costs due to increases in others.³⁴

Existing literature offers some insights into the drivers of drug expenditure in general. However, there remains a need for a more detailed investigation at the key influencers or

predictors of Medicaid drug expenditures that takes into consideration more of the factors mentioned above and which would help explain the wide variations in drug expenditure across state Medicaid programs presented earlier in Table 1. Prior research has mostly restricted its focus to specific programs, policies, and demographic aspects, and therefore, does not examine the interaction among the effects of these determinants. For example – while some studies have examined impacts of demographic and health status determinants on drug expenditure – they have been lacking in consideration of policy or access issues, and vice versa. Additionally, although findings from these studies have shown that demographic characteristics and health status are important influencers of drug utilization, the impact of policy and program measures have been shown to be generally inconclusive, at best. Further, several other potential influencers – like access to medical care, and the basic abilities to seek such care have not been studied at all. Hence, it is difficult for Medicaid policy-makers, based on existing knowledge, be able to identify key policy impact areas available to them; and subsequently, to be able to make appropriate budgetary allocation or intervention decisions.

For the publicly funded drug assistance program to be sustainable in the long term, it is important that potential influencers and predictors of Medicaid drug expenditures are identified, and the degree of their influence and inter-relationships are established. Furthermore, an understanding of state characteristics related to such determinants is important.

Taken together, findings from such a study will not only allow for more informed policy and administrative decisions, but will also enable their customized implementation based on state characteristics. Consequently, this will likely lend a higher level of predictability of the outcomes of policy and program interventions in individual states and at the national level.

1.3 Conceptual framework

The need for a more inclusive examination of the determinants of Medicaid drug expenditures will be addressed by developing a model that attempts to include impacts of as many logical potential determinants of drug utilization and expenditure as possible. Inter-relationships between the identified factors will also be explored to establish relative importance in explaining and predicting state Medicaid program-level drug expenditures.

A review of health policy literature led to the “Andersen’s Behavior Model of Health Services Utilization” (Andersen’s model) which is considered to be a comprehensive model of the demand for health services.³⁵ This model has been widely used for modeling health services utilization as well as for analysis of factors associated with pharmaceutical expenditure.^{36,37} This model concentrates on individual determinants of use-behavior and attempts to capture all socioeconomic and behavioral factors that may influence a person’s decision to use health care.

Some studies of healthcare services utilization have used other kinds of regression-based models like the ‘hierarchical level of determination’ used in epidemiological studies of determinants of an outcome, for example.³⁸ However, the Andersen model fitted our current purpose better than any other since it offers an ideal framework to identify potential determinants of utilization and costs, and is well established in its use in research similar to the study at hand.

Originally, the model was developed to understand why families use healthcare services; to define and measure equitable access to health services; and to assist in developing policies to ensure equitable access. The initial model suggested that people’s use of health services is a function of their predisposition to the use of such services, factors which enable or impede use, and their need for care. According to this version of the model, the decision of an individual to

use health services depended on a sequence of conditions grouped into three components: predisposing characteristics, enabling resources, and the need for healthcare.

The predisposing component includes variables describing individual factors that are indirectly associated with service-use and are not considered to be a specific reason for using medical care services. Predisposing characteristics are endogenous and do not offer much room for external influence or alteration. Demographics like age, gender, race, disabilities, and others that are included in this category represent biological imperatives suggesting the likelihood that people will need health care.

The enabling component includes variables that allow the means for an individual to seek medical care, when necessary. Enabling resources allow the actual use of health services to take place and influence the ability-to-pay for medical care services. Both community and personal enabling resources are required for use to happen. Such resources include the know-how for the people to be able to identify a health care need and to seek out appropriate care. Demand-side factors, such as employment status, monthly income, and expenditure are variables that fall under the enabling component. Also, resources like education, job, and health insurance play major roles as enabling factors.

Given the existence of both predisposing and enabling conditions, use of medical services by individuals finally depends on the perceived ‘need for healthcare’ which is guided directly by some conditions that form the nature of the need. The aspect of need considers how people view their own general health and functional states and how they experience the symptoms of illness, pain, and worries about their health, and whether or not they judge their symptoms to be sufficient and important enough to seek professional help.

A newer, more inclusive version of Andersen's model also adopts externalities and is more suitable to use in the current context.³⁹ This model is shown in Figure 2. In addition to the socio-economic and behavioral components described above, the new version explicitly recognizes the importance of health policy and resources and their organization as important determinants of a population's use of health care services. The importance of policy (in this case, Medicaid program policies) as important drivers of utilization and cost was established in this model.³⁹ Also, the impact of policies on health care delivery resources and their organization has been included in the model.³⁹

The operational model

Andersen's model was modified to make it suitable to the purpose of this study. Since analysis of the outcomes of drugs and medical care utilization (like perceived and evaluated health status, and consumer satisfaction) is beyond the scope of this study, the 'Outcome' component of the model was dropped.

The operational model, shown in Figure 3 was hypothesized using the three major constructs – a) Health system characteristics, b) Population Characteristics, and c) Drug Utilization. Each of these constructs are hypothesized to have individual content, as described in the following section, and are measured by Medicaid or state related variables elaborated in Chapter 3 within the section on operational variables.

1.3.1 Health system characteristics

These are 'environmental' factors that shape and influence access to and utilization of health care services and in turn will include:

Figure 2. Andersen's emerging model of Health Services Utilization

Source: Andersen RM. Revisiting the Behavioral Model and Access to Medical Care: Does It Matter? Journal of Health and Social Behavior. 1995;36(March):1-10

Figure 3. Operational conceptual model

- a) Policy factors: Medicaid and related policy factors are important since they in most parts determine the access and the extent of care available to the lower socio-economic group that is served by Medicaid. More recent policy shifts (beginning in the early 1990s) toward managed Medicaid have placed renewed emphasis on minimizing program expenditures, expanding access, and reducing cost-ineffective interventions.⁴⁰ Medicaid specific policy and program characteristics like enrollment in managed care, program-specific drug cost management interventions (prior authorization, preferred drug lists, prescription and supply limits, among others), or federal matching and supplemental rebates – among others would be some key variables in this area.

For example, more widespread use of generic medications represents an important source of unrealized savings in Medicaid drug coverage programs but the policy has not been adopted by all states to-date.⁴¹

- b) Healthcare resources: these will include environmental or community enabling factors like availability of providers and points of delivery of health care, namely physicians, hospitals, and pharmacies.

Studies have suggested that a large part of the overall problem of health disparities in the United States may be the result of regional or population differences in access to medical care. In a recent analysis, researchers found that black and white patients are largely treated by different physicians; 80 percent of the primary care visits for blacks receiving Medicare are handled by just 22 percent of all physicians.⁴² The study also found that the physicians treating black patients are more likely to face obstacles in getting their patients access to high-quality services.

Since racial and ethnic minority dwellings tend to cluster in areas where physician practice patterns are affected by Medicaid, changes in Medicaid policies are bound to impact minority Medicaid beneficiaries disproportionately.

In addition, the influence of site of care on medication use is a well-reported phenomenon and can operate through a number of pathways. One study evaluating quality of asthma care reported that community health centers are generally unable to provide quality care to traditionally underserved populations because of a lack of adequate resources.⁴³ Another study reported that adherence to practice guidelines, and hence superior quality of care provided, was more common in HMOs than in other settings.⁴⁴ Other studies have identified provider specific variations in practice patterns, such as, lesser adherence to clinical practice guidelines in community- or hospital-based clinics.⁴⁵

While overall health policies will likely have a bigger role to play, Medicaid specific policies are also expected to influence availability of and access to resources. Reimbursement levels and policies directed at ensuring access for Medicaid beneficiaries to specific sites and types of services, including – prenatal care, vaccinations, rural health clinic services, pharmacy services, hospital services, home health care, or the DSH payments to some hospitals – are expected to significantly determine medication utilization levels.

1.3.2 **Population characteristics:**

- i. Predisposing factors: these are factors intrinsic to the Medicaid populations in each individual state. In Medicaid, prescription drug expenditures are disproportionately spent for certain groups – by age, race, or disability status. Hence, these would clearly form the most important determinants of this part of the model construct.

For example, approximately 80 percent of Medicaid drug expenditures nationally are spent for the blind, disabled, or elderly, even though these groups make up only 26 percent of Medicaid enrollees.¹⁵ Studies have shown that African Americans have higher rates of nonprescription drug utilization than white Americans, but lower rates of prescription drug use. Minority utilization of prescription drugs tends to be lower even when disease and insurance coverage are controlled for.⁴⁶ Studies have also presented medical rationale and clinical evidence that suggest racial differences in benefits from specific pharmaceutical treatments for specific diagnoses.⁴⁷

Because African Americans and Hispanic Americans constitute disproportionately large shares of the vulnerable lower socioeconomic population, Medicaid is considered as a force to reduce racial and ethnic disparities in access to insurance coverage. A study found that expansions in eligibility for Medicaid between 1989 and 1995 produced greater reductions in uninsured rates among poor minority children than poor white children.⁴⁸ It seems clear that without Medicaid, any disparities in healthcare access or health outcomes between minorities and others would probably be much worse.

- ii. Enabling resources: Unlike healthcare resources – these enabling factors would be acting more at an individual or a family level. Determinants like education, employment status, income levels and health insurance would comprise the socio-economic enabling factors. These factors are expected to enable (or impede) medication utilization based on availability (or lack of) the knowledge and skills required to be able to identify a need for health services, and the ability – economic and otherwise – to seek out such services.

A study in the rural South for examining access to prescription drugs and coping strategies when households cannot afford prescription drugs found that about half of the households could not always afford needed prescriptions, and ability to pay was related positively to Medicaid coverage.⁴⁹ Households that could not afford prescriptions employed five strategies: prioritizing, financing, rationing, substituting, and postponing drug use – thus directly impacting utilization.

- iii. Need for healthcare: Need for healthcare originally was explained as people's personal assessment of their need for seeking professional help. Such needs will be described in this study in terms of – disease prevalence, severity of diseases and health risk behaviors.

Predisposing factors – since they correlate greatly with social and economic status are expected to influence the need for healthcare as studies have shown that despite much progress in closing the health insurance coverage gap, minorities continue to experience significant disadvantages in health outcomes.⁵⁰ Also, enabling resources will likely influence the need for healthcare in the manner that higher availability of enabling resources will increase the perception of need by creating awareness and the know-how to identify health problems and risk behaviors and to seek out remedial measures for those.

Prevalence of diseases indicates the existence of health problems in the community. Differential rates of diseases will also likely be indicative of the level of awareness and healthcare seeking behavior of the people in the community. Health risk behaviors like smoking, (lack of) exercise, or obesity indicate levels of the health risk such behaviors present.

Disease severity is another important aspect of the need for healthcare. Studies have found strong correlations between disease severity and higher levels of utilization for intensive care services like hospitalization. Two recent studies have established severity scoring as a predictor of hospitalization decisions for cases of acute exacerbation of chronic obstructive pulmonary diseases.^{51,52} Another study found a relationship between depressive symptom severity and hospitalization in patients with asthma.⁵³ Therefore, in the absence of direct comparable information, hospitalization data could likely substitute as a measure for disease severity levels.

Hospitalization costs are the biggest component (41 percent) of total national healthcare expenditure excluding prescription drugs.² In Medicaid, hospital expenditure accounts for about 28 percent of the total expenditure excluding prescription drugs.¹¹ Hence, for the purposes of this study, non-drug Medicaid expenditures would be used as a proxy measure of disease severity in the state Medicaid populations.

1.3.3 Drug utilization:

Finally the model will include the variable of interest (dependent variable) – state Medicaid drug expenditures which in this model will be a function of the determinants and the resulting utilization described earlier. Since state Medicaid programs vary in the size and distribution of populations they serve, total expenditures are likely to be very different and incomparable. Hence, overall drug expenditure per Medicaid eligible person will be considered as a comparable parameter in the model.

1.4 Study data:

Most of the Medicaid related resources and utilization data will be available from the National Pharmaceutical Council reports since they regularly collect and report data using CMS reporting forms that include all Medicaid related statistics at the state and national levels. Other data on population characteristics will be collected from publicly available sources like the Kaiser Family Foundation reports, and the United Health reports, which provide state-level data on demographics, health, and health policy, including health coverage, access, financing, and state legislation and budgets.

1.5 Analyses:

As a first step, correlation matrices among variables measuring different constructs of the study model will allow a quick view of the relationships and dependencies existing among them.

Moving forward, perhaps the most common approach towards evaluating predictors of per capita drug expenditure would be to perform a regression analysis. All identified variables can be regressed on the dependent variable to assess the relative importance and direction of relationship of the predictor variables with the outcome variable described in the model.

However, a straightforward regression will fail to capture potential impacts of time on the nature of the predictor variables. In addition, only one-way impacts (β -weights) will be analyzed in an ordinary multiple regression calculation. Thus, in order to understand inter-relationships among different variable constructs and the variables themselves, a structure equation model will be a preferred analysis method.

Further, a classification method like cluster analysis will be useful in classifying the state Medicaid programs into distinctly similar groups – thus allowing some amount of predictability in the need and potential outcome of Medicaid policy and intervention strategies.

In addition, given the longitudinal nature of the data, time series analyses could be performed to assess time-adjusted effects of the indicator variables. However, while times series usually refers to multiple observations equally spaced over time on a single unit of analysis, panel data usually refers to a relatively few observations on a relatively larger number of cases. Hence, the study data – five years for 48 states, would be more suitable for panel data regression methods to establish a predictive model for Medicaid per capita drug expenditures based on key determinants identified in the model.

1.6 Goal of the study

This study aims to identify determinants of Medicaid drug expenditure per capita and assess their importance in classifying state Medicaid programs into similar groups, and in predicting future prescription drug expenditures.

1.7 Specific Objectives

The above goal will be achieved through the following objectives:

1.7.1 Objective 1

To develop and test a model assessing relationships among potential influencers/ predictors of Medicaid drug expenditures identified based on Andersen's Behavior Model for Health Services Utilization.

As discussed in an earlier section, the examinations of drug cost issues have typically lacked a degree of comprehensiveness which makes their findings rather inconclusive. This study, as indicated, attempts to include all potential types of influencers and determinants of drug costs – from population characteristics to policy issues, to access, and resources available. A detailed account of all potential variables and types are presented later in Chapter 3 in section on ‘operational variables’.

It is critical that a relative importance of these different types of variables is established towards their influence on drug costs. This is because while some types of variables may not be ‘actionable’ (i.e. it may not be possible to intervene and change their values in any way; for example – age, race etc.), there could be others which policy makers may want to allocate higher (or lower) resources for – based on how they impact cost (and health) outcomes.

This objective will propose a structural relationship among the identified potential determinants based on Andersen's model. The model hypothesis will then be tested to evaluate how much it explains the actual relationships among these variables.

1.7.2 Objective 2

To classify state Medicaid programs into homogeneous clusters based on similarities in their characteristics as measured by the prescription drug expenditure and its influencers/ predictors.

Ability to identify homogenous groups among state Medicaid programs will likely be a useful policy input. Such groupings will help customize Medicaid interventions and strategies and members of a group will likely have similar outcomes of any given intervention. The predictability among homogenous groups allows sharing and replication of strategies that have worked for one program to another. It also provides opportunities to rectify and fine tune strategies in one program in view of results achieved in another similar program. It is therefore important to examine if there actually are homogenous groups of Medicaid programs that have similar characteristics and would potentially react similarly to cost intervention strategies.

This objective will attempt to identify homogenous groups (or clusters) of Medicaid programs based on drug expenditures and their determinants.

1.7.3 Objective 3

To establish a predictive model for Medicaid prescription drugs expenditure based on time-adjusted impacts of key influencers/ predictors.

Finally, this study will identify a model to predict Medicaid drug expenditures per eligible. This model will be based on the effects of key variables identified using the Andersen model which will be time-adjusted to tease out pure effects of such variables.

1.8 Significance of the Study

Use of the model described above will allow for a detailed and more extensive analysis of the determinants of Medicaid drug expenditures. This model will not only look at demographic characteristics and policy interventions that have been separately studied earlier – but will also include a view of important factors like available community and personal enabling resources, as

well as the need for healthcare. Hence, this study proposes to add valuable insights into the determinants of Medicaid drug costs per eligible that can be utilized by Medicaid administrators, policymakers, and other interested audiences.

A major benefit of using this model also is the estimation of ‘mutability’ of variables or components of in the model – and hence is expected to be of practical and actionable significance to Medicaid administrators and policy makers. Mutability refers to the extent a factor can be altered or influenced to bring about more favorable outcomes – in terms of utilization and hence, drug costs in this case. Generally, demographic factors are considered not so mutable, at least, not in the short term since the proportions and distributions of gender, race, and age in a population take time to alter – even with policy driven efforts. However, most other determinants in the model can be considered sufficiently mutable and an analysis of their relative degree of influence can provide excellent decision support for policy makers.

Future analyses can incorporate findings from this study into a model using the principles of system dynamics to simulate and test impacts of intervention strategies on the mutable components in a life-like, risk-free economical way – before such interventions are tried out in the real world. Such capabilities will not only allow more informed decisions, but also will expectedly bring about direct savings and optimal allocation and utilization of resources by reducing outcome uncertainties by a considerable degree.

1.9 Limitations

As with any study in the area of health policy – relevance of the variables and their measurement are critical to the study’s making any meaningful contribution to policy inputs. While utmost diligence has been exercised in identifying variables meaningfully relevant in the

Andersen model – there likely would be others that were either not identified, or were not measurable based on publicly available historical data. Additional components, when identified, could be worth adding to the model to increase its fit to the real world. While a good fit for the proposed framework will offer insights into the relationships among different constructs, lack of a fit will also point towards the need for further exploration in terms of key variables that might have been omitted in the current study.

Small size of the sample will likely be a limitation for the study with respect to generalizability of the findings. However, since the data are related to state Medicaid programs there are only 48 data points (excluding Arizona and Tennessee, since they operate differently) available for each year. By using data for five consecutive years, the study will attempt to overcome this limitation and to come up with broad-based findings and recommendations which can be further validated through future research. Although the results and conclusions from this study may have a higher margin of error than those involving larger datasets – indicative inferences from the study are expected to offer useful pointers for policy.

2 Chapter Two: Literature Review

This section offers an overview of the literature in areas related to the study variables and methods. First four sections of the chapter offer additional insights into the Medicaid program, drug related cost containment issues, an assessment of the use of Andersen's model as a conceptual framework, and a look at how structure equation modeling (SEM) has been used in related studies. Rest of the chapter offers existing knowledge about the trends and findings on potential study variables and constructs, and is according to where they belong on the operational model described earlier in chapter one.

2.1 The Medicaid Program

Title XIX of the Social Security Act is a Federal/state entitlement program that pays for medical assistance for certain individuals and families with low incomes and resources. This program, known as Medicaid, became law in 1965 as a cooperative venture jointly funded by the Federal and state governments (including the District of Columbia and the Territories) to assist states in furnishing medical assistance to eligible needy persons. Medicaid is the largest source of funding for medical and health-related services for America's poorest people.⁵⁴

Medicaid is also the single largest source of health care coverage in the nation, providing coverage to an estimated 58 million. This includes approximately 7 million Medicare beneficiaries (dual eligibles) who are also eligible to receive services such as long-term care through Medicaid.⁵⁵ Medicaid is the main source of funding for people in nursing homes. Nearly 60 percent of those in nursing homes have Medicaid as the primary source of payment.⁵⁶ Medicaid also finances one-third of all births in the United states and is the largest source of federal spending for HIV/AIDS care in the country.^{57,58}

The Kaiser Commission on Medicaid and the Uninsured (2003) describes the critical role Medicaid plays in insuring people in rural areas, filling in the gaps in the private insurance system.⁴ Nearly 16 percent of people who live in rural areas have Medicaid coverage – compared with about 10 percent of people in urban areas. Higher rates of Medicaid enrollment in rural areas help to offset lower rates of employer coverage, reducing the number of rural uninsured. Medicaid covers more than one in four children in rural areas. 27 percent of children in rural areas are enrolled in Medicaid, compared with less than 19 percent of children in urban areas. People in rural areas have greater health care needs, which Medicaid helps them cover.⁵⁹

Medicaid indeed is among the most critical public programs for providing healthcare to America's indigent population.

2.2 Medicaid cost containment

Escalating Medicaid costs are high on the health policy agenda, nationally and at the state levels. It is the second most costly federal health care program (after Medicare) and the most costly health program for most, if not all, states. Between 2000 and 2003, Medicaid spending grew by one-third, largely as the result of enrollment growth driven by the economic downturn.⁶⁰ The Congressional Budget Office (CBO) projects that, over the next five years, federal Medicaid spending will grow an average of 7 percent per year, from \$183 billion to \$260 billion.⁶¹ At some point during this year, CBO estimates, Medicaid will provide health or long-term care coverage to over 58 million people, or about one out of every five Americans.

At about \$34 billion, prescription drugs formed 13 per cent of the total net Medicaid expenditures in 2003 at an annual growth rate of 15 percent – almost three times the total expenditure growth rate of 5.8 percent.^{7,11} In fact, overall expenditure on pharmaceuticals in the

United states has been growing at a disproportionate rate compared to the Consumer Price Index (CPI) as well as to the cost of other components of health care.³

As a result of increasing prescription drug costs, all 50 state Medicaid programs have implemented some sort of cost-containment mechanisms in their drug programs over the past few years. These mechanisms have allowed states to contain their pharmacy expenditures and maintain beneficiary access to a vital part of their overall healthcare.⁴ Figure 4 presents some of the key cost containment strategies adopted by states.

Gencarelli (2003) explains the mechanisms being used by states to control their prescription drug spending within the Medicaid program.⁶² The author describes these various strategies as having been directed in one of two ways:

- Strategies Directed at Beneficiary Drug Utilization – including strategies and programs like prior authorization, preferred drug lists/formularies, mandatory use of generic drugs when available, increased co-payments or limits on prescription drugs, disease management, pharmacy benefit managers (PBMs) and managed care organizations (MCOs), step therapy/fail first policies; and
- Strategies directed at drug manufacturers and pharmacies, including: supplemental rebates, changes in dispensing fees and reimbursement formulas, purchasing pools, pharmacy assessment surcharges, etc.

Cost containment in the provision of drug benefits in Medicaid is an issue of national importance and is on the priority lists of states and the Federal government alike.

Figure 4. Putting the brakes on Medicaid spending

Source: Kaiser Commission on Medicaid and the Uninsured, 2004

2.3 Anderson's Behavior Model for Health Services Utilization

Andersen's model (Andersen, 1995), was developed to study determinants of acute care health services use.³⁹ It has since been used frequently in a variety of health services utilization studies. The model posits that health services use is determined by societal factors, health services system factors, and individual factors. Individual or population factors, the focus of many empirical studies, are categorized as predisposing factors, need, and enabling factors. Predisposing factors include age, sex, marital status, education, race/ethnicity, and occupation, as well as a set of beliefs (e.g., attitudes toward health services, knowledge about disease, and values). Enabling factors encompass family and community resources and accessibility of those resources. Need includes individuals' perceived and evaluated functional capacity, symptoms, and general state of health.

The model has been widely used in a variety of healthcare utilization studies.

In a RAND study, Kubrin (1995) used Andersen's model to develop and test predictive expectations about the role of health insurance in the use of hospital and physician services.⁶³ As expected, health insurance status was found to be a predictor of physician use and not of hospital use. However, contrary to expectation, health insurance was also found to be a predictor of hospital and physician use for those in poorer health. The results underscored the national debate concerning the uninsured and their access to health care, particularly for those in poorer health.

Chen and Chang (2002) investigated the factors associated with prescription drug expenditures among children based on the Medical Expenditure Panel Survey (MEPS).⁶⁴ The authors used Andersen's model to construct independent variables that impacted drug expenditure, the dependent variable. Two-step regression method was used to analyze the data. Although not specific to the Medicaid population, the study concluded that socioeconomic

characteristics such as race, insurance status and family income levels had significant impact on pediatric prescription drug expenditure, even after controlling for the influence of health state and medical conditions.

Chern, Wan and Begun (2002) used Andersen's model to examine the relative importance of determinants in predicting future health expenditures, using structural equation modeling.⁶⁵ Based on Andersen's model, the authors evaluated the individual determinants of health expenditure. Indicator variables included prior utilization and measures of health status from 1994 which were analyzed in a longitudinal design for their predictive power for health expenditures in 1995. The authors found that excluding, prior utilization in 1994, health status and having diabetes were two statistically significant predictors of health expenditures in 1995.

Dobalian and colleagues (2003) examined differences in health and access to dental services among a nationally representative sample of patients with HIV using Andersen's model.⁶⁶ This investigation was a longitudinal study that used structural equation modeling to analyze data from the HIV Cost and Services Utilization Study, a probability sample of 2,864 adults under treatment for HIV infection. Key predisposing variables included – sex, drug use, race/ethnicity, education, and age. Enabling factors included income, insurance, and regular source of care. Need factors included mental, physical, and oral health. Dependent variables included whether a respondent utilized dental services and the number of visits to a dentist. More education, dental insurance, usual source of dental care, and poor oral health predicted a higher probability of having a dental visit. African Americans, Hispanics, those exposed to HIV through drug use or heterosexual contact, and those in poor physical health were less likely to have a dental visit. Of those who visited dental professionals, older persons, those with dental

insurance, and those in worse oral health had more visits. African Americans and persons in poor mental health had fewer visits.

The model has also been frequently used to estimate utilization of long-term care. For example, Kim and Kim (2004) employed the model to estimate future demand for institutional long-term care by Koreans.⁶⁷ The variables were identified using Andersen's model. A stronger intention was related to younger age, Christian religion, fewer children, lower family income, higher chronic co-morbidity, and more education.

Galbraith and colleagues (2005) recently used Andersen's model to select predisposing, enabling, and need variables as independent variables that could affect health care use and expenditures in a multivariate analysis.⁶⁸ Predisposing variables included: family size, race/ethnicity, highest educational level, geographic region of residence, and residence in a metropolitan statistical area (MSA). Enabling variables included family income (in categories based on percent of the Federal Poverty Level [FPL]), and health insurance. Need variables included: whether the worst reported health status of any family member was fair or poor, and whether any family member was reported to have any limitation of activity.

Despite the model's wide use, there has been some criticism about its appropriateness for all types of health services utilization research. Bradley and colleagues (2002) proposed that although the Andersen model identifies predisposing, enabling, and need factors as determinants of service use, it does not explore fully how these three domains, or their measures, are interrelated.⁶⁹ For example, the model combines race/ethnicity with other demographic characteristics included as predisposing factors. Although these predisposing characteristics are similar in that they have low mutability, each variable may interrelate with the other factors in

different ways. This is potentially problematic in studies of race/ethnicity, in which omission of such interrelationships may oversimplify the role of race/ethnicity in service use.

Nevertheless, the Andersen model is well accepted as an important framework for explaining and measuring health services use in general. However, no published research was found that used this model to study Medicaid drug expenditures.

2.4 Use of Structure Equation Model in studies of healthcare utilization

SEM has been chosen as an appropriate method for several studies in this area owing to some key considerations as described by Byrne (2001):⁷⁰

- Since SEM takes a confirmatory, rather than an exploratory, approach to the data analysis and since it demands that the pattern of inter-variable relations be specified a priori – it lends itself well to the analysis of data for inferential purposes as in the current study.
- Unlike other multivariate procedures that are incapable of either assessing or correcting for measurement errors, SEM provides explicit estimates of these error variance parameters.
- Although data analyses using other methods is based on observed measurements only, those using SEM procedures can incorporate both, unobserved (or, latent) and observed variables.
- SEM is most suited for non-experimental research studies as the current one, since unlike other methods, SEM offers ease of modeling multivariate relations and of estimating point and/ or interval indirect effects.

Stiffman and colleagues (2001) used a SEM approach similar to this study with variables generated based on the Andersen model.⁷¹ They tested organizational context and provider perception as determinants of service use in mental health. The authors refined and tested an individual client model of service use, and then contrasted it with a similar model of service

provision based on gateway provider perspectives. SEM models demonstrated that provider variables account for more service use variation than client variables. The study found that youth self-reported mental health was not positively associated with increased services, or with provider perception of youth mental health. The provider model demonstrated the critical role played by provider perceptions, which are influenced more by work environment (the organizational predisposing and enabling factors of burden and resource knowledge) than by client problems.

Chern, Wan and Begun (2002) applied SEM techniques to examine the relative importance of determinants in predicting future health expenditures.⁶⁵ Some of their independent variables were based on Andersen's model. They evaluated individual determinants along with prior utilization and measures of health status from 1994 in a longitudinal design for their predictive power for health expenditures in 1995. The authors found that prior utilization in 1994, health status, and having diabetes were the most important predictors. The study concluded that Health status is a powerful predictor of future health expenditures, even when prior utilization is controlled.

A number of other studies have used SEM approaches in the different areas of healthcare. Smith, Avis and Assmann (1999) used SEM to understand how patients make determinations of QOL and whether QOL can be differentiated from health status.⁷² They conducted a meta-analysis of the relationships among two constructs (QOL and perceived health status) and three functioning domains (mental, physical, and social functioning) in 12 chronic disease studies. A single, synthesized correlation matrix combining the data from all 12 studies was used to estimate structural equation models. The authors concluded that, from the perspective of patients, QOL and health status are distinct constructs. When rating QOL, patients give greater

emphasis to mental health than to physical functioning. This pattern is reversed for appraisals of health status, for which physical functioning is more important than mental health. Social functioning did not have a major impact on either construct.

Ferraro, Farmer, and Wybraniec (1997) attempted to examine the dynamic relationships between physical disability and assessments of health among Black and White adults while simultaneously considering changing morbidity.⁷³ Results from structural equation modeling revealed that self-assessed health predicts subsequent change in health, suggesting a cycle between health problems and negative health assessments for both White and Black adults. In addition, self-assessed health among African Americans declined at a faster rate than was the case for White adults.

Hall, Milburn, and Epstein (1993) studied the causal factors in the relationship between patients with better health status, and their high satisfaction with their medical care.⁷⁴ In this study, a longitudinal assessment of these two constructs was undertaken in which older patients in a health maintenance organization were interviewed at baseline and again a year later about their health status and satisfaction with their medical care. SEM using LISREL procedures revealed that the predominant direction of causation went from earlier self-perceived overall health and functional ability to later levels of satisfaction. There was no evidence for causal paths going from satisfaction to later health.

2.5 Policy determinants of Medicaid drug costs

Several policy-related determinants have been studied in the past.

Insurance coverage

A RAND study for the National Institute on Aging (1999) investigated the impact of insurance coverage on demand for and consumption of prescription drugs.²⁵ The authors found that insurance coverage for prescription drugs, including Medicaid, significantly increases the probability of use but not total expenditures.

Administrative Policies/ Program Interventions:

In their study mentioned earlier Simmons, Payne and Smith (1986) identified variables that are linked with a ‘high’ or a ‘low’ cost state Medicaid drug program.²⁹ These authors concluded that the administrative characteristics of the two types of programs are very different. They identified that strategies like supply restrictions, dollar limit on prescriptions, eligibility restrictions, and prescription drug category exclusions tend to lower drug expenditure. On the other hand, larger pharmacist fees, minimum supply requirements, OTC drug category exclusions were found to be associated with higher drug costs. The authors did not find any influence of formulary type – open or closed – in determining overall drug costs.

Lexchin (2002) reviewed several studies from the early days of Medicaid to recent ones involving single or multi-state Medicaid programs to assess the impact of Medicaid administrative cost containment policies.²⁶ Various strategies examined include – restricted formulary, drug category exclusion, prior authorization, prescription cap and co-pay, drug protocol enforcement, and supply restriction.

Preferred Drug Lists

In the Medicaid program, preferred drug lists (PDLs) indicate which drugs providers are permitted to prescribe without seeking prior authorization (PA). In developing a PDL, the appointed committee reviews drugs by class (drugs with similar clinical indications and/or

chemical composition). Based on each drug's effectiveness, safety, clinical outcome data, and cost, several from each class are selected for inclusion in the state's PDL. The state then negotiates for the lowest possible price from the manufacturer of each drug on the list.

Mello, Studdert and Brennan (2004) found that some states have used prior-authorization programs as a vehicle to gain leverage in price negotiations with pharmaceutical companies.⁷⁵ Companies agree to sell their drug to Medicaid at a lower price, and in return, the state agrees to place the medication on the state's PDL.

Owens (2003) explains that for drugs not included on the PDL, providers must obtain approval from the state Medicaid agency (or its contractors) before a particular drug can be dispensed.⁷⁶ Decisions about which drugs to include on a PDL are usually based on the Medicaid program's assessment of relative clinical benefit within a therapeutic class and assessment about the value to the state based on total cost, including all manufacturers' rebates. Hamel and Epstein (2004) found that inclusion on this list is a strong incentive to pharmaceutical companies, which know that prior-authorization requirements are a hurdle that will almost certainly reduce the use of their drug.⁷⁷

Prior Authorization

As the name implies, 'prior-authorization' requires the submission of clinical information for review before Medicaid will pay for medications that are not on the PDL. The process requires prescribers to obtain approval before a prescription can be dispensed by a pharmacist to a Medicaid patient. Some states permit both prescribers and pharmacies to obtain prior authorization. In some states, this information is communicated by telephone; in others, clinicians complete and fax forms.

This mechanism has been a part of state Medicaid programs for many years and has been used to control the use of costly drugs or those subject to abuse. Some argue that prior authorization, which is generally linked to a state's PDL, can serve as an important mechanism for states to control the use of unnecessary or extremely costly drugs.

However, not only is information limited about the effects of prior-authorization programs on clinical outcomes, but also their effects on the costs of health care have not been fully explored. Important questions remain about the effect of prior-authorization programs on clinical outcomes. On the positive side, preferred-drug lists can improve outcomes by excluding drugs that are less safe than other drugs with similar efficacy. On the other hand, prior-authorization restrictions have the potential to reduce patients' access to beneficial drugs, especially when the requirements for documentation are onerous and the appeals process is restrictive.

Payment/ Supply limits

As states continue to explore their options for reigning in prescription drug costs, many are turning to increased beneficiary cost sharing. Although Federal Medicaid law ensures that a beneficiary will be dispensed her medication even if she cannot pay the relevant co-payment to the pharmacy. Still, several states like Georgia, Illinois, New York, North Carolina, and North Dakota have put in place differential co-pay requirements for branded vs. generic drugs.¹¹

In addition to increased co-payments, states have used prescription drug limits for beneficiaries as a means of controlling costs. These include limits on the number of prescriptions that Medicaid beneficiaries are entitled to fill each month or each year, limits on the designated number of days that constitutes a supply for each prescription, and caps on the number of refills permitted.

Soumerai (2003) reviewed the unintended outcomes of Medicaid payment limits on drug utilization vis-à-vis related utilization of other healthcare services.²⁷ The author reviewed stand-alone and comparative studies that analyzed effects of New Hampshire's 3-drug payment limit or cap. He concluded that while the policy was able to reduce the use of prescription drugs among the elderly and the mentally ill patients – it increased hospital and nursing home admissions, partial hospitalizations, distribution of psychoactive drugs by community mental health centers, and use of emergency mental health services. Hence, such containment policies may actually experience adverse effects in cost owing to compensatory measures that create more expenses in other parts of the program.

Domino and colleagues (2004) examined pharmacy expenditures associated with the dispensing of one- or three-month supplies of drugs within the North Carolina state Medicaid program.²⁸ They simulated the effect of a policy change from a maximum of a 100-day supply of prescription medication to where only a 34-day supply was allowed. The authors identified 'drug wastage' as a component of the total drug expenditure. They found that although a 5 to 14 percent saving could be achieved in wastage, such saving was not sufficient to make up for larger increase in administrative costs resulting from higher number of prescriptions being filled, as well as inconvenience for the patients in terms of time and transportation costs to more trips needed to the pharmacy. Hence, the authors concluded that 'supply restriction' may actually increase cost of drug therapy in the North Carolina Medicaid program.

Managed Care

With almost 80 percent of total Medicaid expenditures attributable to the treatment of chronic conditions, including diabetes, asthma, and cardiovascular disease, states are looking to managed care and disease management programs as a means of targeting and monitoring high

risk individuals. Some states outsource their programs to disease management organizations; others develop their own internal systems; and others work with pharmaceutical companies. Some, like Florida, combine more than one approach. Some states, including Tennessee, have chosen to use Pharmacy Benefit Managers (PBMs) to manage their prescription drug benefits. PBMs serve as intermediaries between the state Medicaid program and pharmaceutical manufacturers and are able to negotiate significant discounts. Other states have pulled prescription drugs from their fee-for-service programs and rely on Managed Care Organizations (MCOs) to manage their prescription drug benefit.

The National Pharmacy Council (2004) mentions growth in managed care as an alternative service delivery concept different from the traditional fee-for-service system to be a significant development in Medicaid.¹¹ Figure 5 shows Medicaid managed care enrollment as a percentage of total enrollment.

Figure 5. Managed Care enrollment as a percentage of total Medicaid enrollment

Adopted from: National Pharmaceutical Council. Pharmaceutical benefits Under state Medical Assistance Programs. Virginia: National Pharmaceutical Council, Inc., 2004

Managed care programs seek to enhance access to quality care in a cost-effective manner. Since 1993, managed care enrollment has increased from 14.4 percent to 60.7 percent of total Medicaid enrollment in 2004. As of June 30, 2004, all but four states (Alaska, Mississippi, New Hampshire and Wyoming) were enrolling Medicaid beneficiaries in some type of managed care plan. Under managed care systems, HMOs, prepaid health plans (PHPs), or comparable entities agree to provide a specific set of services to Medicaid enrollees, usually in return for a predetermined periodic payment per enrollee.

In a recent study, Baker and Afendulis (2005) studied two important forms of Medicaid managed care since both Medicaid Health Maintenance Organization (HMO) and Primary Care Case Management (PCCM) plans can have important impacts on health care utilization, access, and satisfaction.⁷⁸ The authors found that increases in Medicaid HMO enrollment are associated with less emergency room use, more outpatient visits, fewer hospitalizations, higher rates of reporting having put off care, and lower satisfaction with the most recent visit. Medicaid PCCM plans are associated with increases in outpatient visits, but also with higher rates of reporting unmet medical needs, putting off care, and having no usual source of care.

Reimbursement rates

Gencarelli (2003) describes Medicaid reimbursements for prescription drugs.⁶² Medicaid payments for prescription drugs include two components: (a) estimated acquisition costs (EAC), and (b) dispensing fees. Both the acquisition costs, which cover the cost of the drug itself, and the dispensing fees, which cover the cost of filling the prescription, are paid to the pharmacy.

According to a recent report from the federal Department of Health and Human Services (2005), most states and the District of Columbia use average wholesale price (AWP) minus a discount percentage in calculating EAC.⁷⁹ Eight states use wholesale acquisition cost (WAC)

plus a markup percentage in their EAC formulas. Six of these eight states use the lower of both AWP and WAC.

AWP and WAC are prices that are published in commercial drug pricing compendia by private companies, such as First Databank and Medi-Span, based on pricing information reported by manufacturers.⁷⁹ Neither AWP nor WAC is necessarily based on actual sales transactions. The AWP is not defined in statute or regulations, and until recently, the same was true for WAC. The AWP is often considered a price for wholesalers to charge retailers. On the other hand, WAC is the manufacturer's list price for the drug to wholesalers or direct purchasers in the United States, not including discounts, rebates or reductions in price.

Motheral and Henderson (1999) noted that the Consumer Price Index (CPI) for prescription drugs grew only 12.2 percent between 1993 and 1997, whereas the average wholesale price (AWP) per prescription rose 36.6 percent during the same time period.⁸⁰

Nevertheless, Gencarelli (2002) finds that though imperfect, the AWP has come to represent a starting point for determining prescription drug reimbursement for public and private payers.⁸¹

Federal matching

The Federal Government pays a share of the medical assistance expenditures under each state's Medicaid program. That share, known as the Federal Medical Assistance Percentage (FMAP), is determined annually by a formula that compares the state's average per capita income level with the national income average. States with a higher per capita income level are reimbursed a smaller share of their costs. By law, the FMAP cannot be lower than 50 percent or higher than 83 percent.

CMS, the Federal agency administering Medicare and Medicaid programs provide some information on FMAPs for recent years.⁶ In fiscal year (FY) 2004, the FMAPs varied from 50 percent in twelve states to 77.08 percent in Mississippi, and averaged 60.2 percent overall. Accordingly, drug rebates under the provisions of OBRA 90 that are provided by manufacturers to state Medicaid programs are split in the same matching percentage.

The Federal Government pays states a higher share for children covered through the SCHIP program. This "enhanced" FMAP averages about 70 percent for all states, compared to the general Medicaid average of 60.2 percent.

A study by Ozawa (1995) indicated that under the then current Medicaid matching formula, fewer federal subsidy dollars per poor person went to states with lower per capita incomes, and to states with a higher percentage of African-Americans than to states with the opposite characteristics.²⁰

More recently, Kronebusch (2004) noted that while the current pattern of federal Medicaid matching payments reduces policy variation to some extent, these effects are found to be rather modest and fiscal incentives provided by matching rates are found to be comparatively weak instruments for national policymakers.¹⁹

Generic Substitution

Whether through mandatory substitution laws or through provider and pharmacy education and incentives, many states are working to steer patients away from costly brand-name drugs to less expensive generic alternatives. Given the potential savings that generics can offer and the relatively modest impact on most beneficiaries and providers, promoting their use has served as an important and effective cost-saving measure. States are allowed to set their own

payment ceilings for multiple source drugs – known as maximum allowable cost (MAC) limits – provided they are lower than the federal limits.

Several states have mandated compulsory dispensing of generic drugs when appropriate. Mott and Cline (2002) found that the opportunity for generic drug use exist for 63 percent of prescription orders.⁸² They also found that prescriptions covered by Medicaid were several times more likely, to be generically substituted relative to uninsured, private third party, and indemnity prescriptions. The authors believe that pharmacists are expected to play a large and important role in generic drug use and efforts to increase generic drug use directed at pharmacists should be maintained. Additional efforts, like academic detailing, to increase generic drug use have also been targeted at prescribers.⁸²

Government support

Expenditure on healthcare is a big chunk of the state budget. Government support to healthcare can be estimated through the proportion of state budgets that are allocated to the care of the indigent. Medicaid, as mentioned earlier, is the biggest component of the state healthcare budget, and is constantly demanding bigger shares of the state budgetary outlay. A study by Fields (2005) found that although most states had collected more tax dollars than originally expected in the first eight months of fiscal 2005 – states are facing rising costs for Medicaid and other health care programs, more than the demands from K-12 education, prisons, state parks, and other sectors.⁸³ In fact, the National Governors Association (NGA) recently reported that Medicaid has surpassed Medicare to become the country's largest health care program and has just surpassed K-12 education as the largest single portion of state budgets.⁸⁴

Thus, policy interventions have shown varying degrees of success in influencing drug expenditure in Medicaid. What is interesting to note, though, is that although effects of

individual policies have been studied in small settings, no research was found that looks at the combined effect of these policies.

2.6 Access determinants of utilization

Access is described as the actual use of personal health services and everything that facilitates or impedes the use of personal health services. It is the link between health services systems and the populations they serve. The conceptualization and measurement of access is key to the understanding and formulating health policy because it predicts health services use, can be used to promote social justice and can be used to promote health outcomes.

Access to Pharmacies

Pharmacy participation in Medicaid and enrollee access to pharmacy services are extremely critical owing to the potential for treatment problems if appropriate drug regimens are not followed. A study by Adams and Gavin (1997) using an economic model of pharmacy participation in Medicaid found that adequacy of Medicaid payments for drugs dispensed to Medicaid enrollees positively affect county-level pharmacy participation.⁸⁵ In turn, participation rates were a positive and significant determinant of the number of prescriptions per enrollee. Pharmacy location, size, and type also affected participation rates and enrollee utilization.

Xiao, Sorofman and Manasse (2000) examined the association of pharmacy closures with prescription drug use by Medicaid recipients. The authors identified a clear decrease in prescription drug use associated with pharmacy closures. The results suggested need for directing policy attention to patients' access to prescription medications in rural areas, as relatively more pharmacies close in rural areas.⁸⁶

Access to Primary Care Physicians

The variance across states both in utilization rates and in such factors as methods of paying for physician services, the availability of physicians, income and others, permits an analysis of several policy issues relevant to the efficient financing and delivery of care to the poor.

A study by Holahan (1975) of the Medicaid providers made some interesting observations about the importance of physician availability and their decision making with respect to utilization of Medicaid drugs and services.⁸⁷ The study concluded that availability of physicians in office-based settings strongly and positively affects the level of expenditure per user of medical services, thus supporting the view that physicians can control the level of demand for their services. The level of expenditures per user was strongly related to generosity of reimbursement. Urban populations were found to be using more physician services. However, non-white Medicaid eligibles were found to have less access than their white counterparts to services of physicians even when care was free and income, education, and other factors were controlled for.

Another recent study by Greene, Blustein, and Rembler (2005) demonstrated that Medicaid managed care penetration is significantly associated with physician participation in Medicaid. This analysis indicated that a 10 percentage point increase in managed care penetration would reduce the likelihood that physicians participate in Medicaid on average by 2.9 percentage points.⁸⁸

The influence of site of care on medication use is a well-reported phenomenon and can operate through a number of pathways. Rust and colleagues (1999) evaluating quality of asthma

care reported that community health centers are generally unable to provide quality care to traditionally underserved populations because of a lack of adequate resources.⁴³

Flores and colleagues (2000) reported that adherence to practice guidelines was more common in HMOs than in other settings.⁴⁴ This finding was supported by Finkelstein and colleagues (2000) who identified lesser adherence to pediatric clinical practice guidelines in community- or hospital-based clinics.⁴⁵

A recent analysis by Bach and colleagues (2004) suggested that a large part of the overall problem of health disparities in the United states may be the result of regional differences in treatment and outcomes.⁴² The researchers found that black and white patients are largely treated by different physicians; 80 percent of the primary care visits for blacks receiving Medicare are handled by just 22 percent of all physicians. That study also found that the physicians treating black patients are more likely to face obstacles in getting their patients access to high-quality services.

Thus, access to medical care resources plays an important role in Medicaid drug utilization.

2.7 Demographic determinants of Medicaid drug costs

Most studies of determinants of drug utilization and expenditure have focused on demographic determinants. Fink and Byrn (2004) concluded in their study that prescription drug expenditures are disproportionately spent for certain groups in Medicaid. For example, approximately 80 percent of Medicaid drug expenditures nationally are spent for the blind, disabled, or elderly, even though these groups make up only 26 percent of Medicaid enrollees.¹⁵

Johnshrud and Lawson (1995) examined the relationships between demographic characteristics, and previous and subsequent prescription costs, prescription utilization, and deviation in prescription costs among Medicaid nursing home residents in Texas.²¹ Using stepwise linear regression methods, the authors produced statistically significant models to predict subsequent utilization and drug costs.

Ash and colleagues (2000) used prospective Diagnostic Cost Group Hierarchical Condition Category (DCG/HCC) models to describe populations and predict costs.²² These models, sponsored by the Centers for Medicare and Medicaid Services (CMS), infer medical problems from diagnoses data and combine that with demographic profiles of patients to predict costs. The authors concluded that these DCG/HCC models predicted costs significantly better than ‘demographics only’ models. They distinguish groups of high- and low-cost individuals and also identify a high-cost tail of a small number of very expensive people.

Fortess and colleagues (2001) attempted to identify specific characteristics of patients, physicians, and treatment settings associated with decreased utilization of essential medications in a chronically ill, elderly population following New Hampshire Medicaid’s three-prescription monthly reimbursement limit.²³ The authors found a mean reduction of over 34 percent in utilization of essential medication for chronic diseases as a result of the cap. Patients with the comorbidities of psychoses/ bipolar disorder, anxiety/ sleep problems, and chronic pain were associated with the largest relative reduction in prescription drug utilization. Generally, significant changes were found with patients who had higher pre-cap utilization. Also, patients of physicians in large-group practices, clinics, or hospitals were found to experience less reduction in utilization than did those who were being treated by physicians practicing solo or in small groups.

Using the Medicare Current Beneficiary Survey (MCBS) data, Wrobel and colleagues (2003) also employed the DCG/HCC methodology to identify major predictors like demographic characteristics and measures of health status.²⁴ These authors used OLS regression analysis to estimate predictability of costs using several models combining demographic characteristics with health status measures. They managed to explain approximately 23 per cent of the variations in drug expenditure – up from only 5 per cent using just demographic variables.

Children

CMS (2005) on their website present national data for 2001 which indicates that Medicaid payments for services for 23.3 million children, who constituted 50 percent of all Medicaid beneficiaries, averaged about \$1,305 per child.⁵ Rowland (2005) reports that in 2003, children formed 48 percent of total Medicaid enrollees and accounted for 19 percent of total expenditures.⁷

Expansions in Medicaid and the state Children's Health Insurance Program (SCHIP) have helped to increase insurance coverage, increase access to care, and reduce the financial burdens facing low-income families. Using data from the Medical Expenditure Panel Survey (MEPS), Selden and Hudson (2005) simulated the net cost of SCHIP, finding that the true cost of this program, both to states and to the federal government, was substantially less than average spending per enrollee.⁸⁹

However, availability of insurance is not the only determinant of children's access to health care. Mansour, Lanphear and Dewitt (2000) reported that among children who had asthma and were living in urban areas, the most commonly cited barriers to care were related to patient and family characteristics, health beliefs, and social and physical environments, in contrast to access to health care, health insurance, or continuity of health care.⁹⁰

The Elderly

Although most elderly persons over the age of 65 are covered by Medicare, there are quite a few who have supplemental benefits under Medicaid also – and are generally referred to as ‘dual eligibles’. CMS (2005) data shows that in 2001, Medicaid payments for services for 4.4 million aged, constituting 9 percent of all Medicaid beneficiaries, averaged about \$10,965 per person.⁵ Rowland (2005) reported that in 2003, elderly Medicaid enrollees continued to be at 9 percent of total enrollees but they accounted for a huge 26 percent of total expenditures showing the critical importance of the elderly in Medicaid populations.⁷

According to a recent study by Holahan and Ghosh (2005), spending growth for the aged and the disabled accounted for 56 percent of all Medicaid benefit spending growth during the 2000 – 2003 time period.⁶⁰

Two main areas of Medicaid expenditure for the elderly are nursing home and home health care services. Data on the Medicaid website shows that the Medicaid program paid for over 41 percent of the total cost of care for persons using nursing facility or home health services in 2001.⁵⁴ That data also shows that Medicaid payments for nursing facility services totaled \$37.2 billion for more than 1.7 million beneficiaries of these services – an average expenditure of \$21,890 per nursing home beneficiary. Medicaid payments for home health services totaled \$3.5 billion for more than 1 million beneficiaries – an average expenditure of \$3,475 per home health care beneficiary. With the percentage of the nation’s population who are elderly increasing faster than that of the younger groups, the need for long-term care is expected to continue to increase.

A study by Safran and colleagues (2005) found that fewer than half of each state’s poor seniors and less than 5 percent of near-poor seniors had Medicaid prescription drug benefits.⁹¹

Among seniors with Medicaid drug coverage, experiences varied widely from state to state, which raises questions about the effect of state policies related to eligibility and benefits.

The Disabled

CMS (2005) data shows that in 2001, Medicaid payments for services for 7.7 million disabled, who comprised 16 percent of beneficiaries, payments averaged about \$10,455 per person.⁵ However, Rowland (2005) reported that disabled persons continued to represent 16 percent of Medicaid enrollees in 2003, but accounted for a disproportionately high 43 percent of total expenditures.⁷

Racial Minorities

Racial disparities in prescription drug and other health service use, and the relationship of these disparities to differences in health have been explored extensively in the literature.⁹² A GAO (2003) study, for example, found that the members of racial minorities are less likely than those of non-minorities to receive appropriate medications for cardiovascular disease and AIDS.⁹³ In another study, Briesacher, Limcangco and Gaskin (2003) found that African Americans have higher rates of nonprescription drug utilization than white Americans, but lower rates of prescription drug use.⁴⁶ Minority utilization of prescription drugs tends to be lower even when disease and insurance coverage are controlled for. In yet another study, Mullins, Blatt and Gbarayor (2005) found that cardiovascular diseases disproportionately affect minority groups and are the leading causes of death among women in the United states, and both groups receive suboptimal care for the disease.⁹⁴ Similarly, Kuno and Rothbard (2002) concluded that black Medicaid beneficiaries with schizophrenia were less likely than their white counterparts to receive appropriate medications.⁹⁵

Because African Americans and Hispanic Americans constitute disproportionately large shares of the nation's vulnerable population, there is little doubt that Medicaid has been a force to reduce racial and ethnic disparities in access to insurance coverage. For example, Racine and colleagues (2001) found that expansions in eligibility for Medicaid between 1989 and 1995 produced greater reductions in uninsured rates among poor minority children than poor white children.⁴⁸

However, race is not always a cause, and differences exist even in the Medicaid policies in different states. Vargas, Davis and McCarthy (2004) found that racial and ethnic differences in health service use among enrollees were not consistent across states, suggesting that local factors, including varied Medicaid policies, may affect racial and ethnic differences in use of health care services.⁹⁶ It seems clear, however, that without Medicaid, any of these disparities in healthcare access or health outcomes between minorities and others would probably be much worse.

Headen and Masia (2005) found that despite much progress in closing the health insurance coverage gap, the disadvantaged outcomes that minorities continue to experience is caused by a host of economic, genetic, and cultural factors associated with patients and providers.⁵⁰ Burroughs, Maxey and Levy (2002) have even presented medical rationale and clinical evidence that suggest racial differences in benefits from specific pharmaceutical treatments for specific diagnoses.⁴⁷

Demographic determinants of health care utilization are thus of paramount importance in consideration of their effects on drug utilization and expenditure.

2.8 Socioeconomic determinants of utilization

Socioeconomic reasons are very commonly used to explain differences in healthcare outcomes and life expectancies between the economically diverse regions of the world. Even within the American society, socioeconomic differences have been proposed as among the most critical determinants of healthcare access, utilization and outcomes. In his study focusing on the health of rich and poor people, Seligman (2004) found that rich people live longer than poor people and those with more income, education and high-status jobs score higher on various measures of health.⁹⁷ The issue goes beyond access, since the health gap between upper and lower classes have widened in spite of programs like Medicaid. The argument presented is that low economic status translates into insecurity, stress and anxiety, all of which increases susceptibility to disease.

Education

Education is vital as consumers must be able to learn about, create and maintain a healthy lifestyle, and when necessary, understand their options for care. Kopps and colleagues (2005) examined the relations between subjective social status, and objective socioeconomic status (as measured by income and education) in relation to male/female middle aged mortality rates.⁹⁸ The authors found that education, and subjective social status of women were more significantly associated with middle aged male mortality, than were male education, male subjective social status, and income. Among the socioeconomic factors, female education was found to be the most important protective factor of male mid-aged mortality.

Poverty

A study by Muening and colleagues (2005) compared with persons living above the poverty threshold with those living below the poverty threshold. The authors found that the poor

live an average of 3.2 million fewer health adjusted life years (HALYs) per year – a difference of 8.5 HALYs per individual between age 18 and death.⁹⁹ Strickland and Hanson (1996) studied the issue of access to prescription drugs and coping strategies when households cannot afford prescription drugs in the rural south.⁴⁹ The authors found that about half of the households could not always afford needed prescriptions, and ability to pay was related positively to Medicaid coverage. Households that could not afford prescriptions employed five strategies: prioritizing, financing, rationing, substituting, and postponing drug use – thus impacting overall utilization and treatment outcomes.

Interestingly, availability of Medicaid coverage may also influence medication usage disproportionately. Rice and colleagues (2005), examining the impact of private and public health insurance on medication use, found that controlling for various demographic, health status, and employment characteristics, those with Medicaid coverage are even more likely than those with private insurance to be taking medications for chronic conditions.¹⁰⁰

Wolfgang (2004) however, point out that Medicaid does not necessarily provide medical assistance for all poor persons.¹⁷ Under the broadest provisions of the Federal statute, Medicaid does not provide health care services even for very poor persons unless they are in one of several designated groups – children, pregnant, aged, blind, or disabled. Low income is only one test for Medicaid eligibility for those within these groups; their resources also are tested against threshold levels (as determined by each state within Federal guidelines). In 2002, for example, it was estimated that only 37 percent of Americans under age 65 living in poverty were covered by Medicaid.¹⁷

Unemployment

Unemployment and lack of income have been found to be significant influencers of health status. The study by Muening and colleagues (2005) mentioned earlier found that the bottom 80 percent of adult income earners' life expectancy was 4.3 years and 5.8 health adjusted life years (HALYs) shorter relative to those in the top 20 percent of earnings.⁹⁹ The income-associated burden of disease appears to be a leading cause of morbidity and mortality in the US.

Socioeconomic enabling factors have thus been found to be extremely important predictors of health services and prescription drug utilization.

2.9 Need for Healthcare

Need for healthcare is determined by a combination of the prevalence and severity of chronic diseases like diabetes, obesity and cardiovascular diseases; and risky health behaviors like smoking.

Diabetes affects millions of people in the United States and is among the leading causes of death in the nation. The prevalence of diabetes has increased almost 50 percent during the past decade and is projected to increase by more than 80 percent in the next 50 years to more than 29 million by 2050.^{101,102} In a population based cross-sectional survey study, Kemple and colleagues (2003) reported that the prevalence of diabetes in the Medicaid population was more than twice that in the general population.¹⁰³ Chin, Aurbach and Cook (2000), studying the quality of provision of diabetes care to low income groups, found that care is frequently substandard, which places this group at great risk of developing complications.¹⁰⁴

A study conducted by the U.S. Centers for Disease Control and Prevention (CDC) and RTI International has estimated that cost of obesity related to medical conditions totaled \$75

billion in 2003. Medicare and Medicaid paid more than half of this cost and the rest was paid by the states which constituted about five percent of the state medical expenditure. Obesity is an even more serious issue for poorer Americans. Kemple and colleagues (2003), in their study mentioned earlier, found that obesity was one and one-half times greater in the Medicaid population than in the general population.¹⁰³ The impact of obesity on society takes other tolls, as well. A recent study by Mees (2004) found that obese employees reported more difficulty getting along with coworkers and severely obese workers missed significantly more days of work.¹⁰⁵ Results of this study suggest a generally lower level of productivity of the obese and would likely further worsen the state of health and finances for the indigent populations.

Cardiovascular diseases are a significant burden in terms of morbidity, mortality, and use of health care services. Hodgson and Cohen (1999) found that expenditures for treating cardiovascular diseases increase with age and these diseases can be expected to command an increasing share of national health expenditures as the number and proportion of the elderly population grows.¹⁰⁶ Additionally, Connor, Gavreau and Jenkins (2005) have recently highlighted variations among states in the frequency of high resource utilization for treatment of heart diseases implying varied disproportionate draws on some state Medicaid budgets compared to others.¹⁰⁷

Prevalence of smoking in the population has an adverse impact on overall health by causing increased cases of respiratory diseases, cancer and other illnesses. Smoking behavior has been well established as a major risk factor for various ailments like lung cancer and cardiovascular diseases. Unfortunately, however, a CDC report (2001) on state Medicaid coverage of tobacco dependence treatments, found that the prevalence of smoking is 50 percent higher in the Medicaid population than in the general population.¹⁰⁸ Additionally, Murphy and

colleagues (2005) noted a marked disparity in the use of smoking cessation pharmacotherapies between the Medicaid population and the general population, which was not explained by differences in age, gender, race, education, or level of addiction.¹⁰⁹

All these factors and their combinations increase the risk of chronic and acute diseases in the Medicaid populations, which would likely lead directly to higher utilization of drugs and medical services.

The other part of need for healthcare is determined by severity of diseases – mainly chronic diseases that would necessitate utilization of health services. Studies have found strong correlations between disease severity and higher levels of utilization for intensive care services like hospitalization.

Two recent studies have established severity scoring as a predictor of hospitalization decisions for cases of acute exacerbation of chronic obstructive pulmonary diseases. Kosmas and colleagues (2004) assessed the effect on severity of adverse events in COPD on hospital admissions by applying a severity scoring system.⁵¹ They also investigated possible correlations of the severity with the length of hospitalization, and the final outcome. The authors concluded that severity scoring correlated with parameters of disease severity, such as the length and final outcome of hospital stay. They further proposed that measuring severity is a useful tool aiding medical decisions such as the need for hospitalization and early institution of therapeutic modalities. Such an approach may also serve to avoid unjustified admissions and to minimize unnecessary healthcare utilization.

In a similar study by Ong, Earnest and Lu (2004) the researchers applied the BODE index in an effort to predict the risk for hospitalization among a cohort of patients with COPD.⁵² In general, the more the severe the COPD stage, the higher was the BODE score. Consequently,

patients with higher BODE scores had significantly greater rates of hospitalization. The authors concluded that disease severity is a good predictor of both mortality and the risk for hospitalization.

Yet another study by Morrison and colleagues (2002) found a relationship between depressive symptom severity and hospitalization in patients with asthma.⁵³ Therefore, in the absence of direct comparable information, hospitalization data could likely substitute as a measure for disease severity levels.

2.10 Conclusions

It is evident that Medicaid is an important component of national health policy. Reviewed literature reiterates the need for containing Medicaid prescription drug expenditures and reports that various efforts in that direction have not met with widespread success. This supports the need for the current study to attempt to identify key determinants of drug expenditure in Medicaid and to understand inter-relationships among such determinants.

Use of Andersen's model for identifying such variables is supported by studies that have successfully demonstrated its usefulness as a conceptual framework for health services utilization research.

Structure equation modeling was also demonstrated as an appropriate analysis approach in eliciting information on structural relationships among constructs and supports the choice of such analysis methodology for achieving the primary study objective.

Review of the literature also helped identify several potential variables belonging to different constructs of the conceptual framework. Studies analyzing these variables also

suggested potential directions of the relationships these variables could have with each other and with the dependent variable.

The next chapter builds on findings of the review and elaborates on operationalization of the identified variables. Detailed methodology of data collection and analyses for each objective is also presented in the next chapter.

3 Chapter three: Methods

The previous chapters outlined the background and the need for identifying key determinants of Medicaid prescription drug expenditure and assessing their inter-relationships. An overview of the existing literature in this area was also provided. Goals and specific objectives of the current study were also outlined.

This chapter focuses on the methodology used to achieve the given objectives. Analysis methods are organized into three sections by the objective they are meant to achieve.

3.1 Data sources

Data used for the study were collected from several publicly available sources, including the ones mentioned below. Specific variable sources are described in the “Operational Variables” section later in this document.

3.1.1 The Henry J. Kaiser Family Foundation (<http://www.kff.org>) – a non-profit, private foundation focusing on the major health care issues facing the nation. The Foundation is an independent voice and source of facts and analysis for policy makers, the media, the health care community, and the general public.

KFF develops and runs its own research and communications programs, often in partnership with outside organizations. Through their policy research and communications programs, the Foundation works to provide reliable information in a health system in which the issues are increasingly complex.¹¹⁰ Within KFF, study data was obtained from the <http://www.statehealthfacts.org> website which provides state-level data on demographics,

health, and health policy, including health coverage, access, financing, and state legislation and budgets.

3.1.2 The National Pharmaceutical Council (<http://www.npcnow.org>) – an organization supported by more than 20 of the nation’s major research-based pharmaceutical companies. NPC sponsors a variety of research and education projects aimed at demonstrating that the appropriate use of pharmaceuticals improves both patient treatment outcomes and the cost effective delivery of overall health care services. They fund several small to mid-size research-based projects, pilot studies, and ongoing educational activities. Through partnerships and research-based initiatives, NPC demonstrates the theoretical value of pharmaceuticals through practical application.¹¹¹

Specific study data were obtained from the annual reports on ‘Pharmaceutical Benefits under state Medical Assistance Programs’ published annually by NPC. Although NPC is supported by commercial interests, validity of the data provided in their reports and included in this study is based on the fact they use federal agency reports as their primary sources. These reports in turn are based on data submitted to CMS by individual states. For example, expenditure and recipient data in NPC reports are taken from CMS’ Medicaid Statistical Information System (MSIS), and state reports known as the CMS-64s or CMS-37s.

3.1.3 The National Center for Education Statistics (<http://nces.ed.gov/ccd/bat/index.asp>) – is the primary federal entity for collecting and analyzing data related to education in the U.S. and other nations. NCES is located within the U.S. Department of Education and the Institute of Education Sciences. NCES fulfills a Congressional mandate to collect, collate, analyze, and

report complete statistics on the condition of American education, conduct research and publish reports, and review and report on education activities internationally.¹¹²

Specific study data were obtained from NCES analyses on state level graduation statistics.

3.1.4 United Health Foundation (<http://www.unitedhealthfoundation.org/shr.html>) – is a nonprofit, private foundation with a mission to support the health and medical decisions made by physicians, health professionals, community leaders and individuals that lead to better health outcomes and healthier communities. To support healthy communities, the Foundation annually publishes ‘America's Health: State Health Rankings’ – a comprehensive, state-by-state analysis of the relative healthiness of the American population. The rankings provide information and tools to stimulate public conversation about health and to facilitate citizen participation in improving the health of their communities and the nation as a whole. To support the health choices made by individuals, United Health Foundation partners with well-respected organizations such as the Centers for Disease Control and Prevention, the National Patient Safety Foundation, and the National Health Council to provide trustworthy and evidence-based educational tips.

Specific study data obtained from United Health included health risk and behavior data for individual states.

3.2 Study sample

Data on all studied variables were available for the five year period 1998 - 2002. Panel data for five years was considered acceptable because of the cyclical nature of the Medicaid program described in a CMS analysis that clearly showed similarities in the trend in drug

spending between the first and second half of the 1990s.¹¹³ Their observations and NPC's analysis showed that the optimum period that state trends appear stable is four years and hence five years was a reasonable length to work with.¹¹

The study sample included 48 US states and Washington D.C. – that administer the Medicaid drug benefits program. Data for the states of Arizona and Tennessee were not included since the Medicaid programs in these states are administered as managed care programs – differently than the 'fee-for-service' structure that the other programs operate in, and hence cannot be measured using the same parameters.

Arizona

The Arizona Health Care Cost-Containment System (AHCCCS) is a Medicaid demonstration project, jointly funded by the federal government and the state of Arizona. Begun in October 1982, it serves as a model for providing medical services to the indigent in a managed care system rather than through fee-for-service arrangements. Typically, Medicaid programs have incorporated independent providers and fee-for-service reimbursement. In contrast, the AHCCCS model works with organized health plans and capitation. In traditional Medicaid programs, the states assume responsibility for contracting with individual pharmacies and for reimbursing them. In the AHCCCS model however, the state contracts instead with pre-paid health plans, HMOs and HMO-like entities. These plans are paid on a capitation basis and are responsible for providing all of the services covered by the program. Thus, the delivery of pharmacy services is the responsibility of each prepaid plan within the system.

Tennessee

Tennessee withdrew from the Medicaid Program in 1994 and implemented an innovative new health care reform plan called TennCare. TennCare replaced the existing Medicaid Program

with a program of managed health care. TennCare required no new taxes and extended health coverage not only to the nearly 800,000 Tennesseans in the Medicaid population, but also to an approximately 400,000 uninsured or uninsurable persons using a system of managed care. Enrollment was open in 1994 to eligible persons in the uninsured, uninsurable, and Medicaid-eligible categories. TennCare services are offered through managed care organizations (MCOs) and behavioral health organizations (BHOs) under contract with the state. These MCOs, spread out over the twelve regions of Tennessee, are paid a fixed amount per enrollee per month for the MCO services. BHOs are paid a fixed rate for priority participants and a variable rate for all other TennCare enrollees. The MCOs and BHOs negotiate payment rates with individual providers. Enrollees have a choice of MCOs (and their corresponding BHO partner plan) from those available in their geographic area.

3.3 Data extraction and cleaning

Data for the study variables were extracted from a combination of reports mentioned above which were available either in electronic or in printed form. Data entry was done in Microsoft Excel by one researcher and was randomly cross-checked for accuracy. Variables were recoded and/or computed as necessary as explained in the following section. The final dataset was converted into a Statistical Package for Social Sciences (SPSS) dataset, as well as into a Statistical Analysis System (SAS) dataset for analyses under the study objectives.

3.4 Operational variables

3.4.1 Dependent variable

Drug payments per Medicaid eligible person for each state for each year of the study period was the dependent variable named DRUGELIG in the dataset. This is a continuous variable computed as:

$$DRUGELIG \text{ (dollars)} = \text{Total Drug Payments (dollars, NPC)} / \text{Total Eligibles (count, NPC)}$$

‘Eligibles’ are people who, based on Medicaid criteria, are covered for their healthcare by the state Medicaid program. ‘Recipients’ on the other hand are a sub-set of the eligible population whose prescription drugs have been paid for by Medicaid. Eligibles were chosen as the denominator in this study instead of ‘recipients’ for a few reasons. First, using eligibles ensures comparability across states of differently sized Medicaid populations and socio-demographic distributions. Second, using eligibles gets each state sample closer to the states’ general population and hence is more appropriate for use with both Medicaid and state specific variables, as will be discussed later in this chapter. Finally, choosing eligibles which is a bigger sample than recipients produces a better sampling distribution and reduces standard error variance.

The expenditures included here are based on pharmacy reimbursements in the ambulatory care setting. However, additional pharmaceutical drug expenditures are incurred during a hospital stay, for example, which are not included since reimbursements for such expenses occur through mechanisms (like Diagnosis Related Group or DRG payments for hospitals) where prescription drugs are paid for as part of an overall claim and hence cannot be individually identified and accounted for.

3.4.2 Independent variables

Potential independent variables were identified and classified according to the Andersen Model. Variables were finally retained in the model, if:

- An appropriate measure was available in publicly available data sources; and
- Data were available for the entire study period.

Following are variables that were included in the final analysis:

3.4.2.1 Health care system characteristics

3.4.2.1.1 Policy factors

These variables define effects of health policy and interventions in general and specific Medicaid program characteristics and interventions. These include:

- i. ***Managed care*** – measures the percentage of a state Medicaid program’s enrollees who are part of a managed care plan offered by Medicaid.

The variable is directly extracted from the NPC reports and is included as percentage values in the continuous variable MAN_CARE in the study dataset.

Since managed care has been touted as a means to control costs without compromising on quality and appropriateness of care, it is expected that total Medicaid costs should either decrease or at least remain at the same level with increase in the proportion of managed care enrollment in the Medicaid populations. However, since managed care efforts are directed more at reducing utilization of higher cost services like hospital stay and emergency room visits – it is likely that there could be a substitution effect which would increase drug utilization and hence drug costs.

- ii. **Support** – measures the support for public health care measured in terms of the proportion of public expenditure directed towards providing healthcare to the state’s poor and needy citizens. The variable SUPPORT is calculated, as shown below, from a United Health ‘Support Ratio’ (explained in the following paragraph) and ‘percent population below 100 percent of the Federal Poverty Line’ available from the NPC reports.

$$SUPPORT\ (percent) = Support\ ratio\ (ratio,\ United) / below\ 100\%\ FPL\ (percent,\ NPC)$$

The ‘Support Ratio’ portion of the variable is calculated as follows: total state and local expenditures for public welfare, health and hospitals are divided by the total general expenditure of state and local units to calculate a percentage. This percentage is then divided by the percentage of the state’s population with an annual household income below \$15,000. The percentage of population with very low income is derived from updated census estimates. The definition of expenditure is broad and varies between states. This component does not include the role of non-government and direct federal expenditures for care of people with low incomes.¹¹⁴

It is expected that with increasing support for publicly funded healthcare – there will be higher utilization and costs for drugs.

- iii. **Preferred Drug List** – measures the presence or absence of a restrictive list of drugs that are favorably reimbursed. This dichotomous variable is named PDL in the dataset and has been directly extracted from NPC reports.

Data were recoded as ‘PDL existing’ = 1 and ‘No existing PDL’ = 0.

Since the PDL is implemented as a drug cost containment intervention, drug costs are expected to reduce with a presence of the PDL. Debate exists in relevant literature about

whether costs controlled by PDL do not necessarily reflect the possible increases in cost due to other services utilization caused by inappropriate medication or drug treatment failure.

- iv. **Reimbursement rates** – is an index created to measure the relative reimbursement levels to a pharmacy by the state Medicaid program for a similarly priced hypothetical drug.

For purpose of this study, the reimbursement rate variable REIMBURS was calculated assuming a standard AWP of \$100 for a drug. For those states that calculated their EACs based on WAC – an appropriate conversion was made based on their relationship as identified in published literature.⁷⁹ Dispensing fee – the other component of reimbursement for pharmacy services was added to the appropriate ingredient cost reimbursement. Where the dispensing fee differed between generic and branded drugs – an average was used for calculation. The final values for the continuous variable were obtained as:

$$REIMBURS \text{ (dollars)} = \$100 + \% \text{ allowable deduction from AWP (or \% allowable addition to WAC, as appropriate; NPC)} + \text{average dispensing fee (dollars, NPC)}$$

It is expected that with higher Medicaid reimbursement rates – more pharmacies will be interested in serving Medicaid patients and thus any locational barriers to utilization will be removed – resulting in greater utilization and expenditures on prescription drugs.

- v. **Federal matching** – measures the federal matching of state Medicaid drug expenditure determined annually by a formula that compares the state's average per capita income level with the national income average. States with a higher per capita income level are

reimbursed a smaller share of their costs. By law, the FMAP cannot be lower than 50 percent or higher than 83 percent.

Accordingly, drug rebates under the provisions of OBRA 90 that are provided by manufacturers to state Medicaid programs are split in the same matching percentage. Hence, the federal matching percentage variable, FMAP for the purpose of this study, is calculated as:

$$FMAP \text{ (percent)} = \text{Federal share of Drug Rebates (dollars, NPC)} * 100 / \text{Total Rebates (dollars, NPC)}$$

It is evident that economically disadvantaged states cannot afford to provide adequate drug benefits to their Medicaid populations in the absence of Federal support. On the other hand however, states that are economically forward – do not have higher levels of Federal support and hence have to provide for a greater portion of their Medicaid expenses from state budgets. That is not a very easy option to pursue as is evident from the many cuts in eligibility and benefits that have implemented by many of the richer states in the recent times.

Hence, overall drug utilization and expenditures are expected to increase with increase in percentage of Federal support.

- vi. ***Generic substitution*** – measures the existence of a mandatory substitution requirement of a branded drug prescription by a multi-source or generic (generally lower priced) drug.

This dichotomous variable, GENSUBST, is directly extracted from NPC reports and has been recoded in the study dataset as mandatory generic substitution of brand name drugs ‘required’ = 1 and ‘not required’ = 0.

Since generic drugs in most cases are less expensive than brand name drugs, it is expected that any increase in the proportion of generic drug use will reduce overall drug payments for Medicaid. Although this measure will not capture the magnitude of such change, the existence of a generic substitution requirement is expected to reduce drug expenditure.

- vii. ***Prior authorization*** – measures the existence of an approval requirement for a ‘non-preferred drug’ by Medicaid agencies or contractors before they can be dispensed by a pharmacy.

This dichotomous variable, PRIORAUT, is directly extracted from NPC reports and has been recoded in the study dataset as ‘required’ = 1 and ‘not required’ = 0.

As a common practice, drugs that are more expensive (owing to less rebates from the manufacturer, or otherwise) and/or are more widely prescribed and utilized (with or without an abuse potential) – are subjected to prior authorization. Hence, it is expected that presence of a prior authorization requirement will facilitate rational drug therapy, and hence reduce overall drug payments for Medicaid.

3.4.2.1.2 Healthcare resources

These variables describe the resources available within the healthcare system that serve Medicaid recipients as key determinants of access to health care and medication prescribing and dispensing services.

These include:

- i. ***Access to Pharmacies*** – measures access to points of sale and dispensing of prescription medication in each state. To make the variable PHARM_AC comparable, the number of

licensed pharmacies in the state is recalculated per 10,000 Medicaid eligible persons. Hence, the continuous variable is measured as:

$$PHARM_AC = \text{Total number of licensed pharmacies in the state (count, NPC)} * 10,000 / \text{total eligibles (count, NPC)}$$

Increased access to pharmacies will likely reduce location or commutation barriers to filling a prescription and hence is expected to increase drug utilization and expenditures.

- ii. ***Access to Primary Care Physicians*** – measures Medicaid eligibles’ access to primary care.

It is an estimate of the physician-to-eligible ratio of care-giving as applied to the Medicaid population in a state. The variable PCP_ACC is calculated in the study dataset as:

$$PCP_ACC = \text{Primary Care Physicians (count, NPC)} * 10,000 / \text{total eligibles (count, NPC)}$$

Like in the case of pharmacies, availability of more physicians for each Medicaid eligible person will reduce the location and commutation barriers to seeking care and getting a prescription. Hence, increase in the value of this variable is expected to bring about an increase in drug expenditures.

- iii. ***Access to Hospitals*** – measures access to inpatient and emergency care available in the state.

Like earlier in the section, the HOSP_ACC variable is also calculated by dividing the number of Medicaid certified hospitals in the state by the number of Medicaid eligible persons to get an estimate of the access to inpatient or emergency care available to every 10,000 persons.

Hence, the continuous variable is calculated as:

$$HOSP_ACC = \text{Total Medicaid certified hospitals (count, NPC)} * 10,000 / \text{total eligibles (count, NPC)}$$

Another way of measuring hospital access could have been to consider number of beds available per 10,000 eligibles. However, not only was that information not available for the entire study period, but also such information exists only for the entire state. Hence, using ‘beds’ data would have necessitated the consideration of the type of hospital, as well as, other specific hospital characteristics (like number or percent of beds allocated to Medicaid, for example) that control access for Medicaid patients.

Hospital access would generally determine utilization of inpatient and emergency services. However, they also are another important source for drug prescriptions from the emergency department as well as at discharge from an inpatient stay. Also, for a similar ailment, minorities have been found to be more prone to visit an emergency department at a hospital than to visit a physician in the ambulatory setting. Hence, drug expenditure is expected to go up in the Medicaid population with increased access to hospitals.

- iv. ***Access to Prenatal Care*** – is a measure of access to and adequacy of prenatal care as reported by United Health. This measure is based on the Modified Kessner Criteria.¹¹⁴

The variable PRENATAL in the dataset is extracted directly from the United Health report.

The National Center of Health Statistics (NCHS, CDC) defines adequate care as having one’s first prenatal visit with a health professional within the first trimester of pregnancy and additional visits as per a recommended schedule. It is not adjusted for age or race.

Pre-natal care reduces risks associated with pregnancy and childbirth and thereby attempts to reduce overall expenditures involved with complications in the birthing process and in the neonate. However, increase in availability of pre-natal care would also mean intake of supplements and medication appropriate for pregnancy and hence would likely increase drug expenditure in the short term.

3.4.2.2 Population characteristics:

3.4.2.2.1 *Predisposing social characteristics*

These are characteristics that the recipient population are inherently predisposed to and include:

- i. ***Children*** – measures the proportion of children and adolescents in the state Medicaid populations. The variable CHILDREN in the dataset is thus calculated as:

$$\text{CHILDREN (percent)} = \text{Number of children 19 years or less in the Medicaid program (count, NPC)} * 100 / \text{total eligibles (count, NPC)}$$

This estimate includes only those children whose families are Medicaid eligible and not those who are included in the SCHIP programs.

While it may not be true for all healthcare services, children do consume less medication in general and hence are less expensive in terms of drug costs to treat. Therefore, increase in the proportion of children in the state Medicaid population is expected to reduce drug costs.

- ii. ***Elderly*** – measures the proportion of elderly persons, 65 years or older, in the state Medicaid populations. The variable ELDERLY in the dataset is thus calculated as:

$$\text{ELDERLY (percent)} = \text{Number of persons 65 years or older in the Medicaid program (count, NPC)} * 100 / \text{total eligibles (count, NPC)}$$

Unlike children, the elderly are more expensive to treat in general. They have higher levels of drug utilization and a huge percentage of them have poly pharmacy. Hence, increase in proportions of the elderly in the state Medicaid population is expected to increase drug costs.

As of July 2005, 44 States and the District of Columbia had established various pharmaceutical assistance programs providing coverage or improved access to the low-income elderly who do not qualify for Medicaid.¹¹ These programs range from state-negotiated discounts or state subsidies, to tax credits for prescription drug costs, and coordinating seniors' access to manufacturers' charitable prescription assistance programs. However, such expenditures are not likely to impact per capita expenditures in the study since these programs are supplemental to Medicaid pharmacy benefits; are not offered to otherwise eligible persons; and are not necessarily in the form of free medication.

- iii. **Disabled** – measures the proportion of blind and disabled persons in the state Medicaid populations. The variable DISABLED in the dataset is thus calculated as:

$$\text{DISABLED (percent)} = \text{Number of blind and disabled persons in the Medicaid program (count, NPC)} * 100 / \text{total eligibles (count, NPC)}$$

The disabled are probably the most expensive-to-treat group in Medicaid. However, a lot of these expenses may also be accounted for by utilization of non-drug therapies and services – like nursing home, home healthcare, prosthetics, wheelchairs. With respect to

prescription drugs, a higher proportion of disabled persons in the Medicaid population will likely reduce expenditure.

- iv. **Whites** – measures the proportion of white persons in the state Medicaid populations. The variable WHITES in the dataset is thus calculated as:

$$WHITES \text{ (percent)} = \text{Number of white persons in the Medicaid program (count, NPC)} * 100 / \text{total eligibles (count, NPC)}$$

Whites in this analysis are used as a representation of the majority population in state Medicaid. As has been discussed earlier, whites would be more likely to receive appropriate and more expensive medications than other minority populations. It is understood that the Medicaid population over-represents racial minorities. However, it has also been seen that although the minorities utilize more of other services like emergency rooms and hospitals, they are generally less likely to have high utilization of prescription drugs. Hence, a higher proportion of whites in the population is expected to increase utilization in general and of more expensive drugs in particular, and is thus expected to increase drug expenditure.

3.4.2.2.2 Enabling resources

These are factors that facilitate or empower recipients to be aware of and to access available health care services, and include:

- i. **High school graduation** – measures the percentage of ninth-graders who graduate within four years and are considered regular graduates by the state.

Data used in the study are collected annually by the National Center for Education Statistics (NCES). The data are not adjusted for the presence or quality of basic health and

consumer health education in the curriculum, for continuing education programs or for other non-traditional learning programs. Also, individual states often alter graduation requirements, which may affect their reported number of regular graduates, their graduation rates, and the comparability of these scores across time.

The data on the variable HSGRAD in the dataset are directly extracted as percentage numbers from the NCES reports.

Education is expected to serve as an enabler for recognizing the need for health care, for seeking out available sources of care, and for actually seeking care. Also, education should enable understanding of appropriate use of drugs and ensure adherence to drug regimens and completion of drug treatments. Hence, overall, a higher proportion educated persons in the population is expected to increase utilization and hence expenditures on prescription medication.

- ii. ***Financial ability*** – measures the percentage of the state’s population whose family income is less than 100% of the Federal Poverty Level as an index of a minimum level of financial ability to seek care.

Values for the continuous variable LT100FPL in the dataset are taken directly from the NPC reports.

Although it is expected that higher levels of purchasing power would increase utilization in general – such an assumption may not be appropriate for the Medicaid population. This is because although they are below certain levels of poverty for all other purposes – that is the same criterion used to ascertain their eligibility into Medicaid. And for Medicaid eligibles, all drugs and other care are available free of charge. Although some

states apply a minimal co-pay, all Medicaid enrollees must, by law, be provided care and medication even if they cannot pay such co-pay amounts.

Hence, it is expected that higher proportions of people with high levels of poverty in the state would increase Medicaid enrollment, and hence would increase overall Medicaid drug utilization and expenditures.

- iii. ***Unemployment*** – measures the proportion of the state’s populations who are unemployed (and hence, could have satisfied the Medicaid eligibility criteria).

The continuous variable UNEMPLOY is measured in percentage and is extracted directly from the NPC reports.

Unemployment is one of the criteria leading to Medicaid eligibility. Hence, higher proportions of unemployed persons in the state would increase Medicaid enrollment; and hence will increase drug utilization and expenditures. However, whether this will increase drug expenditure per capita will depend on the health status of the new enrollees.

3.4.2.2.3 Need for healthcare

These are behavioral and chronic disease risk factors that establish need for seeking and accessing health care and consequent resource utilization. No specific information is available in the public domain on prevalence rates and risks for the Medicaid populations. Hence data will be collected on the entire state’s population.

These variables include:

- i. ***Risk*** – is measured as a composite percentage of risks of diseases and health risk behaviors, namely – prevalence of smoking, hypertension, sedentary lifestyle, and obesity. Estimates of

these diseases prevalence and behaviors are collected regularly by the states for the Behavioral Risk Factor Surveillance System (BRFSS) and the information used in the study has been obtained from United Health reports.

$$RISK (percent) = average of \{smoking (percent, United), hypertension (percent, United), sedentary (percent, United), and obesity (percent, United)\}$$

Prevalence of smoking measures the percentage of the population over age 18 that has smoked at least 100 cigarettes and currently smokes regularly.

Hypertension and sedentary lifestyle are measured as percentages of the state population that is considered to be hypertensive, and as having a sedentary lifestyles, respectively.

Obesity in this study is measured as percentage of the population in the state who are considered obese as measured by their Body Mass Index (BMI) scores. BMI is calculated as the weight in kilograms divided by height in meters raised to the second power. Since 2000, obesity or overweight is defined by the Centers for Disease Control and Prevention, the owners of the BRFSS, BMI exceeding 25.0. Prior years defined overweight as BMI exceeding 27.3 for females and 27.8 for males. This change would have resulted in all states reporting a higher percentage of the population as overweight in the years following 2000 compared with the study period before then.

Studies discussed earlier have shown that the Medicaid population is higher levels of risk for many of the disease prevalence and health risk behavior measures. As most of these risks lead to chronic diseases with heavy drug utilization, a higher level of risk is expected to increase the level of drug utilization and expenditure.

- ii. ***Severity of Disease*** – measures how sick a Medicaid population is. This continuous variable NONDRUGE uses a proxy in the dollars spent in non-drug medical expenditures for Medicaid.

$$NONDRUGE \text{ (dollars)} = \{Total \text{ Medicaid Vendor Payments (dollars, NPC)} - Total \text{ Drug Payments (dollars, NPC)}\} / Total \text{ Eligibles (count, NPC)}$$

As discussed in chapter two earlier, the assumption used here is that more severe diseases will have higher rates (hence, expenses) of medical services encounters and utilization through hospitalization, inpatient stay and procedures performed, Emergency Department (ED) visits, as well as general practice primary office visits. Although the above non-drug expenditures will possibly be highly proportional to severity, the associated drug expenditures are also expected to increase with greater severity of disease. As a result, it is expected that the per capita drug expenditure will also increase with increasing severity as measured by expenditures on non-drug medical services.

3.5 Analysis

3.5.1 Objective 1

To develop and test a model assessing relationships among potential influencers/ predictors of Medicaid drug expenditures identified based on Andersen's Behavior Model for Health Services Utilization.

Null hypothesis: The proposed model is not different from an unrestricted population model.

This objective was achieved using the multivariate Structural Equation Modeling (SEM) method. SEM is a statistical methodology that takes a confirmatory approach to the analysis of a structural theory bearing on some phenomenon. Typically, this theory represents 'causal' processes that generate observations on multiple variables. In SEM, the causal processes under study are represented by a series of structural (regression) equations. These relations were modeled pictorially to enable a clearer conceptualization of the theory under study. The hypothesized model was then tested statistically in a simultaneous analysis of the entire system of variables to determine the extent to which it is consistent with the data. If the goodness of fit is adequate, the model argues for the plausibility of postulated relations among variables; if it is inadequate, the tenability of such relations is rejected.⁷⁰

In the current study, the SEM model was hypothesized based on the conceptual framework described earlier. Following the structure in Andersen's model, the inter-relationships among the several potential determinant variables and the dependent variable – Medicaid drug expenditure per eligible, was hypothesized and modeled.

A SEM software – Analysis of Moment Structures (AMOS®) version 5.0 was used for this analysis. AMOS is a powerful and easy-to-use structural equation modeling (SEM)

software. It allows creation of more realistic models than if standard multivariate statistics or multiple regression models alone were used. Using AMOS, the hypothesized model was specified, estimated, assessed, and presented in an intuitive path diagram to show hypothesized relationships among variables.

AMOS has already been successfully applied to a variety of research applications including:¹¹⁵

- Developing models to understand how drug, clinical, and art therapies affect mood
- Confirming which of three variables—confidence, savings, or research—best predicts a doctor’s support for prescribing generic drugs
- Studying how socioeconomic status, organizational membership, and other determinants influence differences in voting behavior and political engagement
- Evaluating training program outcomes to determine impact on classroom effectiveness
- Modeling how customer behavior impacts new product sales
- Studying how work-related issues affect job satisfaction etc.

The hypothesized model was formulated using the AMOS Graphics interface. A path diagram was drawn with ellipses, boxes, circles and headed arrows representing latent variables, observed (input) variables, errors and residuals, and their relationships. The structural portion of the full structural equation model is represented by the framework presented in Figure 6. The measurement portion of the SE model was established by defining the number and the identity of the indicators to be used for measuring each of the latent variable factors described with multiple structural equations. The broader factors were modeled as latent variables and the observed variables were used in measuring these latent constructs and their inter-relationships.

Figure 6. Structure Equation Model of Medicaid Prescription Drug Utilization

Model Identification

Identification of the structural model depends on the numbers of the data (say, X) and the structural parameters (say, Y). X is the sum of the number of regression coefficients (factor loadings), error variances, factor variances and factor co-variances. Y depends on the number of observed variables in the model and is given by the formula

$$Y = p(p+1)/2 \text{ for } p \text{ observed variables.}$$

Identification subsequently depends on the value of $(Y - X)$ where a value < 0 means the model is ‘underidentified’; $= 0$ means it is ‘just identified’; and > 0 means it is ‘overidentified’. The aim of SEM is to specify a model such that it meets the criterion of overidentification which results in positive degrees of freedom that allow for rejection of the model, thereby rendering it of scientific use.

Such identification process will be run with the hypothesized model in this case.

Model, Parameters and Estimation

Model variables were categorized as either observed or unobserved, and as endogenous or exogenous. A summary of the parameters in the model are presented in the results section. These include all regression weights, co-variances and variances that were estimated.

To establish the scale of each unmeasured factor in the model and for purposes of model identification, one parameter in each set of regression paths was arbitrarily fixed to 1. Now it was possible to determine the appropriate number of degrees of freedom, and ultimately, whether the model is identified.

A summary of the estimation process is also presented in the results section. Achievement of a ‘minimum’ will assure that estimation process yielded an admissible solution.

An overall χ^2 and the associated degrees of freedom and probability value are also presented for a quick overview of model fit.

Parameter Estimates

Generalized Least Squares (GLS) estimates will be obtained of the regression weights – which, in this case, are the estimated path coefficients for the arrows in the model. GLS, although not as commonly used as Maximum Likelihood (ML) estimation method – has been suggested as a useful means for getting reliable model fit estimates in cases of suspected or known multivariate non-normality in the input data.

The primary interest being the extent to which the hypothesized model fits the data – model assessment was done based mainly on parameter estimates. This involves:

- Feasibility of estimates,
- Appropriateness of standard errors, and
- Statistical significance of parameter estimates

Feasibility of the estimates will be determined based on correctness of the sign and size of estimates and their consistency with the underlying theory. Estimates outside the admissible range will signal problems with the model.

Excessively large standard errors on the other hand will indicate poor model fit.

The test statistic in this case will be the critical ratio which represents the parameter estimate divided by its standard error. This operates as a z-statistic in testing that the estimate is statistically different from zero. An alpha-level of 0.05 will be used, in which case, the test statistic needs to be $>\pm 1.96$ before the null hypothesis (i.e. estimate = 0) can be rejected.

Goodness-of-fit Statistics

SEM primarily tests the goodness-of-fit between the hypothesized model and the sample data. The null hypothesis (H_0) being tested is that the postulated model holds in the population, or:

$$\Sigma = \Sigma(\theta) \text{ where,}$$

Σ represents the population covariance matrix, and $\Sigma(\theta)$ represents the restricted covariance matrix implied by the hypothesized model.

Interestingly therefore, unlike traditional statistical procedures, we would hope not to reject H_0 .

The goodness-of-fit statistic that is most commonly used (and will be used in this analysis) is the CMIN (minimum discrepancy) which measures the discrepancy between the unrestricted sample covariance matrix and the restricted covariance matrix per the model. CMIN is most commonly expressed as a χ^2 statistic. The χ^2 statistic tests the extent to which all residuals in the $\Sigma - \Sigma(\theta) = 0$ (following a transformation of the null hypothesis). The probability value associated with χ^2 represents the likelihood of obtaining a χ^2 value that exceeds the χ^2 value when H_0 is true.

Thus, higher the p value associated with the χ^2 , the closer is the fit between the hypothesized model and the perfect fit.

The second fit index we shall look at is the Comparative Fit Index (CFI) that has values ranging from 0 to 1 and is derived from the comparison of the hypothesized model with the independence model. CFI is suggested as the index of choice and a value >0.90 has been considered representative of a good fit.

3.5.2 Objective 2

To classify state Medicaid programs into homogeneous clusters based on similarities in their characteristics as measured by the prescription drug expenditure and its influencers/ predictors.

Null hypothesis: There is no difference among state Medicaid programs in terms of per capita prescription drug expenditure and its determinants.

Cluster Analysis (CA) techniques were utilized to achieve this objective. CA is a way of grouping cases of data based on the similarity of responses to several variables. It seeks to identify homogeneous subgroups of cases in a population. That is, CA seeks to identify a set of groups which both minimize within-group variation and maximize between-group variation. CA produces a classification scheme of individual observations, depending on their relative similarity or nearness to an array of different variables. The basic idea is one of dividing a specific data profile into segments by creating maximum homogeneity within and maximum distance between groups of observations.

CA is an exploratory data analysis tool for solving classification problems. Its object is to sort cases (people, things, events, etc) into groups, or clusters, so that the degree of association is strong between members of the same cluster and weak between members of different clusters. Each cluster thus describes, in terms of the data collected, the class to which its members belong, and this description may be abstracted through use from the particular to the general class or type. CA might reveal associations and structure in data which, though not previously evident, nevertheless are sensible and useful once found. The results of cluster analysis may contribute to the definition of a formal classification scheme thus suggesting statistical models with which to describe individual state Medicaid drug benefit programs.

CA lacks an underlying body of statistical theory and is heuristic in nature. It requires decisions to be made by the researcher relating to the calculation of clusters, decisions which have a strong influence on the results of the classification. CA is useful to classify groups or objects and is more objective than subjective.

Clustering methods may be top down and employ logical division, or bottom up and undertake aggregation. Aggregation procedures which are based upon combining cases through assessment of similarities are the most common and popular will be the focus of this section.

Hierarchical clustering method was considered appropriate for smaller samples like the one in this study. To accomplish hierarchical clustering, we would specify how distance is defined, how clusters are aggregated. The process generates all possible clusters of sizes $1 \dots K$, but the optimum number of clusters will depend on the research purpose as well as the knowledge of practical feasibility and relevance. Since we shall be attempting to identify only the 'typical' types of cluster memberships, it is expected that there will be fewer clusters than if we were identifying 'exceptional' types which may call for many clusters.

In hierarchical clustering, the clusters are nested rather than being mutually exclusive, as is the usual case. That is, in hierarchical clustering, larger clusters may contain smaller clusters. In forward clustering, also called agglomerative clustering, small clusters are formed by using a high similarity index cut-off. Then this cut-off is relaxed to establish broader and broader clusters in stages until all cases are in a single cluster at some low similarity index cut-off. The merging of clusters is visualized using a tree format. Backward clustering, also called divisive clustering, is the same idea, but starting with a low cut-off and working toward a high cut-off. Forward and backward methods need not generate the same results. This study used the forward clustering method since the method is in line with our current objective of starting with each

state Medicaid program and classifying them in to groups based on similarities in program and state characteristics.

Analysis was done using the SPSS Hierarchical Cluster method. To address the issues of unequal variance among variables in the data set, transformation was performed to standardize the variables to 'Z-scores' with mean zero and variance one. All methods are based on the usual agglomerative hierarchical clustering procedure.

Each observation began in a cluster by itself. The two closest clusters were then merged to form a new cluster that replaces the two old clusters. Merging of the two closest clusters was repeated until only one cluster was left. The dissimilarity measure used was squared Euclidian distance which is computed as the number of discordant cases for binary variables and as the sum of the squared differences between the values for the items in case of interval data.

A graphical view of the clustering process was also obtained to help in interpreting the clusters. A dendrogram was produced offering a tree diagram of the clusters. Variations were accounted for at each branching of the tree and as the number of branches grew to the left from the root, the R^2 approached 1.

Once a suitable number of clusters were identified, the same data was subjected to a 'K-Means Clustering' procedure. K-means clustering is an algorithm to classify or to group objects based on attributes or features into the chosen (K) number of groups or clusters. The grouping in this process is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid. In other words, K-means clustering splits a set of objects into a selected number of groups by maximizing 'between' variation relative to within variation. Analogy can be roughly drawn with doing a one-way ANOVA where the groups are formed by making the largest F-value possible by reassigning members to each group.

K-means is an iterative procedure that assigns cases to a specified predetermined number of non-overlapping clusters – which in this case was available from the Hierarchical Clustering method. The procedure iterates through the data until it successfully clusters all the cases. Thus the purpose of K-mean clustering is to classify the data into chosen number of clusters and to describe cluster membership and attribute means.

Data for Objective 2

As the CA methodology is not equipped to handle longitudinal data, only the last year of data (2002) in the study dataset was used for the analysis.

3.5.3 Objective 3

To establish a predictive model for Medicaid prescription drugs expenditure based on time-adjusted impacts of key influencers/ predictors.

Null hypothesis: Proposed determinants of Medicaid drug costs do not predict per capita expenditure on prescription drugs.

This objective was achieved using the Panel Data (or, Time Series) Regression method. A panel is a cross-section or group of people who are surveyed periodically over a given time span. Panel data analysis is a method of studying a particular subject within multiple sites, periodically observed over a defined time frame.

Studies have used longitudinal Medicaid state-level data for health policy analysis in the past. For example, Kitchener, Carrillo, and Harrington (2003) provided a longitudinal analysis of state variation in expenditures and utilization for three Home and Community Based Service (HCBS) programs (waivers, home health and personal care), and for total Medicaid HCBS.¹¹⁶ The first part of the analysis described the nature and scope of state variation for each program in 1999, using such measures as participants per 1,000 population and expenditures per capita – as has been used in the current study. The second part of the analysis presented time-series regression models that estimate socio-demographic, state policy, and market factors associated with intra-state variation in waiver participants and expenditures, and home health, personal care and total HCBS expenditures for the period 1992–99. Among the results, positive state-level factors related to HCBS participants and expenditures include: higher percentages of aged people, greater incomes per capita, and a larger supply of home health agencies.

With repeated observations of enough cross-sections, panel analysis permits the researcher to study the dynamics of change with short time series. The combination of time

series with cross-sections can enhance the quality and quantity of data in ways that would be impossible using only one of these two dimensions.¹¹⁷ Panel analysis can provide a rich and powerful study of a set of people, if one is willing to consider both the space and time dimension of the data.

In this case, since panel data relates to individual states over five consecutive years, there is bound to be heterogeneity in these units. The technique of panel data estimation can take such heterogeneities explicitly into account by allowing for state-specific variables. Essentially, by combining time series of cross-sectional observations, panel data give more informative data, more variability, less collinearity among variables, more degrees of freedom and more efficiency. In short, panel data can enrich empirical analysis in ways that may not be possible if we use only cross-section or time series data.

A panel data regression model is written as

$$y_{it} = \sum_{k=1}^K X_{itk} \beta_k + u_{it} \quad i = 1, \dots, N; \quad t = 1, \dots, T$$

where, N is the number of cross sections, T is the length of the time series for each cross section, and K is the number of exogenous or independent variables.

Estimation of the above equation depends on the assumptions made about the intercept, the slope coefficients, and the error term u_{it} .

Fixed vs. Random effects

Panel data models estimate fixed and/or random effects models using dummy variables. The core difference between fixed and random effect models lies in the role of dummies. If

dummies are considered as a part of the intercept, it is a fixed effects model. In a random effects model, the dummies act as an error term.

The fixed effects model examines group differences in intercepts, assuming the same slopes and constant variance across groups. Fixed effects models use least square dummy variable (LSDV), within effect, and between effect estimation methods. Thus, ordinary least squares (OLS) regressions with dummies, in fact, are fixed effect models.

Since the current study data cannot be considered as random draws from a large population, a fixed effects model was used for the analysis. This is due to the fact that although the intercept may differ across individual states, each state's intercept will not vary over time.

The fixed effect intercept will be allowed to vary among states by the dummy variable technique that will incorporate differential intercept dummies identifying data from each of the 48 states included in the analysis. Hence, the equation for the fixed effects panel data regression model will be:

$$\begin{aligned} \text{DRUGELIG}_{it} = & \beta_1 \text{PRIORAUT}_{it1} + \beta_2 \text{PDL}_{it2} + \beta_3 \text{GENSUBST}_{it3} + \beta_4 \text{SUPPORTR}_{it4} + \\ & \beta_5 \text{MAN_CARE}_{it5} + \beta_6 \text{REIMBURSE}_{it6} + \beta_7 \text{FMAP}_{it7} + \beta_8 \text{HOSP_ACC}_{it8} + \beta_9 \text{PHARM_AC}_{it9} + \\ & \beta_{10} \text{PCP_ACC}_{it10} + \beta_{11} \text{PRENATAL}_{it11} + \beta_{12} \text{RISK}_{it12} + \beta_{13} \text{NONDRUGE}_{it13} + \beta_{14} \text{WHITES}_{it14} + \\ & \beta_{15} \text{CHILDREN}_{it15} + \beta_{16} \text{DISABLED}_{it16} + \beta_{17} \text{ELDERLY}_{it17} + \beta_{18} \text{HSGRAD}_{it18} + \beta_{19} \text{GT100FPL}_{it19} + \\ & \beta_{20} \text{UNEMPLOY}_{it20} \end{aligned}$$

where, values of the dummy variables (D) will be 1 for the cross-section they identify and 0 otherwise, $i = 1$ to 48 for the 48 states considered in the model, $t = 1$ to 5 for the five years considered in the model, and $k = 1$ to 20 for the 20 independent variables included in the model.

Analysis will be done using the SAS® TSCSREG procedure command. The TSCSREG (Time Series Cross Section Regression) procedure analyzes a class of linear econometric models

that commonly arise when time series and cross-sectional data are combined – as in the case of panel data. The TSCSREG procedure deals with panel data sets that consist of time series observations on each of several cross-sectional units.

The input data set used by the TSCSREG procedure must be sorted by cross section and by time within each cross section. Therefore, the first step in using PROC TSCSREG was to make sure that the input data set is sorted using a BY statement. A specific variable STATE (with values 1 through 48) was used to identify the cross section for each observation and the variable YEAR (1998 through 2002) was used to identify the time period for each observation.

In the TSCSREG procedure, the cross section and time series variables were specified in an ID statement. These were listed exactly as in the BY statement. A linear regression model was specified with a MODEL statement like in any other SAS regression procedure.

The reason for using PROC TSCSREG instead of other SAS regression procedures was that we can incorporate a model for the structure of the random errors. It is important to consider what kind of error structure model is appropriate for the data and to specify the corresponding option in the MODEL statement. In this case, a one-way fixed effects model was estimated and was specified by the FIXONE option in the MODEL statement based on reasons stated earlier in this section.

In order to aid in model specification, a specification test F statistic was used to test the null hypothesis that the fixed effects parameters are all zero.

The full SAS program for this analysis is presented in Appendix 1.

3.6 Assumptions and limitations of methodology

One limitation of the methodology was with the selection and measurement of indicator variables. While most of the policy, resources, predisposing, and utilization variables are specific to Medicaid, there are other ‘enabling resources’ and ‘need for healthcare’ variables for which measurements were available only for the entire state.

While it would be useful to obtain measures for these variables limited to the Medicaid population for each state, the state level information was considered acceptable for the purpose of this study – especially since we were able to make assumptions about the direction they could influence the results.

Adverse measures on the enabling resource variables like small proportions of high school graduates, high levels of unemployment, and high percentage of the poor – would generally be considered negative with respect to the overall state economy. However, when considered from a Medicaid point of view – such values would mean increased chances of Medicaid eligibility and hence greater levels of access to healthcare. Therefore, impacts of the enabling resources would likely be overestimated in the current study, especially for the more adverse measures.

The ‘risk’ part of the need for healthcare variables is derived from state level data. As discussed in the literature review section earlier, several studies have established that the propensity for risky health behavior like smoking and obesity, as well as prevalence of chronic diseases are much higher in the Medicaid populations when compared with the overall state populations. Therefore, since Medicaid eligibles are sicker than the rest of the population, impact of the risk variable will likely be underestimated in the study results.

3.7 Conclusion

This chapter provided detailed descriptions of the data procurement and analysis methods. The next chapter will offer descriptive analyses of the variable measures of the model and key results of the analyses described in this chapter. The next chapter will also include discussion and interpretation of the results with respect to the objectives of the study.

4 Chapter four: Results and Discussion

Previous chapters provided an overview of the need for identifying determinants of Medicaid prescription drug expenditures. The specific objectives and the conceptual framework of the study were also outlined. Data sources and detailed methodology employed to meet the study objectives were also provided. This chapter presents the results and discusses the findings of each study result. The chapter is sub-divided into three main sections to discuss results relevant to three objectives of the study. Discussions follow the results in each section.

4.1 Descriptive statistics for model variables

Continuous variables

Table 2 provides descriptive statistics for the continuous, numeric variables in the model. The minimum and maximum values, means, and measures of dispersion (Standard Deviation) are presented.

The minimum drug expenditure per Medicaid eligible person (DRUGELIG) was \$105.40 (New Mexico, 1999) and the maximum was recorded at \$1,248.53 (Montana, 1999). The mean expenditure was \$508.04 ($\pm$ \$166.35).

Managed care (MAN_CARE) was found to be non-existent in the Medicaid populations of states like Alaska or Wyoming, while all Medicaid enrollees were part of managed care for states like Michigan or Montana. The mean percentage of Medicaid population in a state that participated in managed care was 57.1 percent ($\pm$ 26.7 percent).

New York (50 percent, all years) had the lowest share of Federal assistance (FMAP) with Connecticut, Hawaii, Maryland, and Massachusetts following closely. Mississippi had the highest (77.3 percent, 1998) share of Federal matching funds with West Virginia and New

Mexico following closely. The mean Federal assistance to Medicaid drug programs was 60.63 percent (± 8.5 percent).

For any dispensed drug with an AWP of \$100, the minimum reimbursement to pharmacies (REIMBURSE) was \$61.15 (Rhode Island, 1998) and the maximum was recorded at \$113.00 (Massachusetts, 2000). Mean reimbursement levels were around \$91.19 ($\pm \8.16).

New Hampshire (2001) had the highest level of support (SUPPORT) for publicly funded healthcare at 60.4 percent of the state's spending going to healthcare. New Mexico (1998) had the lowest at only 4.6 percent. The average healthcare spending was found to be at 16.4 percent (± 8.3 percent) of the state's overall budgets.

Access to hospitals (HOSP_ACC) was found to be the least in New York (2001) with only 0.3 hospitals available per 10,000 Medicaid eligible persons. North Dakota (1999) on the other hand, had 8.2 Medicaid certified hospitals available to every 10,000 of their state Medicaid population. On an average there were 2.2 (± 1.6) hospitals for every 10,000 Medicaid eligibles nationwide.

South Carolina (2001) was recorded to have had less than one pharmacy (PHARM_ACC) for every 10,000 Medicaid eligibles in the state. North Dakota (2002) had the highest with 74.3 licensed pharmacies available to serve every 10,000 Medicaid eligibles. While North Dakota is an economically disadvantaged rural state, the density of pharmacies with respect to the state's population could have made such high access possible. On an average, there were 21.8 (± 11.7) licensed pharmacies available for every 10,000 Medicaid eligibles nationwide.

Only 21.3 primary care physicians (PCP_ACC) were available to provide care to every 10,000 Medicaid eligibles in Mississippi (2002). However, the highest physician-to-patient ratio was recorded in North Dakota (2001) with 134.3 primary care physicians being available to treat

every 10,000 Medicaid eligibles. The national average was 61.3 (± 21.2) physicians per 10,000 Medicaid eligibles.

Prenatal care (PRENATAL) levels were lowest in New Mexico (53.7 percent, 2000) while they were highest in New Hampshire (88.0 percent, 2000). Nationally, 76.0 percent (± 6.3 percent) pregnancies received prenatal care for an overall state population. However, given that prenatal care is among the mandated services provided by Medicaid, percentages would be higher in the Medicaid populations in each state and hence impact of this variable would likely have been underestimated in this study.

Whites (WHITES), representing an overall majority race, comprised only 21.7 percent of the Medicaid population in Hawaii (1999). On the other hand, Maine (1998) had 99.2 percent of the state's Medicaid population comprising of whites. On an average 79.2 percent (± 13.9 percent) of the national Medicaid population was white.

Despite the availability of Medicare coverage for seniors, 20.8 percent of Maine's Medicaid population comprised of people over the age of 65 (ELDERLY). New Mexico (2002), on the other hand, had only 5.1 percent elderly persons in their Medicaid population. Nationally, the elderly comprised 10.3 percent (± 2.6 percent) of the Medicaid population.

Maine (34.4 percent, 2002) had the highest percentage of disabled persons in their Medicaid population, while Alaska (9.8 percent, 2000) had the least. On an average, 16.9 percent (± 4.4 percent) of a state's Medicaid population were disabled.

The least percentage of children in the Medicaid population was found in Oregon (26.3 percent, 1998) and the highest in New Mexico (65.2 percent, 1998). National average for the percentage of children in a state Medicaid population was 50.2 percent (± 6.4 percent).

Less than 1 percent of the South Carolina (1998) population was unemployed, while 8.2 percent of Oregonians (2002) did not have a job, followed closely by the Alaskans (2002) 8.0 percent of whom were jobless. Nationally, 3.6 percent (± 1.6 percent) were unemployed.

88.7 percent of the Iowa population (1999) was at least high school graduates while less than half (48.0 percent) of the South Carolina population had such education. On an average 70.4 percent ($+8.9$ percent) of a state's population was found to have at least had high-school education.

New Hampshire (2000) was found to be the richest state with only 4.8 percent of its population below 100 percent of the Federal Poverty Line. New Mexico (1998) was the poorest with 21.9 percent. An average state was found to have 11.7 percent (± 3.2 percent) of its population below 100 percent of FPL.

Average risk of disease was 28.34 percent (± 4.4) for any state with a minimum of 17.6 percent in Utah (2002) and a maximum of 40.03 percent in Kentucky (2000).

Annual Medicaid payments per eligible person for items other than prescription drugs was least for Washington (\$1,966.49, 2000), and was highest for New York (\$8127.62, 2000). National average for such payments was \$3,944.53 ($+\$1,242.00$).

Categorical variables

Descriptive statistics for the categorical variables have been analyzed only for the last available year of data (2002). Table 3 provides descriptive statistics for the three dichotomous categorical variables that have been included in the model.

46 (95.8 percent) out of the 48 states included in the study had Prior Authorization requirement in place. The 2 states that did not have such a program were – Connecticut and North Dakota.

34 (70.8 percent) of the 48 states had passed laws on mandatory substitution of brand name drugs with generic or multi-source drugs at the pharmacy. The 14 states that did not require such substitution were – Alabama, California, Colorado, Connecticut, Illinois, Kansas, Louisiana, Michigan, Missouri, Nebraska, New Mexico, North Dakota, Ohio, and South Dakota.

18 (37.5 percent) of the 48 states had a Preferred Drug List within their state Medicaid drug benefit program. These states were – Alaska, Arkansas, California, Florida, Georgia, Indiana, Kansas, Kentucky, Maine, Michigan, Ohio, Oregon, Rhode Island, Vermont, Virginia, Washington, West Virginia, and Wyoming

4.2 Correlations

Bivariate Correlations among Policy variables

Correlations among Policy variables are presented in Table 4. Only FMAP showed a strong negative correlation with SUPPORT (-0.634, $p < 0.001$). Weak positive correlations exist among MAN_CARE and PRIOR_AUT (0.175, $p = 0.007$); PRIOR_AUT and GENSUBST (0.134, $p = 0.038$). Weak negative correlation exists between PDL and SUPPORT (-0.170, $p = 0.008$).

Bivariate Correlations among Health System Resource variables

Correlations among Health System Resource variables are presented in Table 5. HOSP_ACC showed a strong positive correlation with PHARM_ACC (0.765, $p < 0.001$); a weak positive correlation with PCP_ACC (0.281, $p < 0.001$), and a weak negative correlation with PRENATAL (-0.146, $p = 0.023$). PHARM_ACC had a positive correlation with PCP_ACC (0.347, $p < 0.001$), and a weak negative correlation with PRENATAL (-0.163, $p = 0.011$).

Bivariate Correlations among Predisposing variables

Correlations among Predisposing variables are presented in Table 6. WHITES were positively correlated with ELDERLY (0.160, $p=0.013$) which in turn is correlated positively with DISABLED (0.404, $p<0.001$) and negatively with CHILDREN (-0.167, $p=0.01$). DISABLED are also negatively correlated with CHILDREN (-0.215, $p=0.001$).

Bivariate Correlations among Enabling Resource variables

Correlations among Enabling Resource variables are presented in Table 7. UNEMPLOY showed a weak negative correlation with HSGRAD (-0.191, $p=0.003$); and HS_GRAD is negatively correlated with LT100FPL (-0.420, $p<0.001$).

Bivariate Correlations among Need for Healthcare variables

Correlations among Health System Resource variables are presented in Table 8. RISK had a weak negative correlation with NONDRUGE (-0.201, $p=0.002$).

Table 2. Descriptive statistics of continuous variables

<i>Variable</i>	<i>Description</i>	<i>Unit</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Mean</i>	<i>SD</i>
DRUGELIG	Drug expenditure per eligible	\$	105.40	1,248.53	508.04	166.35
MAN_CARE	Medicaid population in Managed Care	%	0.0	100.0	57.1	26.7
FMAP	Federal Matching funds	%	50.0	77.3	60.6	8.5
REIMBURS	Reimbursement to pharmacy for a \$100 AWP drug	\$	61.2	113.0	91.2	8.2
SUPPORT	Proportion of public funds spent on healthcare	%	4.6	60.4	16.4	8.3
HOSP_ACC	Access to hospital per 10,000 eligibles	Rate	0.3	8.2	2.2	1.6
PHARM_ACC	Access to pharmacy per 10,000 eligibles	Rate	0.0	74.3	21.8	11.7
PCP_ACC	Access to physicians per 10,000 eligibles	Rate	21.3	134.4	61.3	21.2
PRENATAL	Access to prenatal care	%	53.7	88.0	76.0	6.3
WHITES	Proportion of whites in Medicaid	%	21.7	99.2	79.2	13.9
ELDERLY	Proportion of >65 yrs in Medicaid	%	5.1	20.8	10.3	2.6
DISABLED	Proportion of whites in Medicaid	%	9.8	34.4	16.9	4.4
CHILDREN	Proportion of whites in Medicaid	%	26.3	65.2	50.2	6.4
UNEMPLOY	Proportion of whites in state	%	0.9	8.2	3.6	1.6
HSGRAD	Proportion of whites in state	%	48.0	88.7	70.4	8.9
LT100FPL	Proportion of whites in Medicaid	%	4.8	21.9	11.7	3.2
RISK	Aggregate disease prevalence	%	17.6	40.0	28.3	4.4
NONDRUG	Severity of disease	\$	1,966.49	8,127.6	3,944.53	1,242.00

Table 3. Descriptive statistics for dichotomous categorical variables

<i>Variable</i>	<i>Description</i>	<i>Category</i>	<i>Frequency</i>	<i>Percentage</i>
PRIORAUT	Prior Authorization program	Not required	2	4.2
		Required	46	95.8
GENSUBST	Mandatory generic substitution	Not required	14	29.2
		Required	34	70.8
PDL	Preferred Drug List	Not present	30	62.5
		Present	18	37.5

Table 4. Bivariate Correlations among Policy variables

<i>Variable</i>		<i>MAN_CARE</i>	<i>FMAP</i>	<i>PRIORAUT</i>	<i>REIMBURS</i>	<i>GENSUBST</i>	<i>PDL</i>	<i>SUPPORT</i>
<i>MAN_CARE</i>	Pearson correlation	1	-.083	.175**	-.053	.046	.126	.042
	Significance		.200	.007	.410	.474	.051	.514
<i>FMAP</i>	Pearson correlation		1	.015	.111	.005	.022	-.634**
	Significance			.813	.088	.933	.729	.000
<i>PRIORAUT</i>	Pearson correlation			1	-.088	.134*	.096	-.058
	Significance				.173	.038	.140	.373
<i>REIMBURS</i>	Pearson correlation				1	-.083	-.048	-.041
	Significance					.199	.464	.532
<i>GENSUBST</i>	Pearson correlation					1	-.040	.080
	Significance						.538	.220
<i>PDL</i>	Pearson correlation						1	-.170**
	Significance							.008
<i>SUPPORT</i>	Pearson correlation							1
	Significance							

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

Table 5. Bivariate Correlations among Health System Resource variables

<i>Variable</i>		<i>HOSP_ACC</i>	<i>PHARM_ACC</i>	<i>PCP_ACC</i>	<i>PRENATAL</i>
<i>HOSP_ACC</i>	Pearson correlation	1	.765**	.281**	-.146*
	Significance		.000	.000	.023
<i>PHARM_ACC</i>	Pearson correlation		1	.347**	-.163*
	Significance			.000	.011
<i>PCP_ACC</i>	Pearson correlation			1	.123
	Significance				.056
<i>PRENATAL</i>	Pearson correlation				1
	Significance				

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

Table 6. Bivariate Correlations among Predisposing variables

<i>Variable</i>		<i>WHITES</i>	<i>ELDERLY</i>	<i>DISABLED</i>	<i>CHILDREN</i>
<i>WHITES</i>	Pearson correlation	1	.160*	.123	-.017
	Significance		.013	.057	.792
<i>ELDERLY</i>	Pearson correlation		1	.404**	-.167**
	Significance			.000	.010
<i>DISABLED</i>	Pearson correlation			1	.215**
	Significance				.001
<i>CHILDREN</i>	Pearson correlation				1
	Significance				

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

Table 7. Bivariate Correlations among Enabling Resource variables

<i>Variable</i>		<i>UNEMPLOY</i>	<i>HSGRAD</i>	<i>LT100FPL</i>
<i>UNEMPLOY</i>	Pearson correlation	1	-.191**	.037
	Significance		.003	.570
<i>HSGRAD</i>	Pearson correlation		1	-.420**
	Significance			.000
<i>LT100FPL</i>	Pearson correlation			1
	Significance			

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

Table 8. Bivariate Correlations among Need for Healthcare variables

<i>Variable</i>		<i>RISK</i>	<i>NONDRUGE</i>
<i>RISK</i>	Pearson correlation	1	-.201**
	Significance		.002
<i>NONDRUGE</i>	Pearson correlation		1
	Significance		

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

4.3 Results for Objective 1

To develop and test a model assessing relationships among potential influencers/ predictors of Medicaid drug expenditures identified based on Andersen's Behavior Model for Health Services Utilization.

The hypothesized model drawn using the Amos Graphics interface is shown in Figure 5. As shown in the diagram, the model tests for influences of five latent constructs (latent variables) – Policy, Resources, Predisposing, Enablers, and Need on the dependent construct Utilization and on each other.

The arrows point in the direction of influence between each pair of constructs. However, arrows going from the latent variables to the observed ones show which indicators are used to measure the relevant latent variable.

Total number of variables in the model is 53. Of those, 21 are observed variables, namely – PDL, FMAP, PRIORAUT, REIMBURS, GENSUBST, MAN_CARE, SUPPORT, PHARM_AC, HOSP_ACC, PCP_ACC, PRENATAL, RISK, NONDRUGE, DRUGELIG, CHILDREN, DISABLED, ELDERLY, WHITES, UNEMPLOY, HSGRAD, LT100FPL.

There were 32 'unobserved' variables in all. Of those, 6 were endogenous (latent) variables, namely – Policy, Resources, Need, Utilization, Predisposing, Enablers (our structural model); and 26 were exogenous, including – 21 error variables and 5 residuals associated with the observed variable measures and the endogenous latent variables, respectively. Table 9 presents the latent constructs, the observed variables that measure each latent variable and the other latent variables that are impacted/ influenced by each latent variable, as hypothesized.

Model identification

Model identification was performed as described in the ‘methods’ section of this document to compute degrees of freedom:

- Number of distinct sample moments (for 21 observed variables) = $(21*22)/2 = 231$
- Number of distinct parameters to be estimated = 23 regression weights + 26 variances = 49
- Degrees of freedom = $(231 - 49) = 182$

Hence, the model is ‘over-identified’ – which is a desirable situation for SEM analysis.

Model fit summary

Table 10 presents the results of overall model fit tests. Each measure is calculated for three models. "Default model" is the model as specified by the researcher. The "independence model" is the model in which variables are assumed to be uncorrelated with the dependent(s), so if the fit for "Default model" is no better than for the "independence model," then our model should be rejected. The "saturated model" is one with no constraints and will always fit any data perfectly, so normally our model should have a measure of fit between the saturated and independence models.

The chi-square fit index is a common fit test that tests the hypothesis that an unconstrained model fits the covariance/correlation matrix as well as the given model. P is the probability of getting as large a discrepancy as occurred with the present sample. That is, P is a “p value” for testing the hypothesis that the model fits perfectly in the population. If P(CMIN) is less than 0.05, we reject null hypothesis that the data are a perfect fit to the model.

In this case the chi-square value $CMIN = 212.6$ ($P = 0.06$) is not significant and hence the proposed model cannot be rejected – which, in this case, is a desirable outcome. By this criterion, we fail to reject the present model.

CMIN/DF is the minimum sample discrepancy divided by degrees of freedom. This is called relative chi-square or normal chi-square. Some researchers allow values as large as 5 as being an adequate fit, but conservative use calls for rejecting models with relative chi-square greater than 2 or 3. The study CMIN/DF is 1.17. Hence, by this criterion, again, we fail to reject the present model.

Goodness of Fit

Table 11 presents data on Goodness of Fit indices. The most commonly used index is the GFI for which the value of 1 represents perfect fit. The model fit of 0.78 in this case is acceptable. Like the 'R-squared' value in regression, GFI can be thought of as the amount of variance explained by the hypothesized model. The Adjusted Goodness of Fit (AGFI), much like the Adjusted R-squared in regression methods, takes into account the degrees of freedom available for testing the model. A value of AGFI = 1 denotes perfect fit and the level in our study 0.72 is considered acceptable in this kind of model.

Table 12 presents the Hoelter's critical N values for the model at the 0.05 and 0.01 levels. Hoelter's N is the size the sample size must reach for us to be able to accept the model by chi-square. For the 0.05 level, Hoelter's N is computed as $((2.58 + (2df - 1) * 2) * .5) / ((2chisq) / (n - 1)) + 1$, where chisq is model chi-square, df is degrees of freedom, and n is the number of subjects. Hoelter's N should be greater than 200 for an acceptable model fit to the sample. By this criterion again, the model cannot be rejected since the model Hoelter's Ns are 240 and 247 at the 0.05 and 0.01 levels.

Parsimony Adjusted Measures

Table 13 shows the Parsimony Adjusted measures. The parsimony ratio (PRATIO) expresses the number of constraints in the model being evaluated as a fraction of the number of

constraints in the independence model and an ideal value for it should be 1. The study model has a PRATIO = 0.87 which is in the acceptable range showing that the model is parsimonious with respect to the completely unrestricted model.

Baseline Comparisons

Table 14 presents values of the baseline comparisons of model fit. Normed Fit Index (NFI) values less than 0.9 are considered acceptable fit. By this measure our study model NFI = 0.28 is hence acceptable. Incremental Fit Index (IFI) and Comparative Fit Index (CFI) values close to 1 are deemed good fit. Our study values of RFI = 0.73 and CFI = 0.64 are considered acceptable.

Measures of the Error of Approximation

The overall model discrepancy incorporates no penalty for model complexity and will tend to favor models with many parameters. Such error owing to model complexity is compensated for by dividing the discrepancy measure by the number of degrees of freedom for testing the model. Taking the square root of the resulting ratio gives the population “root mean square error of approximation”, called RMSEA. Table 15 presents the RMSEA values for the study model.

It is suggested that a value of the RMSEA of about 0.05 or less would indicate a close fit of the model in relation to the degrees of freedom since for exact fit the RMSEA will be equal to 0.0. A value of about 0.08 or less for the RMSEA would indicate a reasonable error of approximation, and a model with a RMSEA greater than 0.1 will not be acceptable. By this criterion, again, since our model RMSEA is 0.04, we can accept the model. Even the lower limit and upper limit of a 90% confidence interval for the population value of RMSEA (columns labeled LO 90 and HI 90) in this case are within the acceptable range (LO 90 = 0.0 and HI 90 =

0.06). PCLOSE is a “p value” for testing the null hypothesis that the population RMSEA is no greater than 0.05. Since, a RMSEA of 0.05 or less indicates a “close fit”, PCLOSE gives a test of close fit. In this case we fail to reject the null hypothesis and hence RMSEA estimates for the model indicate a close fit.

Parameter estimates

Table 16 presents the GLS parameter estimates for the model variables. Column ‘Estimate’ presents the regression weights, column ‘S.E.’ presents the approximate standard errors of measure, column ‘C.R.’ presents critical ratio (measured as – the parameter estimate divided by an estimate of its standard error), and column ‘P’ provides the p value for estimate for the null hypothesis that the population critical ratio equals zero.

Structure parameters

At the 0.10 level of significance, it was found that the latent variable ‘Predisposing’ significantly impacts the latent variable ‘Enablers’ ($p = 0.08$) in the positive direction; and the latent variable ‘Enablers’, in turn, significantly impacts ‘Utilization’ ($p = 0.01$), also in the positive direction.

Measurement parameters

Among the observed variables, HOSP_ACC significantly influences (describes) the latent variable ‘Resources’ ($p < 0.0001$). PCP_ACC also describes ‘Resources’ significantly ($p = 0.00$). RISK describes the latent ‘Need’ variable significantly ($p = 0.00$). At a 0.10 level, DISABLED and ELDERLY variables have significant influence on the value of the latent variable ‘Predisposing’ ($p = 0.06$ and $p = 0.07$ respectively). Finally, the latent construct ‘Enablers’ is adequately described by the observed variable LT100FP ($p = 0.01$).

Table 9. Model variables

Latent Variables	Measured by (observed variables)	Proposed Impacts on
Policy	PDL	Resources
	FMAP	Utilization
	PRIORAUT	
	REIMBURSE	
	GENSUBST	
	MAN_CARE	
	SUPPORT	
Resources	PHARM_AC	Utilization
	HOSP_ACC	
	PCP_ACC	
	PRENATAL	
Predisposing	CHILDREN	Need Enablers
	DISABLED	
	ELDERLY	
	WHITES	
Enablers	UNEMPLOY	Utilization
	HSGRAD	
	LT100FPL	
Need	RISK	Policy
	NONDRUGE	Utilization
Utilization	DRUGELIG	-

Table 10. Overall model fit summary

<i>Model</i>	<i>NPAR</i> ¹	<i>CMIN</i> ²	<i>DF</i> ³	<i>P(CMIN)</i> ⁴	<i>CMIN/DF</i> ⁵
Default model ^a	49.00	212.60	182.00	0.06	1.17
Saturated model ^b	231.00	0.00	0.00		
Independence model ^c	21.00	295.44	210.00	0.00	1.41

a. Model specified by the researcher

b. Model that has no constraints

c. Model in which variables are assumed to be uncorrelated with the dependent

1. Number of parameters being estimated in the model

2. Chi-Square at the minimum sample discrepancy

3. Degrees of Freedom

4. p-value for the Chi-Square

5. Relative Chi-Square or the minimum sample discrepancy divided by degrees of freedom

Table 11. Hoelter's Critical N

<i>Model</i>	<i>Hoelter 0.05¹</i>	<i>Hoelter 0.01²</i>
Default model ^a	240	247
Saturated model ^b	224	229
Independence model ^c	172	174

a. Model specified by the researcher

b. Model that has no constraints

c. Model in which variables are assumed to be uncorrelated with the dependent

1. Required sample size for accepting the model by chi-square at 0.05 level

2. Required sample size for accepting the model by chi-square at 0.01 level

Table 12. Goodness of Fit test summary

<i>Model</i>	<i>GFI¹</i>	<i>AGFI²</i>	<i>PGFI³</i>
Default model ^a	0.78	0.72	0.62
Saturated model ^b	1.00		
Independence model ^c	0.70	0.67	0.63

a. Model specified by the researcher

b. Model that has no constraints

c. Model in which variables are assumed to be uncorrelated with the dependent

1. Goodness of Fit Index

2. Adjusted Goodness of Fit Index – accounting for degrees of freedom

3. Parsimony Goodness of Fit Index - penalizes GFI by multiplying it times the ratio formed by the degrees of freedom in the Default model and the independence model

Table 13. Parsimony Adjusted Measures

<i>Model</i>	<i>PRATIO</i> ¹	<i>PNFI</i> ²	<i>PCFI</i> ³
Default model ^a	0.87	0.24	0.56
Saturated model ^b	0.00	0.00	0.00
Independence model ^c	1.00	0.00	0.00

a. Model specified by the researcher

b. Model that has no constraints

c. Model in which variables are assumed to be uncorrelated with the dependent

1. Parsimony ratio – the ratio of the degrees of freedom in the Default model to the independence model

2. Parsimony normed fit index, equal to the PRATIO times NFI (see table 14)

3. Parsimony comparative fit index, equal to PRATIO times CFI (see table 14)

Table 14. Baseline comparisons

<i>Model</i>	<i>NFI</i>	<i>RFI</i>	<i>IFI</i>	<i>TLI</i>	<i>CFI</i> ⁵
	<i>Delta1</i> ¹	<i>rho1</i> ²	<i>Delta2</i> ³	<i>rho2</i> ⁴	
Default model ^a	0.28	0.17	0.73	0.59	0.64
Saturated model ^b	1.00		1.00		1.00
Independence model ^c	0.00	0.00	0.00	0.00	0.00

a. Model specified by the researcher

b. Model that has no constraints

c. Model in which variables are assumed to be uncorrelated with the dependent

1. Normed Fit Index

2. Relative Fit Index

3. Incremental Fit Index

4. Tucker-Lewis coefficient

5. Comparative Fit Index

Table 15. RMSEA

<i>Model</i>	<i>RMSEA¹</i>	<i>LO 90²</i>	<i>HI 90³</i>	<i>PCLOSE⁴</i>
Default model ^a	0.04	0.00	0.06	0.69
Independence model ^b	0.07	0.05	0.08	0.07

a. Model specified by the researcher

b. Model in which variables are assumed to be uncorrelated with the dependent

1. Root Mean Square Error of Approximation – incorporates the discrepancy function criterion (comparing observed and predicted covariance matrices – error owing to model complexity), and the parsimony criterion (degrees of freedom)

2. Lo end of 90% confidence limits on the coefficient

3. Hi end of 90% confidence limits on the coefficient

4. Tests the null hypothesis that RMSEA is no greater than .05

Table 16. Generalized Least Squares parameter estimates

<i>Pathway</i>			<i>Estimate</i>	<i>Std. Error</i>	<i>P</i>
Need	-	Predisposing	85.13	83.63	0.31
Policy	-	Need	0.00	0.00	0.66
Resources	-	Policy	-86.90	198.23	0.66
Enablers	-	Predisposing	0.42	0.24	0.08
Utilization	-	Policy	-1,594.35	3,613.61	0.66
Utilization	-	Resources	0.29	2.63	0.91
Utilization	-	Need	0.02	0.03	0.56
Utilization	-	Enablers	51.03	19.98	0.01*
PDL (Preferred Drug List)	-	Policy	1.00		
FMAP (Federal Matching)	-	Policy	119.13	273.76	0.66
PRIORAUT (Prior Authorization)	-	Policy	3.79	8.56	0.66
REIMBURSE (Reimbursement)	-	Policy	132.89	301.88	0.66
GENSUBST (Generic Substitution)	-	Policy	-1.45	4.19	0.73
MAN_CARE (Managed Care)	-	Policy	-112.29	309.83	0.72
SUPPORT (Public health support)	-	Policy	-119.56	268.72	0.66
PHARM_AC (Access to Pharmacies)	-	Resources	1.00		
HOSP_ACC (Access to hospitals)	-	Resources	0.12	0.03	0.00*
PCP_ACC (Access to physicians)	-	Resources	0.99	0.33	0.00*
PRENATAL (Access to prenatal care)	-	Resources	-0.12	0.09	0.19
RISK (Aggregate disease prev.)	-	Need	0.00	0.00	0.00*
NONDRUGE (Severity of disease)	-	Need	1.00		
DRUGELIG (Drug payments/ eligible)	-	Utilization	1.00		
CHILDREN (% Children in Medicaid)	-	Predisposing	1.00		
DISABLED (% Disabled in Medicaid)	-	Predisposing	-1.31	0.71	0.06
ELDERLY (% >65 yrs. in Medicaid)	-	Predisposing	-0.63	0.34	0.07
WHITES (% Whites in Medicaid)	-	Predisposing	0.90	0.99	0.37
UNEMPLOY (% Unemployed in state)	-	Enablers	1.00		
HS_GRAD (% state High School grads)	-	Enablers	0.35	0.80	0.67
LT100FPL (% below 100% FPL)	-	Enablers	-0.87	0.35	0.01*

* Significant at the 0.05 level

4.3.1 Power of the SEM analysis

Performing power analysis and sample size estimation is an important aspect of experimental design, because without these calculations an experiment may lack the precision to provide reliable answers to the questions it is investigating.

Given the limitation of data availability explained earlier – power for the current analysis was expected to be low. Nevertheless, a post-hoc power analysis was performed based on methodology suggested by McCallum, Browne, and Sugawara (1996).¹¹⁸ Their method uses RMSEA measures in conjunction with the alpha level, sample size (N), and the available degrees of freedom (d) in the model to calculate power. The authors have established that power is consistently low when d is small even when N is relatively large. For studies with moderate to large d, reasonable power is achieved with moderate sample sizes, and very high power is achieved with large samples. Based on these general observations power for the current analysis is expected to be high for $d = 182$, and $N = 240$, since, for example, a power of 0.87 can be achieved with a $d = 100$ and $N = 200$, as shown by the above authors.¹¹⁸

However, there is yet another aspect to the power equation at hand. Power calculated in this method is a function of the difference between RMSEAs for the null hypothesis (R_0) and that of the actual model (R_a). In power analysis terminology, the difference between the two RMSEAs reflects the effect size, conceptualized as the degree to which the null hypothesis is incorrect. SAS code used for power calculation in this method is shown in Appendix 2.

Although arbitrary, it is standard practice to use 0.05 as the value of RMSEA for the null hypothesis. The model R_a is 0.04 as mentioned earlier. The above authors have also established that if these two values are specified as very close together, as in this case, resulting power estimates will generally be low.

Hence, for an alpha level of 0.05, $d = 182$, and $N = 240$, the calculated power was 0.42. It was further calculated that to get to a power of 0.80 with similar determinants, the sample size needed would be 509 – which would in this case means 11 years worth of data on all 48 states included in the study. Needless to mention, such volumes of data were not available at the time the study was done.

4.3.2 Discussion for Objective 1

The SEM analysis allowed us to look at the varied factors (and their determinants) influencing Medicaid prescription drug expenditure. The overall model fit, although acceptable, could have been better. Although there are recommended levels of various fit indices for acceptance of model fit (ex. that GFI should be 0.90), authors have observed that these cut-offs are arbitrary.¹¹⁹ A more salient criterion may be simply to compare the fit of one's model to the fit of other, prior models of the same phenomenon. Since no other Medicaid specific drug utilization model was found in the literature to-date, it is difficult to compare our model with any prior work.

The GFI measure – the percent of observed co-variances explained by the co-variances implied by the model – is often compared with the R-squared in regression methods. However, while R-squared in multiple regression deals with error variance, GFI deals with error in reproducing the variance-covariance matrix. When degrees of freedom are large relative to sample size, as in this case, GFI is biased downward – a situation that our GFI might have experienced. However, other measures, like the RMSEA (0.04 for the model) and the corresponding PCLOSE (0.69) assure us of a reasonable model fit.

Latent variable relationships: the structural model

Under the moderate fit, however, several determinants were found to have significant impact on Medicaid drug expenditure. The relationships among the latent variables are the main outcome from the SEM model. While it is useful to look at individual observed variables and their relationship with the latent construct – effects of latent variables on each other are what determine the usefulness of findings from the model.

We found that the ‘Predisposing’ construct significantly impacts the latent construct of ‘Enablers’ in the positive direction as expected. This result support findings from several other studies that have conclusively established the relationship between predisposing characteristics like race and disability status with unemployment and poverty, for example.⁶⁴ Predisposing characteristics have also in general been found to be extremely important in describing variations in drug expenditure across states.^{21,22,23,42}

Also, the latent variable ‘Enablers’, in turn, significantly impacts ‘Utilization’ – also in the positive direction as expected. This is understandable, since the components of the Enablers construct – unemployment, poverty and education (which is related to both the others) – serve as the eligibility criteria for receiving Medicaid benefits. Hence, as the percentages of unemployed and/ or poor people increase in the overall state population, a lot of them are going to end up being covered by Medicaid, and that will likely drive up the Medicaid drug utilization.

Although not significant at the chosen levels, other latent constructs in the model also show expected directionality in their relationships. The effect of ‘Predisposing’ characteristics like age and race have been proven to describe disparities in ‘Need’ as described by disease prevalence and health risk behaviors. Studies have shown that older populations are generally sicker and are in greater need for care for chronic diseases like diabetes and cardiovascular

ailments. Also, health risk behaviors like smoking and sedentary lifestyles have been shown to be more prevalent among the racial minorities, and hence would increase the Need for healthcare.

Positive effects of ‘Need’ on ‘Policy’ can be understood by looking at the variables that have described the two latent constructs.

The ‘Policy’ construct showed a negative relationship on the ‘Resources’ construct. This may be explained by the fact that for fee-for-service Medicaid programs (as have been included in this study), a lot of the access issues with respect to Resources considered in this study (namely, primary care physician services, hospitals, and pharmacies) depend on levels of reimbursement and other policy intervention that tend to contain costs by restricting profitability for the service providers. For example, studies show that physicians are not happy about PDLs as these allegedly restrict their ability to provide optimum care to their patients.¹²⁰

‘Policy’ also showed a negative relationship with ‘Utilization’. This was very much expected since the indicator variables for this construct include Medicaid policy and program interventions like, Managed Care, PDL, Generic Substitution and Prior Authorization – that are directed at reducing drug utilization and costs. Studies have shown cost reducing effects of such interventions, at least in the short run.^{26,75,72,75,77,82}

‘Utilization’ is impacted by ‘Resources’ in a positive relationship. We can intuitively conclude that with greater access to caregivers and points of care delivery – like hospitals and pharmacies, the chances of any individual to seek care will be higher. Hence, the direction for this relationship is also in accordance with what one would expect.

Similarly, ‘Need’ for healthcare shows an expected positive relationship with ‘Utilization’, since sicker people will likely seek care more than healthy persons. Since the Need

variable is constituted of disease prevalence and severity – a higher value for this variable would obviously denote a sicker population and hence would be expected to result in higher utilization. This is more specifically expected in the case of prescription drugs since the Risk variable includes chronic diseases which are mostly treated or managed with medications over a long time period.

Observed variable relationships: the measurement model

The observed variables in the model were included to describe and measure the latent variables they were attached to and hence to indirectly contribute to explaining the variance in the dependent variable measures. A significant and a directionally sensible relationship between an observed and a latent variable would be evidence of a good degree of representation of the latent construct in the model as well as a higher power to explain variances in the degree of impact the construct has on the dependent measure. Hence, it will be appropriate to discuss these relationships individually for each latent construct.

Policy Factor variables

Unfortunately, none of the indicators of Policy achieved significance in terms of their effects on the latent construct. It is possible that there are other indicators which might describe the construct better and were not identified in this model and investigating such variables could be a useful starting point for future research.

However, a look at the directions of these relationships in the current model offers useful insights and validation on their contributions to the model.

Results show that increasing Federal Assistance (FMAP) increases drug utilization (of course, through the Policy latent construct). This is what we expected, since states would likely be less concerned about drug payments out of local budgets if they are heavily subsidized by the

Federal government. Prior research has noted that while the current pattern of federal Medicaid matching payments reduces policy variation to some extent, these effects are found to be rather modest and fiscal incentives provided by matching rates are found to be comparatively weak instruments for national policymakers.¹⁹

It was not expected that Prior Authorization (PRIORAUT), being a utilization and cost-containment intervention, would actually have a positive relationship with (i.e. contribute to an increase in) drug expenditure since studies have shown that states use PA as a vehicle to gain leverage in price negotiations with manufacturers, which in turn should reduce costs.⁷⁵ One explanation of our results could be that although the actual expenditure goes up, the reductions in overall drug expenditures are realized by means of rebates obtained from manufacturers – which are not reflected in the actual expenditure numbers. A second, more oblique explanation could be an extension of the most common complaint of the medical fraternity against PDLs which are strongly linked with PA. Prior Authorization causes potentially inappropriate medication and restricts access to beneficial drugs if they are not on the PDL – which in turn causes complications or suboptimal cure which drives the overall costs up by increased utilization, repeat therapy etc.¹²⁰

Studies have shown that larger pharmacy dispensing fees would increase access and drug costs.²⁹ Pharmacies would likely be more accepting of Medicaid patients and prescriptions if they are reimbursed better by the program. Hence, the overall utilization and drug payments would be expected to go up as in the direction of the reimbursement rate (REIMBURS) indicator variable in the current model.

As means of cost containment, both requirement of mandatory generic substitution (GENSUBST) and increased percentage of managed care (MAN_CARE) were both expected to

reduce drug as well as overall costs – which is the case in this model. Studies have found that the opportunity and likelihood of generic substitution is higher in Medicaid than in any other form of coverage or in the uninsured.⁸²

It is not quite expected that drug utilization and costs will reduce if there is additional government support to public healthcare – as described by increase in percentage of state expenditure on healthcare vis-à-vis the overall budget. However, one plausible explanation for the support variable (SUPPORT) to have a negative relationship could be that such support could be directed towards better health education, awareness, screening, and provision of managed care and not necessarily for paying for more prescription drugs. The indirect effects of such measures could have had an effect on guiding and reducing drug costs while some of the cost to other areas.

A word on Drug Rebates

Adoption of many of the above policies like PA or PDL, are dictated in part by the availability of rebates from the manufacturers – under OBRA '90 and/or under state-negotiated supplemental rebate contracts. Since the expenditure numbers are based on 'pre-rebate' actuals, the full impact of above policy indicators may not have been captured adequately in our analysis, and may in part have led to the non-significance of the policy construct. While rebate figures were located in the NPC reports for the federal rebates, state supplemental rebates (which are more crucial with respect to the cost-containment effects of PDL and PA) were not available from the sources consulted. In addition, the federal rebate numbers could not be taken off the expenditure directly since the rebates are not necessarily linked with corresponding purchases and are usually paid by manufacturers to the states on a schedule different from how expenditures are recorded. There was no information available that supported an assumption of

a standard uniform time lag in availability of the rebate information. For all these reasons, rebates were not included as part of the study. However, the importance of complete rebate information must be emphasized in order to assess the actual effects of policy interventions like PDL or PA and future studies should seek and utilize such information, if available.

Healthcare Resource Variables

Among the Resource variables, both access to hospitals (HOSP_ACC) and access to primary care physicians (PCP_ACC) significantly influenced and/ or described the latent construct ($p < 0.0001$, and $p = 0.00$, respectively). The positive directions of these relationships also provide additional support to the strength of these relationships and their role in the model. Since prescription medication would require a prescription to be dispensed, increased access to points of delivery for such prescriptions, namely – physician offices, hospital discharges, emergency departments etc., would be expected to increase the number of prescriptions written and hence will increase utilization. These results are similar to what was found in earlier studies which concluded that availability of physicians in the office-based settings strongly and positively effects utilization and expenditure for medical care.⁸⁷

Our calculations using national data from NPC show that while annual number of eligibles have grown by 24.6 percent overall from 1998 – 2002, total number of prescriptions Medicaid paid per year for grew by 57.0 percent over the same period of time.¹¹ Additionally, number of prescriptions per eligible per year grew by 26.0 percent and the number of prescriptions per primary care physician per year grew by 77.5 percent. Access to physicians also tends to be different based on race of the patient, as studies have shown that 80 percent of blacks are treated by only 22 percent of all physicians.⁹⁶

The independent variable, access to prenatal care (PRENATAL), shows a negative direction in its influence. Although not significant, the direction of this influence is as expected since the better management of a pregnancy, although could increase utilization of medication and supplements, would likely reduce pre- and ante-natal complications which might require administration of more expensive medication both by the mother and the newborn.

Need for Healthcare variables

Earlier research has found Medicaid populations to be at greater risk of chronic diseases like diabetes, cardiovascular diseases, and obesity; and thus drive drug utilization in Medicaid.^{102,103,104} Medicaid populations also had significantly higher levels of health risk behaviors like smoking when compared to the non-Medicaid population.¹⁰⁷

The RISK variable shows a significant effect – which again is very well understood since increase in prevalence and risk of diseases (mainly, chronic diseases) would likely translate into increased utilization and hence payments for Medicaid patients. Our findings agree with prior research of the effects of health status and need on drug utilization.⁶⁴

However, the small magnitude of the relationship may be explained by the fact that not all risks are immediately translated into disease and also might have non-drug treatments and management modalities which do not necessarily increase drug payments drastically.

Predisposing Characteristics variables

The percentage of disabled (DISABLED) and elderly (ELDERLY) persons in the state Medicaid populations significantly impact drug payments per eligible. Prior studies have shown

that spending growth for the aged and disabled accounted for more than half of the Medicaid spending growth.

Direction of the effect is as expected with respect to the disabled, since, although the group is expensive to care for, a lot of the expenses associated with their disabilities might well be non-drug in nature. However, the negative effect of the elderly on drug expenditure is not as we expected it to be. One explanation for this unexpected result could be that increasing proportions of the elderly are being managed through managed care, at nursing homes or through the provision of home health care – all of which are separate cost areas for Medicaid.⁵⁴ In addition, with Medicare coming into the picture in 2006 with their drug benefit program – the relevance of Medicaid as the sole payer for prescription medication for the elderly, will be diminished significantly.

Increase in the percentage of white (WHITES) persons in the state Medicaid population will likely influence an increase in drug payments, although not significantly. This result is as expected, since studies have shown that, although minorities have greater rates of utilization of hospitalization and emergency department services, they are less likely to have a high rate of prescription drug utilization.^{46,93} Race has also been established as an important influencer in other studies.^{64,68} Access to physicians was also found to be higher for whites than blacks.⁸⁷

Enabler variables

The percentage of a state's population that is below 100 percent of the Federal Poverty Level (LT100FPL) shows a significant negative effect on the 'enabler' variable and hence on drug expenditure. This result is in line with prior research that showed that family income levels were important predictors of drug utilization.^{64,99}

The importance of this variable is understandable, since Medicaid eligibility in all states is linked to an extent with levels of family income and financial need. However, the negative direction of this effect is not well understood since we would expect an increase in overall utilization with increasing drug payments. However, one plausible and likely explanation for this phenomenon could be that an increase in the percentage of the poor, although will likely increase the number of Medicaid eligibles – may not necessarily mean the additional people are equally sick as the current population. Hence, it is not unlikely that such increase in number of eligibles with potentially less prescription drug utilization – will actually bring down drug expenditures per eligible – by disproportionately increasing the denominator of our dependent variable.

Finally, the percentage of high school graduates (HSGRAD) shows an insignificant positive effect on the ‘enabler’ variable; and this is expected since studies have shown that education facilitates a higher level of awareness about personal health needs, helps identification of the need for care and also enables seeking out of appropriate care.⁶⁶ A result of all these, is a likely increase in prescription drug utilization.

4.4 Results for Objective 2

To classify state Medicaid programs into homogeneous clusters based on similarities in their characteristics as measured by the prescription drug expenditure and its influencers/ predictors.

As mentioned earlier, Cluster Analyses for this objective were performed on the last available year's (2002) data.

As a first step, Hierarchical Cluster Analysis was performed to identify an appropriate number of clusters. Data were standardized to Z scores with mean 0 and standard deviation of 1. Squared Euclidian distance was used for the proximity measure.

Figure 6 presents a Dendrogram for the clustering process where smaller clusters combine in successive stages to form bigger clusters. The appropriate number of clusters is chosen based on a subjective assessment of balance of size and depth of each cluster. The chosen level clustering is shown with arrowheads on Figure 6. Based on the dendrogram, 8 clusters were identified as appropriate for grouping all state Medicaid programs. This was because cutting off at an earlier level would leave us with the states themselves and cutting off at a level higher would make the clusters too big to obtain any meaningful insights on the distinctions across clusters.

Following this, the same data was subjected to a K-Means Clustering process with K=8 as the predetermined number of clusters. Table 17 shows the number of states in each cluster and Table 18 presents individual cluster membership information for each state arranged alphabetically.

Table 19 shows the values for the final cluster centers. The values in the table are the means for each variable within each final cluster. The final clusters centers reflect the attributes

of the prototypical case for each cluster. The overall profile of each cluster is defined by the relative weights of the cluster center values of the means of variables within each cluster – compared to the same in other clusters.

Table 20 presents the Analysis of Variance of variable mean values across the identified clusters. The null hypothesis tested here is that of “no difference among the mean variable values across clusters”, or

$$\mu_{m1,n1} = \mu_{m1,n2} = \mu_{m1,n3} \dots = \mu_{m1,n8}, \text{ where,}$$

$\mu_{m,n1}$ is the cluster mean value for variable m and cluster n. In this analysis, m = 1 to 21 variables, and n = 1 to 8 clusters. All variables were F tested at 7 and 40 degrees of freedom for the 8 clusters and 48 states.

Several variable means were found to be significantly different across clusters – thus rendering stability to the cluster membership.

At the 0.05 significance level, level Policy variables FMAP (F=2.44; p=0.035), PRIORAUT (F=2.50; p=0.031), and SUPPORT (F=4.62; p=0.001) were found to be significantly different across clusters. Resource variable PCP_ACC (F=6.21; p<0.001) was significantly different. Enabling factor variable HSGRAD (F=2.37; p=0.040), and Need variable NONDRUGE (F=336.92; p<0.001) were also found to be different across the identified clusters.

Additionally the Utilization variable DRUGELIG (F=2.16; p=0.059), and Enabling factor variable LT100FPL (F=2.06; p=0.072) were also found to be significantly different across clusters at the 0.10 level.

Cluster characteristics

Since these clusters would have some distinctive characteristic that would differentiate them from the others, it was considered worthwhile to look at each cluster with respect to the

variable means for the cluster and how they compare with those of other clusters. The comparison was limited to those variable means that were found to be significant, namely – FMAP, PRIORAUT, SUPPORT, PCP_ACC, HSGRAD, NONDRUGE, DRUGELIG, and LT100FPL.

Clusters were ranked in the descending order of values for each variable. Since there were 8 clusters, variable ranks 1 and 2 were considered ‘High Values’; variable ranks 3 to 6 were considered ‘Medium values’; and variable ranks 7 and 8 were considered ‘Low values’. Table 21 presents these ranks for each variable value for each cluster and are shaded differently for easier identification.

Cluster 1 is characterized by all medium values for the classification variables.

Cluster 2 is characterized by a high level of support for public healthcare, high access to primary care physicians, high level of education and high severity of diseases in the Medicaid population. However, the cluster is low on Federal matching, and has a lower level of poverty.

Cluster 3 is characterized high values for drug expenditure per eligible, and for education level. Low values are for the percentage of poor people – meaning people are less poor in the member states.

Cluster 4 is almost the opposite of cluster 3 with lows on most areas except a high level of poverty in terms of percentage of the population under 100 percent of FPL.

Like Cluster 1, Cluster 5 also is a cluster of medium values on everything.

Cluster 6 is a cluster is characterized with high values for some variable – drug expenditure, support for public healthcare, access to primary care physicians, and severity of diseases. However, the cluster has low mean values for federal matching, and education level.

Cluster 7 is characterized by high values for Federal matching and medium values for all the rest of the classification variables.

Cluster 8 has high values for Federal matching and poverty. However, all the rest of the variable means are lower compared to other clusters.

Figure 7. Dendrogram from Hierarchical Cluster Analysis

Table 17. Number of states in each cluster from K-means Clustering

<i>Cluster number*</i>	<i>Number of States</i>
Cluster 1	9
Cluster 2	2
Cluster 3	6
Cluster 4	1
Cluster 5	8
Cluster 6	2
Cluster 7	11
Cluster 8	9
Total	48

* See table 18 for cluster membership

Table 18. Cluster Membership from K-means clustering

STATE	Cluster	Distance*	STATE	Cluster	Distance*
Indiana	1	125.27	Virginia	5	211.34
Kentucky	1	251.13	Wisconsin	5	47.53
Louisiana	1	61.95			
Maryland	1	338.60	New Hampshire	6	47.34
Missouri	1	80.87	New York	6	47.34
Nebraska	1	119.64			
North Carolina	1	207.87	Delaware	7	113.81
South Dakota	1	142.99	Georgia	7	88.33
Washington	1	179.92	Illinois	7	85.38
			Maine	7	145.76
New Jersey	2	291.09	Nevada	7	146.79
Pennsylvania	2	291.09	New Mexico	7	406.08
			Oregon	7	122.66
Connecticut	3	288.37	Texas	7	134.93
Iowa	3	336.95	Utah	7	61.32
Massachusetts	3	201.41	Vermont	7	212.59
Minnesota	3	236.23	West Virginia	7	208.45
North Dakota	3	363.16			
Rhode Island	3	93.60	Alabama	8	75.10
			Arkansas	8	111.95
California	4	0.00	Florida	8	189.82
			Hawaii	8	179.22
Alaska	5	259.25	Idaho	8	150.43
Colorado	5	189.63	Mississippi	8	262.88
Kansas	5	510.46	Oklahoma	8	312.69
Michigan	5	355.64	South Carolina	8	67.57
Montana	5	284.62	Wyoming	8	184.50
Ohio	5	167.93			

* Distance from cluster center – smaller numbers being more representative of cluster characteristics

Table 19. Cluster means for classification variables from K-means clustering

<i>Variable</i>	<i>Description</i>	<i>Unit</i>	<i>Cluster number</i>							
			<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>	<i>7</i>	<i>8</i>
DRUGELIG	Drug payments per eligible	\$	667.94	563.34	687.60	384.68	613.10	873.56	557.97	551.88
MAN_CARE	Proportion in managed care	%	72.8	73.6	70.9	52.0	53.3	33.6	59.6	44.6
FMAP	Federal matching	%	61.5	52.5	56.0	53.0	58.4	50.1	61.7	67.4
PRIORAUT	Prior Authorization		1	1	1	1	1	1	1	1
REIMBURS	Reimbursement	\$	92.46	93.87	82.29	94.05	88.11	88.63	90.86	93.04
GENSUBST	Mandatory generic substitution		1	1	1	0	1	1	1	1
PDL	Preferred Drug List		0	0	0	1	1	0	0	0
SUPPORT	Federal support	%	16.7	31.1	20.7	12.4	15.5	38.2	14.2	11.0
HOSP_ACC	Access to hospitals	Rate	2.10	1.26	2.51	0.47	2.56	1.60	1.34	1.84
PHARM_ACC	Access to pharmacies	Rate	19.84	21.86	26.78	6.64	20.59	17.10	16.21	18.61
PCP_ACC	Access to physicians	Rate	45.36	69.29	62.95	28.61	58.26	66.45	42.01	35.41
PRENATAL	Access to prenatal care	%	76.6	71.1	81.6	80.0	76.5	77.2	74.2	73.7

Table 19 contd. Cluster means for classification variables from K-means clustering

<i>Variable</i>	<i>Description</i>	<i>Unit</i>	<i>Cluster number</i>							
			<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>	<i>7</i>	<i>8</i>
WHITES	Percent whites in Medicaid	%	80.8	78.8	87.5	63.3	81.8	82.2	81.9	71.3
ELDERLY	Percent >65 yrs in Medicaid	%	9.2	11.9	11.3	7.1	9.6	10.3	9.9	9.0
DISABLED	Percent disabled in Medicaid	%	16.0	20.4	16.0	10.6	16.5	14.6	16.1	16.3
CHILDREN	Percent children in Medicaid	%	54.6	46.3	46.4	37.1	51.8	50.8	48.4	53.6
UNEMPLOY	Percent unemployed in state	%	5.5	5.8	5.0	6.7	5.9	5.3	5.8	5.6
HSGRAD	Percent HS grads in state	%	68.3	81.8	77.8	68.7	72.9	66.6	68.6	64.0
LT100FPL	Percent below 100% FPL	%	11.7	8.7	9.4	13.1	10.3	9.9	12.4	13.9
RISK	Aggregate disease prevalence	%	24.4	23.0	21.5	20.3	22.9	21.9	23.4	24.4
NONDRUGE	Severity of diseases	\$	4,212.53	6,922.87	6,065.56	2,495.49	4,816.45	7,908.05	3,608.59	3,196.59

Table 20. ANOVA for cluster means for model variables from K-means clustering

<i>Variable</i>	<i>Description</i>	<i>Cluster</i>		<i>Error</i>		<i>F</i>	<i>P</i>
		<i>Mean Square</i>	<i>df</i>	<i>Mean Square</i>	<i>df</i>		
DRUGELIG	Drug payments per eligible	45,759.82	7	21,145.45	40	2.164	.059
MAN_CARE	Proportion in managed care	922.47	7	582.76	40	1.583	.169
FMAP	Federal matching	143.73	7	58.81	40	2.444	.035*
PRIORAUT	Prior Authorization	0.08	7	0.03	40	2.500	.031*
REIMBURS	Reimbursement	82.84	7	54.38	40	1.523	.187
GENSUBST	Mandatory generic substitution	0.26	7	0.20	40	1.298	.276
PDL	Preferred Drug List	0.26	7	0.24	40	1.099	.383
SUPPORT	Federal support	261.42	7	56.61	40	4.618	.001*
HOSP_ACC	Access to hospitals	1.81	7	2.17	40	0.833	.566
PHARM_ACC	Access to pharmacies	91.81	7	131.52	40	0.698	.673
PCP_ACC	Access to physicians	858.88	7	138.32	40	6.210	.000*
PRENATAL	Access to prenatal care	49.32	7	43.60	40	1.131	.363
WHITES	Percent whites in Medicaid	198.44	7	165.36	40	1.200	.325
ELDERLY	Percent >65 yrs in Medicaid	5.54	7	8.09	40	0.685	.684
DISABLED	Percent disabled in Medicaid	10.41	7	24.67	40	0.422	.883
CHILDREN	Percent children in Medicaid	87.63	7	48.81	40	1.795	.115

* Significant at the 0.05 level

Table 20 contd. ANOVA for cluster means for model variables from K-means clustering

<i>Variable</i>	<i>Description</i>	<i>Cluster</i>		<i>Error</i>		<i>F</i>	<i>P</i>
		<i>Mean Square</i>	<i>df</i>	<i>Mean Square</i>	<i>df</i>		
UNEMPLOY	Percent unemployed in state	0.67	7	1.22	40	0.553	.789
HSGRAD	Percent HS grads in state	158.23	7	66.71	40	2.372	.040*
LT100FPL	Percent below 100% FPL	17.58	7	8.55	40	2.055	.072
RISK	Aggregate disease prevalence	8.21	7	7.46	40	1.101	.381
NONDRUGE	Severity of diseases	11,305,025.36	7	33,554.55	40	336.915	.000*

* Significant at the 0.05 level

Table 21. Cluster characteristics

	CL1	CL2	CL3	CL4	CL5	CL6	CL7	CL8
DRUGELIG	3	5	2	8	4	1	6	7
FMAP	3	7	5	6	4	8	2	1
SUPPORT	4	2	3	7	5	1	6	8
PCP_ACC	5	1	3	8	4	2	6	7
HSGRAD	6	1	2	4	3	7	5	8
LT100FPL	4	8	7	2	5	6	3	1
NONDRUGE	5	2	3	8	4	1	6	7

High values

Medium values

Low values

CL = cluster number

4.4.1 Discussion for Objective 2

For want of better decision inputs, Medicaid program and policy interventions are adopted partly based on their successes in other neighboring states or in states that are similarly sized, have similar economic standing and demographic distribution. However, successes are not necessarily transferable in such straightforward manner when one considers myriad of other characteristics that states may differ in despite being similar on the above parameters. It is little surprise, therefore, strategies that work for some states may not work for others even when they are neighbors, have similar economic, or socio-demographic distribution.

The Cluster Analysis process allows a means to group Medicaid programs on the basis of their drug expenditure per eligible and a variety of policy, resource, demographic, and health status variables that might impact such expenditure. The significant differences in the cluster means for several of the indicator variables shows the distinct differences that lie beyond just geographic location, or size and economic considerations. However, since there is was no published research found that had made such analyses, comparisons cannot be made of our results with earlier findings. These results could, however, serve as useful starting points for future research in this area.

While it is useful even to find out potential clusters among the state Medicaid programs, the main usefulness of the cluster analysis process lies in the final analysis of the cluster characteristics. Based on the final analysis described in the earlier section, characteristics profiles of each cluster can be suggested.

Cluster 1 is a cluster of medium values – since the resultant means of none of the variables is on the high or the low end. For example, in the case of drug costs per Medicaid

eligible – although the cluster has Kentucky (3rd highest) as a member, it also has Washington (36th highest) which likely reduces the cluster center value for this variable.

Cluster 2 comprising of New Jersey and New Hampshire are high on many parameters and have been rightly classified together. Evidently, the cluster has valid reasons to be high on support for public healthcare (NJ – 3rd highest; PA – 5th highest), access to primary care physicians (NJ – 2nd highest; PA – 11th highest), level of education (NJ – highest; PA – 14th highest), and disease severity measured by non-drug expenditure per Medicaid eligible (NJ – 4th highest; PA – 5th highest). On the other hand the low scores for the cluster couple other variables are also explained by the state values: Federal matching (NJ – 44th highest; PA – 33rd highest), and poverty levels (NJ – 45th highest; PA – 36th highest).

The high values for the two variable means, and the member states that cause such values for Cluster 3 are: drug costs per eligible (Massachusetts – 5th highest; Iowa – 6th highest), and high school education (North Dakota – 2nd highest; Iowa – 4th highest; Minnesota – 5th highest). The low value of poverty levels is caused by the presence of some of the richer states in the cluster (Minnesota – 47th highest; Connecticut – 44th highest;

Cluster 4, formed by California alone, shows a high level of poverty (15th highest); and low levels of drug expenditure (47th highest), support for public healthcare (35th highest), access to primary care physicians (45th highest), and severity of diseases (48th highest – last).

Cluster 5, like Cluster 1 is a cluster with medium values for all variable means. Here again, the variable means for member states pull each other in different directions resulting in medium values for all. For example, while the cluster has Wisconsin (7th highest) and Montana (10th highest) which increase the cluster mean for education, there also are states like Alaska (37th highest) which reduce it.

Cluster 6, comprising of New Hampshire and New York show somewhat similar characteristics as Cluster 2. This cluster is rightly high on drug expenditure (New York – highest; New Hampshire – 2nd highest), support for public healthcare (New Hampshire – 2nd highest), access to primary care physicians (New Hampshire – highest), and severity of diseases (New Hampshire – highest; New York – 2nd highest). This cluster is, however, low on Federal matching (New York – 47th highest; New Hampshire – 41st highest), and high school education rates (New York – 44 highest).

Cluster 7 is yet another cluster of medium values, except for Federal support which is driven by 3 of the 11 states that are in the top ten for receiving Federal matching funds (West Virginia – 2nd highest; New Mexico – 4th highest; Utah – 10th highest).

Cluster 8, like Cluster 4 is low on all classification variable mean values except for Federal matching with 5 member states in the top 1 for this variable (Mississippi – highest; Arkansas – 5th highest; Idaho – 6th highest; Alabama – 7th highest; and Oklahoma – 8th highest); and the percentage of poor people in the state with 4 member states in the top 10 in the category (Arkansas – highest; Mississippi – 2nd highest; Alabama – 7th highest; and South Carolina – 8th highest).

This analysis demonstrates the importance of looking at combinations and interactions of different categories of variables in determining similarities among state Medicaid programs from a policy implementation point of view. Although more of a subjective nature, the current Cluster Analysis brings to light the need for customizing Medicaid drug program interventions to address specific high or low value characteristics of various states. For example, while an awareness campaign might work for the states in clusters 2 or 3, who have higher percentages of educated people; such strategies might fall flat in states in Clusters 6 or 8 where the proportions

of education people are low. Similarly, while increasing support with public funding of healthcare might be a policy option for states in Clusters 4 and 8, allocating monies for health education might be a better option for Cluster 6.

Finally, this classification might also be useful to predict outcomes of strategies employed in states that belong in the same cluster as similar states are expected to behave similarly to interventions that are customized based on the characteristics that put these states in the same cluster in the first place.

4.5 Results for Objective 3

To establish a predictive model for Medicaid prescription drugs expenditure based on time-adjusted impacts of key influencers/predictors.

Panel data regression was performed using the PROC TSCSREG command in SAS.

Syntax for the method is presented in Appendix 1.

A one-way fixed effects model was specified using the ‘Fixone’ option in the regression model statement. The model used 48 cross sections (CS, 48 states) for a time series (TS) length of 5 years.

Model fit statistics

Table 21 presents the overall model fit statistics. The R-squared value of 0.8944 signifies that the model is able to explain 89.4 percent of the variance present in the data and hence can be accepted as an adequate level of model fit.

Test for fixed effects

The TSCSREG procedure outputs the results of one specification F test for fixed effects presented in Table 22. The specification test reported is the conventional F-statistic for the null hypothesis tested here is that dimensional vector of fixed effects parameters = 0. The F statistic value at 47 and 172 degrees of freedom was 10.37 ($p < 0.001$) which shows that the model error structure (one way fixed effects) has been correctly specified.

Parameter estimates

The TSCSREG procedure allowed us to look at the ‘pure’ effects of the independent variables on the dependent variables DRUGELIG, since the effects of time was taken out and intrinsic differences between individual states were fixed. Estimates of the regression weights for model variables are presented in Table 23.

For each regressor, the table presents – name of the regressor, the degrees of freedom, the parameter estimate, the standard error of the estimate, a t statistic for testing whether the estimate is significantly different from 0, and the significance probability of the t statistic.

As shown in Table 22, parameter estimates for several predictor variables were found to be significantly different from 0 at the 0.05 significance level. These include – the Policy variable FMAP ($p=0.0201$); the Resource variable PCP_ACC ($p=0.0085$); the Need variable NONDRUGE ($p<0.001$); and the Enabler variables UNEMPLOY ($p<0.001$) and HSGRAD ($p=0.0393$).

It is interesting to note that all constructs from the proposed model are represented by one or more variables belonging to those constructs which have significant ‘pure’ effects on Medicaid drug expenditure even when time effects and other intrinsic (not studied) state differences are controlled for. In addition, the directions for such influences are also found to be logical and will be discussed in more detail in the following section.

Hence, based on the study data, a predictive model for Medicaid drug expenditure could be:

$$\begin{aligned} DRUGELIG = & \beta_0 + 7.90 PRIORAUT - 0.44 PDL + 0.39 GENSUBST + 2.04 SUPPORT + 0.74 \\ & MAN_CARE - 0.39 REIMBURSE + 7.91 FMAP + 1.61 HOSP_ACC - 0.04 PHARM_AC + 1.16 \\ & PCP_ACC + 4.96 PRENATAL + 0.50 RISK + 0.09 NONDRUGE - 0.89 WHITES + 0.02 \\ & CHILDREN - 5.83 DISABLED + 5.79 ELDERLY - 5.34 HSGRAD - 3.32 LT100FPL + 33.60 \\ & UNEMPLOY + e \end{aligned}$$

where, the variables are as described in this study, β_0 is the intercept and e is the unexplained variance.

However, the key regressor variables from the study can be further used to predict changes in drug expenditure using the following equation:

$$\delta(DRUGELIG) = 7.91 * (\delta FMAP) + 1.16 * (\delta PCP_ACC) + 0.09 * (\delta NONDRUGE) + 33.60 * (\delta UNEMPLOY - 5.34 * (\delta HSGRAD) + e$$

where, δ is the change in the value of the indicator variables.

Table 22. Model fit statistics

<i>The TCSCREG Procedure</i>	
Dependent variable: DRUGELIG	
<i>Fit Statistics</i>	
Sum squares error	698,156.19
Degrees of freedom	172
Mean square error	4,059.05
Root mean square error	63.71
R-square	0.89

Table 23. F-test for No Fixed Effects

<i>The TSCSREG Procedure</i>			
Dependent variable: DRUGELIG			
<i>F Test for No Fixed Effects</i>			
<i>Numerator DF</i>	<i>Denominator DF</i>	<i>F value</i>	<i>Pr > F</i>
47	172	10.37	<.0001

Table 24. Parameter estimates

<i>Variable</i>	<i>Description</i>	<i>DF</i>	<i>Estimate</i>	<i>Std. Error</i>	<i>T value</i>	<i>Pr > t </i>
Intercept		1	-328.708	414.100	-0.79	0.428
PDL	Preferred drug List	1	-0.439	16.031	-0.03	0.978
FMAP	Federal Matching	1	7.908	3.371	2.35	0.020*
PRIORAUT	Prior Authorization	1	26.482	22.870	1.16	0.248
REIMBURS	Pharmacy reimbursement	1	-0.391	0.785	-0.50	0.619
GENSUBST	Mandatory generic substn.	1	0.390	15.328	0.03	0.980
MAN_CARE	Managed Care	1	0.736	0.572	1.29	0.200
SUPPORT	Support for public health	1	2.039	1.541	1.32	0.188
PHARM_ACC	Access to pharmacies	1	-0.042	1.049	-0.04	0.968
HOSP_ACC	Access to hospitals	1	1.610	11.937	0.13	0.893
PCP_ACC	Access to physicians	1	1.156	0.434	2.66	0.009*
PRENATAL	Access to prenatal care	1	4.963	3.086	1.61	0.110
RISK	Aggregate prevalence	1	0.504	1.576	0.32	0.750
NONDRUGE	Disease severity	1	0.085	0.009	9.83	<0.000*
CHILDREN	Percent children	1	0.019	1.292	0.01	0.988
DISABLED	Percent disabled	1	-5.825	3.488	-1.67	0.097
ELDERLY	Percent elderly	1	5.798	4.905	1.18	0.239
WHITES	Percent whites	1	-0.897	1.630	-0.55	0.583
UNEMPLOY	Percent unemployed	1	33.604	3.904	8.61	<0.000*
HSGRAD	Percent HS graduates	1	-5.344	2.573	-2.08	0.039*
LT100FPL	Percent below 100% FPL	1	-3.327	4.482	-0.74	0.459

4.5.1 Discussion for Objective 3

The panel data regression model has a good fit – explaining about 90 percent of the variance in the estimate of drug expenditure based on independent variables identified using Andersen’s model. This gives the predictive model reasonable power to predict potential drug expenditure per eligible person in individual state Medicaid programs.

Several variables, belonging to different categories of the Andersen Model were found to have significant effect on drug expenditures. The directions of such estimated relationships are also important and need to be examined closely. Unfortunately, no study was found in the existing literature that could be used to compare the current results. However, applying the predictive model on another year’s data will offer sufficient validation and could be an interesting starting point for future research.

A 1 percent increase in Federal matching is expected to increase drug payments by almost \$8 per eligible person which would translate to over \$412 million additional annual expenditure at the 2002 eligibility levels. This is understandable since greater level of Federal assistance reduces strain on the state’s budget and fiscal demands are less for providing healthcare to the poor. It is likely therefore that states will be less stringent with policies and interventions to control drug utilization and payments, and that in turn would drive up expenditure.

An increase in access to primary care physicians, as gatekeepers to prescription drug utilization, is expected to increase drug expenditure. As seen earlier, our calculations using national data from NPC show that for the period 1998 – 2002, total number of prescriptions Medicaid paid per year for grew by 57.0 percent and the number of prescriptions per primary care physician per year grew by 77.5 percent.¹¹

Non-drug expenditure as a measure of severity of diseases impacts drug expenditure positively. This is an expected direction of the relationship since more severe sicknesses are expected to require more expensive medication therapy for extended periods of time – thereby driving drug payments up. Earlier research has found Medicaid populations to be at greater risk of chronic diseases like diabetes, cardiovascular diseases, and obesity; and thus drive drug utilization in Medicaid.^{102,103,104} Medicaid populations also had significantly higher levels of health risk behaviors like smoking when compared to the non-Medicaid population.¹⁰⁷ However, this challenges the basic premise of the value of pharmaceutical innovation which claims to reduce overall costs by replacing more resource intensive therapies (like surgery, for example) with prescription drugs.

Increase in percentage of the disabled in a state Medicaid population is expected to reduce prescription drug expenditure. This is possible as the disabled, although they are an expensive-to-treat group, may not necessarily have higher levels of drug utilization. The additional costs associated with disabled persons are those of prosthetics, devices, and wheelchairs among others, which do not necessarily influence an additional degree of drug utilization.

Unemployment is an important criterion for being eligible for Medicaid coverage – including drug benefits and has shown a positive effect on drug expenditure. The current model shows that even when time and state specific variations are controlled for, a 1 percent increase in the percentage of unemployed population increases drug expenditure by \$33.60 per eligible person. This translates to an additional drug expenditure burden of \$1.7 billion on Medicaid with each percent increase in state unemployment rates at the 2002 eligibility levels.

Percentage of educated people in the state, measured by high school graduation rates, has been shown by the model to have a negative directional relationship with drug expenditure. While this finding is contradicting our earlier finding in the SEM model, both could have plausible explanations based on the perspective used for such evaluation. Ordinarily, higher proportion of educated people would mean easier or faster diffusion of the awareness about therapy innovations through information sources like ‘direct to consumer’ marketing or the internet. Such elevated awareness is likely to induce more people to seek care and hence drive up Medicaid drug payments. However, the negative relationship, especially when adjusted for time, can be explained by the potential for health awareness leading to people’s being more conscious and adherent to treatment regimens. This will likely not only control utilization of provider services, but would also reduce prescription drug expenditure by preventing complications of non-compliance to the drug treatment regimen.

5 Chapter five: Summary and Overall Conclusions

5.1 Conclusions for Objective 1

To develop and test a model assessing relationships among potential influencers/ predictors of Medicaid drug expenditures identified based on Andersen's Behavior Model for Health Services Utilization.

Study results show that it is meaningful to attempt to describe Medicaid prescription drug costs using the Andersen conceptual framework involving Policy, Resource, Predispositions, Enablers, and Need for Healthcare constructs. Results from our Structural Equation Model analysis showed that Predisposing factors like proportion of elderly persons, and disability status in the Medicaid population, significantly influence Enabling Resources like percentage of the population below 100 percent of the Federal poverty level. The Enabler construct, in turn was found to significantly impact Drug Utilization. All other latent constructs had relationships, in directions that were expected – but were not statistically significant.

All latent constructs were adequately described by at least one indicator variable included in the model, except the policy construct. The relevant indicator variables included in this study were not appropriate measures of the Policy construct and can be further identified in future studies.

Based on the study results, we conclude that Medicaid policy and program interventions, as described in this model, do not influence drug costs significantly. Population characteristics like predispositions and enabling resources determine drug costs in the state Medicaid programs.

5.2 Conclusions for Objective 2

To classify state Medicaid programs into homogeneous clusters based on similarities in their characteristics as measured by the prescription drug expenditure and its influencers/ predictors.

The null hypothesis for this objective was that characteristics for all state Medicaid programs were similar. Study results from our Cluster Analyses showed that there were 8 different possible clusters of state Medicaid programs that were distinctly different in the characteristics of their member states.

Federal matching, support for publicly funded healthcare, access to primary care physicians, high school graduation rates, severity of diseases, Medicaid drug payments and poverty levels – were identified as the key classification variables that differentiate between the 8 clusters. These and other variables were identified based on Andersen's model.

Based on the study results, therefore, we conclude that state Medicaid programs can be reasonably grouped into eight different clusters with distinct characteristics defined by some key classification variables. Medicaid program and policy interventions can be developed and implemented recognizing these peculiarities; and also, similar outcomes of such interventions could be expected among states in the same cluster.

5.3 Conclusions for Objective 3

To establish a predictive model for Medicaid prescription drugs expenditure based on time-adjusted impacts of key influencers/ predictors.

Null hypothesis for this objective was that none of the predictors in the model has any influence on the dependent variable drug expenditure.

A very well fitting model was identified using panel data regression methods using predictor variables identified according to Andersen's model. Study results showed that, when the effects of time series and cross section differences were controlled for, then – Federal matching, access to primary care physicians, access to prenatal care, disease severity as measured by non-drug expenditures, disability, unemployment, and high school graduation rates – were found to have had significant impacts on the dependent variable.

Hence, we conclude that a predictive model using just the above indicators will adequately estimate drug expenditure per eligible person in each state Medicaid program.

5.4 Study limitations

Small size of the sample will likely be a limitation for the study with respect to generalizability of the findings. However, since the data are related to state Medicaid programs there are only 48 data points (excluding Arizona and Tennessee, since they operate differently) available for each year. By using data for five consecutive years, the study has attempted to overcome this limitation and to come up with broad-based findings and recommendations which can be further validated through future research.

Relationships in the Andersen model were hypothesized based on the literature and logical expectations of the researchers. However, in the complicated system of drug utilization, there could be many other aspects to the relationships which were our model failed to identify and address.

Another limitation of the present study was with availability of measures and data in the public domain on other potential indicator variables. It is possible that there are other variables that might contribute to further or better explaining and predicting the dependent variable. We

used the variables based on theoretical relevance in the Andersen model and obviously, availability of a measure for the variable was a major criterion that determined ultimate inclusion in the model. One such variable is Medicaid Drug Rebates. The expenditures included in the study do not include the effect of federal as well as state-negotiated supplemental rebates which bring costs down for individual programs. Since such net costs are the basis of several policy intervention decisions like PDL and PA, their real effect may not have been captured in this study. However, although data on total rebates under OBRA '90 were available, the supplemental rebate information was not. Hence, assessing real impacts of PDL or PA was not possible.

For the identified variables, one methodological limitation was with the measurement of indicator variables. Most of the variables were specific to Medicaid, but some were measured for the entire state. While it would be useful to obtain measures for these variables limited to the Medicaid population for each state, the state level information was considered acceptable for the purpose of this study – especially since we were able to make assumptions about the direction they could influence the results, as discussed in the chapter three.

Yet another limitation was inherent to the data. The NPC reports, based on reports from the states, sometimes show significant swings for both total program and prescription drugs expenditures. This is possible for a variety of reasons. For example, all of the Medicaid data systems are on a cash basis rather than an accrual basis. States often have cash flow concerns that require that they pay claims on one side or the other at the end of the state fiscal year. Many states have the same Fiscal Year as the Federal government, which can result in FY data showing decreases followed by substantial increases in expenditures. In addition, states may incur large settlements with CMS and/or providers in a particular year.¹¹ These, and a variety of other

factors, may have led to real swings in the expenditure data which was accounted for in the model.

Although the results and conclusions from this study may have a higher margin of error than those involving large datasets – indicative inferences offered are expected to offer useful directions and insights for policy makers and administrators.

5.5 Implications of Research Findings

The current study recognized the need for explaining significant variations in Medicaid drug expenditure levels across different state programs and has attempted to address this need by performing a comprehensive analysis of the predictors of such costs. There have been no studies done before this which with a scope as inclusive as the current endeavor. This in itself lends serious importance to the study findings which can serve as a useful starting point for future research efforts in this area.

Findings from this study are expected to contribute towards a better understanding of critical relationships among various determinants of Medicaid drug expenditures. It will also provide a sense of the extent of mutability among key variables and will help identify cost-effective intervention opportunities. The study can be useful in developing interventions and/ or strategies directed specifically at altering the direction or magnitude of some variable(s) to create a favorable change in the dependent variable values.

The study also allows an understanding of the similarities and distinguishing characteristics of state Medicaid programs and their determinants. Such understanding will likely add valuable insights into planning and implementing customized strategies to specific clusters of states with characteristics that are being targeted. Such understanding will also offer a

greater sense of predictability of the outcomes of an intervention on members of the same cluster.

In summary, findings from this study are expected to reduce the ‘unknowns’ which Medicaid policy and administrative decision-making is faced with today – at least to a little but useful extent.

5.6 Directions for Future Research

Future research can attempt to remove some or all of the limitations that the current study faces. The same methods can be applied on a longer time series to address the issue of sample size for statistical analyses.

Additionally, other indicator variables (like, supplemental rebate information) and their data sources can be identified and incorporated to achieve greater model fit and power to better explain and predict Medicaid drug expenditures.

Using additional patient level data, research may also be directed in individual states at specific variables of interest from our model to investigate trends and mutability of such variables in the state’s Medicaid population.

6 Appendices

Appendix 1: SAS code for Panel Data Regression Analysis

```
proc sort data = sasuser.cleaned;

by STATE YEAR;

run;

proc tscsreg data = sasuser.cleaned;

id STATE YEAR;

model DRUGELIG = PDL FMAP PRIORAUT REIMBURS GENSUBST MAN_CARE
SUPPORT PHARM_ACC HOSP_ACC PCP_ACC PRENATAL RISK NONDRUGE
CHILDREN DISABLED ELDERLY WHITES UNEMPLOY HSGRAD LT100FPL/

fixone;

run;
```

Appendix 2: SAS code for Power calculation in SEM

```
data SEM;

alpha = 0.05;

rmsea0 = 0.05;

rmseaA = 0.04;

d = 182;

n = 240;

ncp0 = (n-1)*d*rmsea0*rmsea0;

ncpA = (n-1)*d*rmseaA*rmseaA;

cval = cinv(alpha, d, ncp0);

power = probchi(cval, d, ncpA);

run;

proc print data = SEM;

var rmsea0 rmseaA alpha d n power;

run;
```

7 *Curriculum vitae*

Sanjoy Roy, B.Pharm, M.S.
P.O. Box 9510, RC Byrd Health Sciences Center
West Virginia University, Morgantown, WV 26506

ACADEMIC QUALIFICATION:

Current

PhD student of Pharmaceutical Systems and Policy

West Virginia University, Morgantown, WV

Fall 2003 – Spring 2006

Master of Science (MS) in Pharmaceutical Systems and Policy

Thesis: A Comprehensive Analysis of the Determinants of State Medicaid Prescription Drug Expenditures

West Virginia University, Morgantown, WV

1990 – 1994

Bachelor in Pharmacy (B. Pharm.)

Jadavpur University, Calcutta, India

- Professional bachelor's program leading to eligibility for a practicing pharmacist license.
- Merit scholar. Awarded first class with distinction

RESEARCH MANUSCRIPTS:

1. **Roy S**, Roy AN, Madhavan SS. Societal perspective in analyzing the impacts of Medicaid Formularies. (in development for the Pharmacoeconomics journal)
2. **Roy S**, Madhavan SS. Academic Detailing: a career option for Pharmacists. (in development)
3. **Roy S**, Roy AN, Madhavan SS. Academic Detailing in the Ambulatory Care Setting. (in development)
4. Manley W, Homer J, Hoard M, **Roy S**, Furbee P, Summers D, Blake R, Kimble R. A Dynamic Model to Support Surge Capacity Planning in a Rural Hospital. Paper presented at the 23rd International Conference of the System Dynamics Society, Boston, MA. July 17 – 21, 2005
5. **Roy S**, Outtersson K. Pharmaceutical Innovation. Report to the Select Subcommittee C on Pharmaceutical Availability and Affordability with respect to H.B. 4084. West Virginia Pharmaceutical Cost Management Council. State Department of Administration, Charleston, WV. September 2004
6. **Roy S**. An overview of Pharmaceutical Reference Pricing and Reimbursement: Analysis of the Australian Pharmaceutical Benefits Scheme. West Virginia Pharmaceutical Cost Management Council. State Department of Administration, Charleston, WV. September 2004. Available at: <http://www.wvc.state.wv.us/got/pharmacycouncil/>

RESEARCH ABSTRACTS:

1. Smith MJ, **Roy S**. Injury-Related Medical Services Use in a State Medicaid Program. Accepted for poster presentation at the 2nd North American Congress of Epidemiology to be held from June 21-24, 2006 in Seattle, WA
2. **Roy S**, Madhavan SS. Cluster Analysis of State Medicaid Programs. Poster presentation accepted for the ISPOR 11th Annual International Meeting, May 20-24, 2006, Philadelphia, PA
3. **Roy S**, Roy AN, Miller LA. Cost-effectiveness analysis of oral pharmacological treatments of Erectile Dysfunction. Poster presentation accepted for the ISPOR 11th Annual International Meeting, May 20-24, 2006, Philadelphia, PA
4. **Roy S**, Madhavan SS. Making a case for employing societal perspective in the evaluation of Medicaid formularies. *Value in Health*. 2005;8(3):286-287
5. Roy AN, **Roy S**, Madhavan S, Bochna K, Joseph F, Huffman K, Hodges B, Dunsworth T, Lucas K, Terpening C, Kavookjian J, Ogershok P, Whetsel T. Implementation and early impact assessment of an 'academic detailing' program. Poster presentation accepted for the American Pharmacists Association (APhA) 2005 Annual Meeting & Exposition, April 1 - 5, 2005, Orlando, FL
6. **Roy S**, Roy AN, Madhavan S, Bochna K, Joseph F, Huffman K. Academic detailing to ambulatory care physicians – results of two surveys. Poster presentation accepted for the American Pharmacists Association (APhA) 2005 Annual Meeting & Exposition, April 1 - 5, 2005, Orlando, FL
7. Summers D, **Roy S**, Manley W, Kimble R, Hoard M, Haque A, Fulton A. Training of communities, pre-hospital and hospital personnel in disaster awareness/ preparedness. Poster presentation at the Grantees Meeting of the federal Health Resources and Services Administration (HRSA). August 2004. Washington, DC
8. Manley W, **Roy S**, Homer J, Hoard M, Haque A, Summers D, Furbee M, Helmkamp J. System Dynamic approach to analyzing surge capacity in a rural hospital. Poster presentation at the Grantees Meeting of the federal Health Resources and Services Administration (HRSA). August 2004. Washington, DC
9. Roy AN, **Roy S**, Madhavan S, Bochna K. Assessment of physician satisfaction with Academic Detailing in two cities in West Virginia. Podium presentation at the Midwest Pharmacy Administration Meeting, Purdue University, July 29-31, 2004. West Lafayette, IN
10. **Roy S**, Hoard M, Manley W, Furbee PM, Williams J. Do local health departments collaborate with hospitals in public health emergency preparedness activities? Poster presentation at the Southern Pharmacy Administration Conference 2004, Nova South Eastern University, June 10-13, 2004, Ft. Lauderdale, FL
11. **Roy S**, Hoard M, Manley W, Furbee PM, Williams J. Do local health departments collaborate with hospitals in public health emergency preparedness activities? The 132nd Annual Meeting of the American Public Health Association (APHA), November 6-10, 2004. Washington, DC. Available at: http://apha.confex.com/apha/132am/techprogram/paper_89041.htm
12. **Roy S**, Roy AN, Madhavan S, Bochna K, Susman T, Joseph F, Hodges B, Dunsworth T, Lucas K, Terpening C, Kavookjian J, Ogershok P, Whetsel T. Assessment of the impact of 'Academic Detailing' in promoting generic drug prescription among ambulatory care physicians in West Virginia. *Value in Health*. Volume 7, No. 3, 2004. pg 374

OTHER CONTRIBUTIONS:

1. Manuscript Peer Reviewer for Research in Social and Administrative Pharmacy (2005)
2. Manuscript development support acknowledged in: Hoard M, Homer J, Manley W, Furbee P, Haque A, Helmkamp J. Systems modeling in support of evidence-based disaster planning for rural areas. *Int. J. Hyg. Environ.-Health* 208 (2005) 117–125
3. Reference Group member feedback to the ISPOR Randomized Clinical Trial – Cost Effectiveness Analysis (RCT-CEA) Task Force on: Best Practices For Economic Analysis Alongside Clinical Trials: An ISPOR RCT-CEA Task Force Report. December 20, 2004
4. Small S, **Roy S**. Drug Utilization Review of a prescription opioid medication in the WV State Medicaid population: Report to the Office of the Attorney General, State of West Virginia. Charleston, WV. February 2004
5. **Roy S**. JAMA. 2003;Vol. 291 No. 6, February 11, 2004. Letter to the Editor in response to: Stewart WF, Ricci JA, Chee E, Morganstein D, Lipton R. Lost Productive Time and Cost Due to Common Pain Conditions in the US Workforce. JAMA. 2003; 290:2443-2454
6. **Roy S**. West Virginia - creating a healthy environment at school. *Am J Public Health*. 11 November 2003. Letter to the Editor in response to: French SA, Story M, Fulkerson JA, Gerlach AF. Food Environment in Secondary Schools: À La Carte, Vending Machines, and Food Policies and Practices. *Am J Public Health* 2003; 93: 1161-1168

ACADEMIC RESEARCH EXPERIENCE:

Aug '05 – March '06

A Descriptive Analysis of Injury-Related Healthcare Resources and Services Utilization Among Recipients in the West Virginia Medicaid Program – grant funded research
- *Injury Control Research Center, West Virginia University, Morgantown, WV*

July '05 – ongoing

Rational Drug Therapy Program – graduate research assistantship with the prior authorization program for West Virginia Medicaid as well as West Virginia Public Employees Insurance Agency
- *West Virginia University, Morgantown, WV*

June '05 – August '05

West Virginia Bureau for Medical Services (WV Medicaid Program) – research assistantship to the Director of Pharmacy Services working on multiple projects including:

- management reporting system from Unisys
- estimation of Home Infusion preparation and dispensing fees and reimbursement using S codes
- 340B drug procurement and dispensing fee reimbursement issues

- *West Virginia University, Morgantown, WV*

Aug '04 – June '05

Accessible Intelligent Medication Strategies – graduate research assistantship with the Academic Detailing program sponsored by West Virginia Public Employees Insurance Agency
- *West Virginia University, Morgantown, WV*

May '04 – Sep '04

The West Virginia Pharmaceutical Cost Management Council – research support to the Reference Pricing Committee sponsored by the Governor and Legislature of the state of West Virginia
- *State Department of Administration, Charleston, WV*

Jan '04 – Feb '04

Drug Utilization Review of a prescription opioid medication in the WV State Medicaid population – sponsored by the Office of the Attorney General of the State of West Virginia.
- *Rational Drug Therapy Program, Morgantown, WV*

Dec '03 – Sep '04

Survey and analysis of the impact and acceptance of 'Academic Detailing' as a beneficial intervention towards drug prescribing decisions by primary care physicians of West Virginia – sponsored by the State-run Public Employees Insurance Authority (PEIA) of West Virginia.
- *Accessible Intelligent Medication Strategies (AIMS) program, West Virginia University, Morgantown, WV*

Nov '03 – Aug '04

System Dynamics modeling of Surge Capacity for a rural West Virginia hospital – sponsored by the Federal Health Resources and Services Administration (HRSA), U.S. Department of Health and Human Services (HHS).
- *Center for Medical Preparedness, Center for Rural Emergency Medicine, West Virginia University, Morgantown, WV*

Aug '03 – Aug '04

Rural Emergency Preparedness Program – sponsored by the Federal Health Resources and Services Administration (HRSA), U.S. Department of Health and Human Services (HHS).
- *Center for Medical Preparedness, Center for Rural Emergency Medicine, West Virginia University, Morgantown, WV*

Aug '03 – Oct '03

Assessment of the level of collaboration among Local Health Departments and Hospitals in West Virginia for Public Health Emergency Preparedness Activities.
- *Center for Medical Preparedness, Center for Rural Emergency Medicine, West Virginia University, Morgantown, WV*

PROFESSIONAL EXPERIENCE:

Aug '01 – Jul '03

Senior Manager, Sales and Business Development
Strategic Intelligence Research – Singapore

Key accomplishments:

- Developed company's capabilities and new client base with strategic research in Life Sciences for global companies – including Novartis, Roche, Johnson & Johnson etc.
- Set and consistently achieved revenue and profitability goals – helping to lead the company through a severe recession in Singapore.
- Gained hands-on exposure and proficiency in several key types and techniques of primary and secondary market research in varied industry sectors

Jan '01 – Jun '01

Marketing Manager

Eli Lilly and Company (India) – New Delhi, India

Key accomplishments:

- Managed marketing for 70% of the company's (product) revenue portfolio with challenging growth and profitability objectives.
- Supervised performance and professional development of four product managers responsible for anti-infective, oncology, cardiology and women's health therapy areas.
- Established standardized communication processes and encouraged accountability within the marketing team and with the interface the team had with other functions.

Jan '00 – Dec '00

Marketing Services Manager – Asia Pacific

Eli Lilly Asia Pacific HQ – Singapore

Key accomplishments:

- Led designing and implementation of a 'Voice of the Customer' perception market research study and determined priority interventions and competitive actionable conclusions for management at regional and affiliate offices in 11 Asia Pac countries.
- Served as the Marketing Manager for Asia Pacific for a new product for the treatment of Erectile Dysfunction. Conducted secondary research based initial regional launch plans, budgets and forecasts.
- Developed high level Asia Pacific regional e-Commerce strategy, through secondary and primary customer research and resulting in business case and recommendations for corporate IT investments in this area.
- Led implementation of regional corporate communications campaign – including production of a full-length video focusing on the company's history and research focus worldwide and in Asia Pacific and a global re-branding exercise.

Jun '98 – Dec '99

Project Leader – Year 2000 program – Asia Pacific & Greater China

Eli Lilly Asia Pacific HQ – Singapore

Key accomplishments:

- Led corporate Year 2000 program for 14 affiliate offices and 5 manufacturing set-ups in Asia Pacific countries to a 'zero-incident' success. Received awards and invitation to dine with the CEO.
- Through secondary research - acquired extensive understanding of business processes, healthcare delivery systems and the IT interface in the pharmaceutical value chain in local markets across the region.
- Led development of previously non-existent Business Processes Risk Management and Contingency plans for all functions and affiliate set-ups across the region – and secured affiliate management buy-in for regular reviews, updates and implementation.

Dec '97 – Jun '98

Product Associate (Marketing and Sales)

Eli Lilly and Company (India) – New Delhi, India

Key accomplishments:

- Launched and established market leadership for a high-priced new anti-platelet molecule for angioplasties in an extremely price-sensitive market
- Supervised a sales team of 7 specialist sales representatives to exceed previous growth, market share and revenue forecasts.
- Developed effective marketing programs including interventionist education programs, pricing structures, delivery channels and an extensive network of top cardiac healthcare providers in India.

Aug '96 – Dec '97

Associate – New Products Planning and Business Development

Eli Lilly and Company (India) – New Delhi, India

Key accomplishments:

- Launched 3 new molecules – a cancer chemotherapy agent, an anti-platelet agent and a fast-acting human insulin analog – and several line extensions of existing molecules
- Acquired extensive exposure and first-hand understanding of the launch process, including: market estimation, clinical trials, FDA approval, trademark and regulatory issues, product sourcing, packaging and labeling, pricing, pre-launch marketing, sales force training, launch event, post-launch surveillance etc.
- Established and led a cross-functional team that identified opportunities and reduced 'time-to-market' for new products from a historical 2+ years to a few months.
- Gained hands-on experience in corporate business planning and co-marketing deals.

Aug '95 – Aug '96

Marketing Associate- Critical Care Products

Eli Lilly and Company (India) – New Delhi, India

Key accomplishments:

- Owned and managed marketing strategies, tactical plans and implementation of marketing programs to driving revenues and profitability for a cardiac product, and three parenteral antibiotics.
- Revived the cardiac product from being written-off through innovative and cost-effective marketing programs.
- Established excellent rapport with sales force resulting in their buying into aggressive marketing strategies for relatively older molecules – leading to tremendous success of the plans.

Jul '94 – Aug '95

Territory Manager (Sales Representative)

Eli Lilly and Company (India) – Calcutta, India

Key accomplishments:

- Achieved and exceeded sales targets in a highly competitive and price-sensitive branded generics market place.

- Developed excellent professional relationship and network with top clinicians in the territory.
- Established deep credibility among peer group and was looked at as leader in most company initiatives in the area.

OTHER SKILLS AND ACCOMPLISHMENTS:

- **Software Proficiency:**
 - **End user:** Microsoft Word, Excel, PowerPoint, Projects etc.
 - **Statistical & Epidemiological:** SAS, SPSS, AMOS, JMP, Epi-Info (CDC)
 - **Database, Datamining & Reporting:** FoxPro, BrioQuery
 - **Bibliographic:** Reference Manager
 - **Simulation Modelling:** Vensim (System Dynamics), Data (Decision Analysis)
- **Grantsmanship:**
 - Contributed significantly to the development of a “Building Research Infrastructure and Capacity (BRIC)” planning grant (Principal Investigator: S. Suresh Madhavan) awarded by the Agency for Healthcare Research and Quality (AHRQ) in 2006. Grant amount: \$250,000
 - Co-authored a seed grant proposal titled – “A Descriptive Analysis of Injury-related Healthcare Resources and Services Utilization among Recipients in the West Virginia Medicaid program” (Principal Investigator: Michael J Smith) awarded by the West Virginia University Injury Control Research Center in 2005. Grant amount: \$25,000

AFFILIATIONS:

- Chair, Membership Outreach Committee 2005-06 – International Society for Pharmacoeconomics and Outcomes Research (ISPOR) Student Council
- Member – Rho Chi Pharmaceutical Honor Society
- Member – Outreach Committee, ISPOR Student Council 2004-05
- Reference Group member – ISPOR Randomized Clinical Trial-Cost Effectiveness Analysis (RCT-CEA) Task Force
- Student member – ISPOR
- President 2004-05 – WVU ISPOR Student Chapter (recognized as ‘Active President’)
- Treasurer 2003-04 – WVU ISPOR Student Chapter

REFERENCES: Will be made available on request.

Last updated: April 17, 2006

8 *Bibliography*

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www.cms.hhs.gov/charts/default.asp. Accessed: September 2005
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