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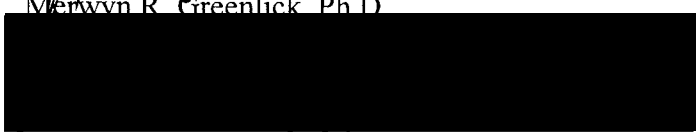

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IMPACT OF A PRESCRIPTION DRUG COPAYMENT POLICY ON PRESCRIPTION DRUG AND HEALTH SERVICES UTILIZATION IN AN OREGON MEDICAID POPULATION

By

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A MASTERS THESIS

Presented to the Department of Public Health and Preventive Medicine

and the Oregon Health & Science University School of Medicine

in partial fulfillment for the degree of

Master of Public Health

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ACKNOWLEDGMENTS

During my thesis, I was fortunate to have the counsel and expertise of several individuals who played key roles in the successful completion of my research project.

Mitch Greenlick: As my thesis advisor, Mitch was very generous with his time during the entire process despite having many ongoing commitments and priorities. His extensive expertise and experience were invaluable to the completion of my project and it was a great honor for me to work with him.

Matthew Carlson: Matt's knowledge of Oregon Medicaid population, his assistance with the interpretation of several of my findings, along with providing me practical guidance for some of the more frustrating logistical aspects of this project were essential to the completion of my study.

Dale Kraemer: Dale assisted with many of my complex statistical analyses along with providing me with important methodological feedback about the evaluation.

Dean Haxby: I could not have completed this project with out Dean's support from the idea conception to final manuscript completion. Additionally, his expertise and insights into drug policy were useful in the interpretation of my observations.

While not formally on my thesis committee, this project would not have been completed without the knowledge and previous work of Kathy Ketchum, at the Oregon State University College of Pharmacy, who has, and continues to be instrumental in teaching me the nuances of using Oregon Medicaid claims datasets.

ABSTRACT

Background: Health care costs associated with the Medicaid program have become a significant burden to individual states across the county. Prescription drugs are a key driver of these costs and as such have been focus of a wide variety of cost-containment policies. Copayments (copays) for prescription drugs are a particularly common strategy aimed at controlling costs among Medicaid programs. However, little is known about the impact of copay policies in Medicaid patients on medication use as well as health status. The goals of this analysis were to quantify the impact of copay policy for prescription drugs on medication and health services utilization in the Oregon Medicaid program.

Methods: Using aggregated monthly pharmacy and medical claims data, segmented ordinary least squares regression models were used to evaluate changes in prescription drug and health services utilization related to implementation of a copay policy on January 1, 2003. Trends in emergency department (ED) encounters, office visits, and hospitalizations were used to evaluate the impact of this policy on unintended adverse effects. Finally, we evaluated drug utilization among cohorts of patients with diabetes mellitus, cardiovascular disease, reactive airway disease, depression, and schizophrenia to explore differences in response among drugs used for that particular condition compared to drugs not used for that condition. First degree autocorrelation was adjusted for in each model.

Results: During the study period, between 53,000 and 62,000 unique individuals were eligible and subject to copays for prescription drugs. After activation of the copay policy, utilization of prescription drugs declined significantly immediately by 17.2% and drug costs were reduced by

6.3%. This pattern was observed at varying degrees for all drug classes investigated. After the policy was implemented there was no evidence of increased rates ED visits, office visits, or hospitalizations. For all cohorts except those with cardiovascular disease, drugs used to treat the condition decreased significantly less than drugs not used to treat the cohort condition. The largest immediate utilization reduction was observed in patients with depression who exhibited a 17.3% decline in the use of antidepressants and a 16.5% decrease in non-antidepressants. This finding also corresponded with an 18.5% ($p=0.0922$) increase in the monthly rate of office visits in the cohort.

Conclusions: These data suggest that in a Medicaid program modest copays of $2 to $3 are associated with significant reductions in the utilization of prescription drugs. This reduction was observed among all evaluated drug classes. Overall, there was no evidence indicating the prescription drug copay was associated with increases in unintended health service encounters. Patients with most specific chronic diseases appeared to show a preference to reduce the use of drugs not indicated for their disease over drugs used to treat their condition. However, the large reduction in drug utilization observed among patients with depression that also corresponded to an increase in office visits is concerning and needs to be explored further.

BACKGROUND

Prescription drugs have become a major focus in the ongoing debate over the rising costs of health care in the United States. Recent estimates indicate that the United States spends in excess of $1.7 trillion dollars annually on health care, approximately 15.3% of the gross domestic product, and $5452 per capita.[1] While spending on prescription drugs only represents approximately 10% of total health expenditures, it has been the fastest growing component of health care for more than a decade.[2] These increases have been particularly difficult to manage for state Medicaid programs, which have experienced an average annual increase of 18% between 2000 and 2002, while simultaneously managing a significant downturn in revenue.[3]

Health care payers have developed a wide variety of tools to help manage the rising costs of pharmaceuticals. Among them, cost-sharing is common tool used in almost all sectors of health care delivery. Cost-sharing is typically implemented as one of two different schemes: co-insurance is where the patient would pay a set percentage of the cost of the prescription and co-payments (copays) involve the patient paying specific amount per prescription. In recent years, cost-sharing arrangements have become increasingly sophisticated with payers now incorporating components such as multi-tiered copays based on formularies, and reference-based pricing. However, the basic premise behind cost-sharing is to sensitize consumers to some aspect of a product or service. Currently, cost-sharing is one of the most prevalent methods of benefit management employed by both commercial and publicly provided health plans in the nation. Over 98% of employer sponsored health plans use some form of cost-sharing as a component of drug benefit management.[4] Publicly provided health plans such as the Department

of Veterans Affairs, the Department of Defense, and Medicaid, also employ cost-sharing. A 2003 survey of state Medicaid agencies found that more than 80% had cost-sharing for prescription drugs as a component in their benefit management program.[5]

Despite widespread use, little is actually known about the impact of these policies on health outcomes. Data generated on the topic has generally originated from commercial health plans or single payer international systems outside the United States. Research to date about cost-sharing for prescription drugs is summarized in Appendix A. Research on prescription drug copays within Medicaid programs is particularly sparse. Federal Medicaid law stipulates that "nominal" copays are allowed and providers must not deny necessary services to patients if they cannot pay. However, even nominal copays could represent significant financial barriers for many patients receiving Medicaid benefits. Further compounding this problem, a recent survey of pharmacists serving Medicaid clients indicated that a large majority have fair to poor knowledge of Medicaid copay policies.[6] The only research on prescription drug copays conducted in a Medicaid program was completed in early 1980s, and did not ascertain the impact of this policy on health outcomes. Nelson and Reeder conducted retrospective pharmacy claims-based time series analysis of the implementation of $0.50 copay in South Carolina in the late 1970s.[7-9] In their study, enactment of this policy lead to statistically significant reductions in the magnitude and rate of overall prescription drug utilization and expenditures.[8] Further analysis of these data revealed a differential effect which varied by medication class. Immediate reductions in utilization were observed for all classes except the analgesic and sedative/hypnotic drug classes.[7] Numerous other investigators exploring the impact of prescription drug copays on drug utilization and medical encounters within commercial health plans have corroborated these general findings.[10-12]

Tambyln et al. published the most comprehensive and rigorous evaluation of prescription drug copays from a government sponsored drug plan for low income and elderly clients living the province of Quebec, Canada.[13] Using an interrupted time-series design with 3 years of prescription drug and medical claims data, these investigators observed that implementation of a 25% coinsurance policy was associated with a 16% overall reduction in prescription drug utilization. Medication reductions differed depending on the clinical importance of the drug class. Drugs classified as clinically essential (e.g. insulin, anticoagulants, anti-hypertensives, etc.) saw reductions of 14.4% as compared to 22.4% for drugs classified as less essential (e.g. benzodiazpines, dipyridamole, meperidine, etc). Additionally, statistically significant increases in the rate of adverse events and emergency department visits, as identified through the medical claims dataset, were also associated with the policy implementation. The rate of adverse events, defined as first occurrence of acute care hospitalization, long-term care admission, or death, among patients reducing medication use increased significantly by 12.9 events per 10,000 person-months (95% confidence interval 10.2-15.5). Emergency department visits increased by 54.2 events per 10,000 person-months (95% confidence interval 33.5 – 74.5).

Similar findings have been reported from studies using differing methodologies. Using Medicare Current Beneficiary Survey data on clients who were dually eligible in both Medicare and Medicaid, Stuart and Zacker explored the relationship between self-reported prescription drug use and health status in copay and non-copay requiring states.[14] Their findings indicate that patients residing in copay states report using fewer prescription drugs annually (19.6) than patients in non-copay states (24.6). They also found that while prescription drug utilization was similar between copay and non-copay states in patients reporting excellent or very good health,

as health status deteriorated prescription drug use did not increase at equivalent levels. Specifically, among those patients reporting poor health, the average number of prescriptions per year in copay states was 28.4 compared to 36.0 for patients residing in non-copay states. While not definitive, these data support that hypothesis that copay policies have the potential to adversely affect health.

In summary, the evidence to date shows that cost-sharing for prescription drugs within low income populations has a predictable impact on drug utilization. The magnitude of impact is related to the degree of cost-sharing (e.g. tiered schedule, coinsurance), the economic status of those impacted, and the therapeutic category of the drug. It is less established if cost-sharing for prescription drugs has an adverse impact on health outcomes. Data from Canada suggest that cost-sharing among state welfare recipients and elderly patients produced significant reductions in the use of essential medications temporally related to an increasing incidence of ED visits and other adverse events. The coinsurance rate in this study was 25% with an annual $200 maximum deductible, considerably higher than what is currently permitted in Medicaid. However, these data suggest that when cost-sharing is applied to patients with little economic reserve, adverse consequences related to non-compliance and therapy discontinuance could result. Even less is known about the impact of cost-sharing on health outcomes in patients with specific conditions. Goldman et al. studied the effects of doubling of copays in different classes of drugs in the general population and among patients with documented diagnoses for several common conditions such as depression, hypertension, and diabetes.[15] They found that utilization of disease-specific medications in individuals with those diseases showed modest but significant

cost sensitivity of between 8%-23% depending on class. Cost sensitivity or responsiveness is the degree to which consumers alter their demand in response to changes in price.

On January 1, 2003, the state of Oregon implemented a copay requirement for prescription drugs and a variety of outpatient services for clients enrolled in the fee-for-service (FFS) Medicaid program, the Oregon Health Plan (OHP). At the time of implementation, all enrolled clients were responsible for the same cost-sharing requirements. Copays for prescription drugs were set at $2 for generics and $3 for brand name drug products. In addition, $3 copays were charged for outpatient services, including office visits, home visits, outpatient hospital services, outpatient surgery, outpatient treatment of chemical dependency, outpatient treatment for mental health, occupational and physical therapy, speech therapy, restorative dental work, and vision exams. Copays were waived for family planning services and drugs, drugs for HIV or cancer, prescription drugs ordered through the mail order pharmacy program, pregnant women, clients less than 19 years old, clients residing in nursing or community based care facilities, and Native Americans. One month later, in February of 2003, the OHP was split into two distinct benefit packages: OHP Plus and OHP Standard. OHP Plus was offered for those clients who met traditional federally mandated eligibility criteria (e.g. pregnant, under age 19, blind/disabled). OHP Standard was offered to clients who failed to meet traditional Medicaid eligibility, but were enrolled in the OHP as a part of the federal waiver expansion program (i.e. adults and couples below 100% federal poverty limit). For the OHP Standard, cost-sharing requirements were increased, monthly premiums were introduced, and the benefit package was reduced. Preliminary analyses have suggested that implementation of these policies produced significant decreases in enrollment because of missed premium payments and reduction in prescription drug

and medical service.[16] The benefit package or cost-sharing requirements did not change during this time for clients enrolled in OHP Plus.

In May of 2005 the Secretary of the United States Department of Health and Human Services commissioned a group to explore proposals to ensure the long-term sustainability of the Medicaid program, and specifically to achieve $10 billion dollars in savings over a 5 year period.[17] A key recommendation of this report was granting states the authority to increase copays for prescription drugs beyond their current levels. Several of these provisions were included in the Deficit Reduction Act of 2005 signed by President Bush in February of 2006.[18] Specifically, the Act give states the latitude to increase copays to up to 10%-20% of the cost of the service or product depending on the enrollee's income, well above the nominal amounts allowed currently. Additionally, the law gives providers the ability to deny services or access if a patient is unable to pay the cost-sharing amount. Given the widespread implications of this policy and paucity of data on the impact in this population, research evaluating both intended and unintended consequences of Medicaid copayments for prescription drugs is sorely needed. The goal of this study is to evaluate the impact the implementation of OHP prescription drug copay policy on prescription drug and medical service utilization and cost for beneficiaries receiving the OHP Plus package.

METHODS

Overview of Study Design

The goals of this study were to explore the impact of a copay requirement for OHP Plus clients on prescription drug utilization and heath care encounters. The study design was a pre/post trend analysis using aggregated claims data.[19, 20] Monthly pharmacy and medical encounter claims data for 12 months before and 24 months after January 1, 2003 (policy implementation date) was used to estimate utilization and cost. The first objective of this study was to quantify overall and drug class specific prescription drug utilization and cost changes after the copay policy was introduced. Secondly, changes in the utilization of medical services such as office visits, emergency room (ER) visits, and hospitalizations were evaluated after policy implementation. Finally, we examined the impact of this policy on cohorts of patients identified as having specific diseases such as diabetes mellitus (DM), cardiovascular disease, reactive airway disease (RAD), depression, and schizophrenia.

Study Populations

The average monthly enrollment in OHP Plus during the study period was approximately 90,000 clients. However, several important client groups were excluded from the analysis because they were exempt from the copay policy. Pregnant women, children (age <19), clients in home- or community-based nursing facilities or intermediate care facilities for persons with mental retardation, and Native Americans were all exempt from the copay policy. The remainder of Oregon Medicaid recipients, eligible at any point during the study period, were included in the analysis. After exclusions, the average monthly enrollment was approximately 24,000. In addition, pharmacy claims for family planning drugs, infant formula, and claims filled by

mailorder pharmacies were exempt from the copay policy and were excluded from this study. Demographic data (sex, age, race, eligibility category) was characterized for the population overall and on a monthly basis to assess the stability over the study interval. Table 1 shows the data coding for the inclusion and exclusion criteria.

In order to assess the impact of the copay policy on patients with specific diseases individuals with the following diseases were identified: depression, schizophrenia, RAD, cardiovascular disease, and DM. Continuously enrolled cohorts for each disease were identified by having 1 or more medical encounters with one of the ICD9 codes outlined in table 2 every 6 months from January 1, 2002 to December 31, 2003 (4 - 6 month periods). Utilization was used to construct cohorts to reduce the impact small lapses in eligibility that are common within Medicaid populations.[21] Only 2 years of study were evaluated to ensure adequate cohort numbers with continuous enrollment. Study demographics were similarily described in these subgroups.

Data Sources

Pharmacy and medical service reimbursement claims data were used for this study. Pharmacy and medical encounter data for the OHP FFS program are collected in a central relational database (Decision Support Surveillance and Utilization Review System) by the state. These data were then imported into Microsoft (MS) Access for data manipulation. The Oregon State University College of Pharmacy, under interagency agreement with the Oregon Department of Human Services, is provided access to these data for drug utilization review and policy consultation. This research was approved by the Oregon Health & Science University Institutional Review Board.

Outcome Variables

Prescription Drug Utilization: The primary outcome variable was an aggregated monthly utilization estimate calculated by using the count of prescriptions dispensed divided by a count of subjects enrolled each month. This is commonly referred to as per member per month (PMPM) utilization. While the number of days in a month varies between 28 (29 on leap years) and 31, most studies using this or similar metrics make do not formally address this non-uniformity.[11, 22-27] Furthermore, because we are using a series of 36 consecutive monthly time periods, the impact of regularly repeating shorter and longer monthly is likely negligible. Long-acting opioids, statins, proton pump inhibitors, and non-steroidal anti-inflammatory drugs (NSAIDs) were eliminated from this analysis because they were affected by inclusion on the state's preferred drug list, implemented from August 2002 to October 2003.

Utilization trends were measured for all affected individuals in addition to a subset of members having one of the conditions outlined in table 2. Members identified with one of the conditions in table 2 had utilization trends measured for drugs specific to their disease as well as drugs not specific to their disease to determine if a differential impact existed. Table 3 is a list of individual drug and drug classes specific to diseases of interest.

Prescription Drug Costs: Drug costs were defined as the reimbursed ingredient cost without taking into account rebates. Total costs each month were divided by the associated number of enrolled clients to calculate the PMPM costs.

Medical Service Utilization: Changes in the rates of office visits, ED use, and hospitalizations was evaluated using the number of encounters PMPM. Medical encounter claims were differentiated using the coding criteria in table 4. Medical service encounters were analyzed in the entire population as well as the disease specific cohorts.

Covariate Analysis: Analysis of the policy was statistically adjusted for aggregated measures of individual characteristics (age, sex, and race), disease severity, and the clients' program eligibility codes (e.g. Adult Blind or Disabled). These variables are described in detail below.

Individual Characteristics – age, sex, and race are coded for each submitted claim. Each variable was averaged or categorized, depending on data type, for each monthly interval. Race is categorized in the OHP datasets in the following way: White, Black, Hispanic, Asian or Pacific Islander, American Indian or Alaskan Native, other, or unknown. For analysis, the categories other and unknown were collapsed.

Program Eligibility – Clients are enrolled in Medicaid under different eligibility categories, several of which are mandated by federal Medicaid law. The main categories in this study were Temporary Assistance to Needy Families (TANF), Aid to the Blind and Aid to the Disabled (AB/AD), and Old Age Assistance (OAA). The proportion of clients in each category for each month was considered the covariate unit of analysis. These categories were defined by the program eligibility codes listed in table 1.

Disease Severity – The adapted Charlson Comorbidity Index was used to estimate disease severity. The Charlson Index was originally developed by Charlson et al as a predictor of mortality in medical patients as a function of other comorbid conditions and is frequently used in observational studies as an overall indicator of health status.[28, 29] It has subsequently been adapted and validated for use in administrative claims.[30, 31] Table 5 shows the composition of the adapted Charlson Index. An individual's Charlson Index was calculated by determining the number of diagnoses from table 5 that are present during the study period and adding the total assigned weights during the period.

Urbanicity – Urbanicity of each client was defined by the urban or rural designation of their mailing address according to the Oregon Office of Rural Health.[32]

Statistical Analysis Plan

This study was a retrospective, observational analysis of aggregated pharmacy and medical claims before and after implementation of the copay policy. The unit of analysis for this study was the aggregate number of paid claims for drugs and medical services adjusted PMPM. Similarly, all covariates were aggregated, that is, averaged in the population adjusted PMPM for each monthly time unit. Monthly trends before and after the policy were compared using a segmented (piece-wise) ordinary linear squares (OLS) regression models adjusted for 1st order autocorrelated errors. This was required because of violations in the OLS regression assumption that error terms be independent. The consequence of positive or negatively correlated error is an inflation beta-coefficient variance and consequently spuriously low p-values. First order autocorrelation (correlation between adjacent data points), most frequently encountered type of

correlation in time series data, was assumed and adjusted in all models.[33] During the modeling process, several regression models exhibited significant Durban-Watson tests indicating first-order autocorrelation. This approach is advocated by many in the econometric and health services research field.[27, 33, 34] The autoregressive corrective procedure (PROC AUTOREG) was used to evaluate changes in the trend (prescriptions dispensed PMPM, cost PMPM, encounters PMPM) from the pre period to the post (copay policy) period. The regression model had the general structure:

$$y = \beta_0 + \beta_1 x_t + \beta_2 z_1 + \beta_3 (x_t - 12) z_1 + \beta' x + \varepsilon$$

y = monthly PMPM utilization

X_t= month number

Z_1= period indicator variable 0=pre period, 1=post period

β_0 = Estimate of intercept (mean utilization for first month)

β_1 = Estimate of pre-period time trend (slope)

β_2 = Estimate of level change after copay

β_3 = Estimate of change in trend in post-period

$\beta'x$ = Covariates

ε = error term

Covariates explored in the model included the proportion of clients in specific eligibility, racial, sex, and urban setting groups, as well as average age and Charlson Index. Covariates were selected first using a best subsets regression on the outcome variable based on the r-squared statistic and Mallow's C statistic.[35] The best fit covariates were then entered into the model containing segmented regression variables. The best subsets technique was repeated using the Akaike's information criterion (AIC) as the determining predictor to evaluate the consistency of

covariate selection. Covariates that exhibited significant associations at the 0.25 level were retained in the final model. Multicollinearity between covariates was assessed using a Spearman and Pearson's correlation coefficient and variables exhibiting significant associations were not included in the same model. All dummy time variables were retained regardless of their statistical significance. Beta-coefficients from regression models were expressed in two ways. The trend, or slope of trend line, before (β_1) and change after the intervention (β_3) will be reported as the absolute initial trend and the absolute change in slope during the policy period. The change in slope after the intervention (β_3) is sometimes interpreted as the long term impact of a policy. The absolute change immediately following the policy implementation was described by β_2 and will be expressed as a percentage change of what would be expected if the policy had not been implemented, or the counterfactual trend. The counterfactual trend was calculated by $Y=\beta_0 +\beta_1*13$, where 13 indicates the first interval after the policy was implemented. Both covariate adjusted and unadjusted models are presented.

For the analysis of the differential effects between drug classes for the disease-specific cohorts the following model was specified:

$$y = \beta_0 + \beta_1 x_t + \beta_2 z_1 + \beta_3 (x_t - 12) z_1 + \beta_4 z_2 + \beta_5 x_t z_2 + \beta_6 z_1 z_2 + \beta_7 (x_t - 12) z_1 z_2 + \varepsilon$$

Y = monthly PMPM utilization

X_t= month number

Z_1= period indicator variable 0=pre period, 1=post period

Z_2= drug type indicator 0 = drugs not for condition 1 = drugs for condition

β_0 = Estimate of intercept (mean utilization for first month)

β_1 = Estimate of pre-period time trend (slope)

β_2 = Estimate of level change after copay

β_3 = Estimate of change in trend in post-period

β_4 = Estimate of difference between drugs for condition and drugs not for condition

β_5 = Estimate of difference of pre trend between drug types

β_6 = Estimate of difference of level change after copay between drug types

β_7 = Estimate of difference of post trend between drug types

ε = error term

The resultant beta-coefficients 1-3 are interpreted to be the estimates for drugs not used for a specific condition (e.g. migraine medications for a person with DM). Coefficients β_5 - β_7 are estimates of the difference between drugs for condition and drugs not for condition. The addition of coefficients β_1 and β_5, β_2 and β_6, and β_3 and β_7 represent the pre period trend, immediate segment change, and post period change in trend in utilization of drugs specific for a person's condition (e.g. insulin for a person with DM) respectively.

All data manipulation and statistical analyses was conducted with MS Access and SAS® 9.1 for Windows® respectively.

RESULTS

Subject Demographics

The yearly demographics for the studied OHP Plus population are presented in table 6. There was an overall increase in the studied population size from around 53,000 in 2002 to 62,000 in 2004. However, the relative distributions of patient characteristics remained generally stable. The mean age of the population was approximately 39 years old and predominately female. A majority of subjects lived in urban areas. Approximately 84% of study subjects were White, followed by 6%-7% Hispanic, 5% Black, and 3-4% Asian. A shift in eligibility groups was noted as the proportion of clients enrolled in TANF increased from 60% to 64% and the ABAD declined from 31% to 28%.

Overall Prescription Drug Trends

Tables describing the aggregate changes in trend of both utilization and cost of dispensed prescriptions and health services (Tables 7, 8, 9, 10, 12, 13) are structured by describing what the initial slope trend before the policy (pre-trend), the percent decline in magnitude of utilization or cost the month immediately following the policy change (segment change), and the change in trend slope following the policy (trend change). The features of this model are graphically represented in figure 1. The trend in cost and utilization of prescription drugs dispensed PMPM during the study period is shown in figure 2. The unadjusted segmented regression model detected the utilization of prescription drugs decreased significantly by 19.4% (95% CI -22.7% – -18.5%, $p<0.0001$) immediately after the copay policy was introduced. Additionally, the trend in prescriptions dispensed PMPM declined significantly by 0.0291 (95% CI -0.0410 – -0.0172, $p<0.0001$). When adjusted for significant covariates, the immediate decline was reduced to

17.2% (95% CI -20.7% – -13.6%, p<0.0001) and the trend change declined to a non-significant -0.0108 (95% CI -0.0351 – 0.0135, p=0.3894). The overall optimum covariates selected for the model remained the same regardless of the selection criteria used; Cp or AIC. The details of the covariate modeling variable selections can be found in Appendix B. Qualitatively similar results were found when the drug costs PMPM were regressed on the same unadjusted model as shown in table 8. When covariate adjustments were made, the change in costs PMPM declined, but remained statistically significant, to -6.3% (95% CI -13.7% - 2.3%, p=0.0046) immediately after the policy. The trend change after policy implementation did not change significantly in the adjusted analysis

Drug Specific Utilization

The copay policy appeared to have a different impact contingent on the drug class investigated. Overall, significant declines in the use of all studied classes were observed immediately after the policy was enacted. Figure 3 and table 9 show the results of both unadjusted and adjusted segmented regression models. Utilization of DM-related medications decreased significantly after policy implementation by 14.3% (95% CI -18.9% – -9.7%, p<0.0001). This finding is shown in the row labeled segment change of table 9 and reflects the immediate decline in utilization the month immediately following the policy. The trend in DM-related utilization was also decreased by 0.1267 prescriptions per 100 patients per month (95% CI -0.1945 – -0.0589, p=0.0009). This finding reflects the overall change in the slope of the utilization line between the pre period and post-policy period and is described in the rows labeled trend change of table 9. Drugs dispensed for cardiovascular disease decreased immediately (segment change) by 13.2% (95% CI -18.1% - -8.3%, p<0.0001) and the trend in utilization (trend change) decreased by -

0.2267 prescriptions per 100 patients per month (95% CI -0.4390 – -0.0144, p=0.04). The use of drugs for RAD demonstrated the largest immediate decline (segment change) of 20.7% (95% CI -26.4% – -15.0, p<0.0001), although no change in the trend of use of these drugs was observed. Antidepressant and drug for schizophrenia both declined (segment change) significantly by 20.1% (95% CI -23.8% - -16.4%, p<0.0001) and 15.5% (95% CI -19.1% - -10.0%, p<0.0001) respectively following policy implementation. Statistically significant reductions in the monthly trend was also observed for both mental health drug classes. Adjustment for significant covariates had little impact on the overall findings of the unadjusted estimates.

Medical Service Encounters

Trends in outpatient office visits, hospitalizations, and ED encounters were analyzed in a similar fashion and are shown in table 10 and figure 4. No immediate changes for any medical service outcome were observed after implementation of the copay policy. The trend in hospitalizations increased significantly after policy implementation; however, this was observed after a period of decline which was also statistically significant. The covariate adjusted models demonstrated similar findings. No covariates were significant in the regression models of hospitalizations and office visits.

Disease Specific Cohort Analyses

Demographic information about the five disease specific cohorts is summarized in table 11. The largest cohort was the DM group at 1222 patients and the smallest was the RAD group at 451 patients. The other demographic information generally followed what is known about the

characteristics of these conditions. For example, the schizophrenia cohort was younger and predominately male. The DM group had the highest average Charlson Comorbidity Index and the largest proportion of Hispanic patients. Patients in the cardiovascular disease cohort were, on average, the oldest. The cohort with depression contained the highest proportion of females.

Table 12 shows the segmented regression model coefficient estimates comparing drugs specific for each condition and drugs not used for the condition in addition to the model evaluating the difference (interaction terms) between the two groups. All disease cohorts except the cardiovascular group demonstrated a significantly different immediate response (segment change) between utilization of drugs for their condition compared to drugs not for their condition. There was no change in utilization trend between drug groups among the DM and cardiovascular disease cohorts. Among patients with DM, utilization of DM-related drugs declined non-significantly after the policy change by 7.2% (95% CI -16.6% - 1.6%; p=0.3092) compared to a significant decline of 11.6% for drugs not used for that condition (95% CI -18.4% - -4.9%; p=0.0107). The trend in utilization declined significantly for both drug types in the DM cohort. Patients with RAD reduced the use of non-RAD drugs by 8.3% (95% CI -14.4% - -2.1%; p=0.0521) compared to no appreciable decline (-0.1%, 95% CI -5.3% - 5.1%; p=0.4375) for drugs used to treat RAD. Again, the slope in utilization was significantly reduced for both drug types for patients with RAD. The use of antidepressants and non-antidepressants among patients with depression were both reduced significantly by -17.3% (95% -26.1% - -8.4%, p=0.0032) and -16.5% (95% CI -21.7 – 11.3%, p<0.0001), respectively, in the month after copays were implemented. The difference in these reductions was also statistically significant with a p=0.0007. The slope of utilization was also reduced for both drug types among patients

with depression, but more so for drugs not used for depression ($p<0.0001$). For patients with schizophrenia, a significant reduction in antipsychotics immediately after the copay policy was not observed. However, a significant decline in the slope of utilization of antipsychotics was observed in the period after the copays were introduced. In contrast, the use of non-antipsychotics among patients with schizophrenia declined significantly in the period following the copay by 15.2% (95% CI -20.7 - -9.8%, $p<0.0001$). The difference in immediate response between antipsychotics and non-antipsychotics was statistically significant ($p=0.0165$). In general, among patients with cardiovascular disease, there were no significant differences in utilization changes between drugs for cardiovascular disease and drugs not used for cardiovascular disease. The utilization of both drug types did not change significantly immediately after the policy was implemented. A significant decline in the trend of cardiovascular drug utilization was observed ($p=0.0379$), however, this was not significantly different than the pattern of use for non-cardiovascular drugs ($p=0.5124$). The trend in utilization for each cohort is presented in figures 5-9. Changes in medical service utilization within these cohorts were explored and are presented in table 13. The low sample size of the cohorts prohibited a sufficient number of encounters to be observed for several of the disease cohort outcomes. Trends were statistically analyzed if more than 100 events per month were observed.[27] Among patients with DM, no significant changes were observed after the policy was implemented for office visits or ED encounters. The trend in office visits for patients with cardiovascular exhibited a significantly lower slope during the policy period. A non-significant 19% (95% CI -4.5% - 41.4%, $p=0.0922$) increase in office visits was observed in the depression cohort. The RAD showed no significant changes in the monthly use of office visits.

DISCUSSION

In this study, implementation of a prescription drug copay policy was associated with a statistically significant immediate 17 % reduction (segment change) in the drug utilization. Cost trends followed a similar pattern. The data does not, however, suggest an overall change in trend of prescription drug utilization or costs after the policy was implemented. Reduction in prescription drug use was observed in every therapeutic category studied to differing extents. Additionally, all drug classes except those for RAD and cardiovascular exhibited a significant decline in trend upon initiation of the copay policy. In contrast with the overall estimate of trend change, this finding possibly suggests that the impact on specific drug classes was more pronounced on longer term utilization. The use of cardiovascular medications was reduced the least amount and the use of drugs for depression and RAD were reduced the most. Despite these impressive reductions, changes in medical service utilization were not observed subsequent implementation of the copay policy. Within the disease specific cohorts studied, patients with DM, RAD, depression, and schizophrenia appeared to discriminate between drugs used for their conditions and drugs not used for their conditions. The most striking example of this occurred in patients with RAD who did not appear to immediately cut back on drugs for their condition (-0.1% immediate decline) compared to drugs not used for their condition (8.3% immediate decline). This pattern of response was also apparent for patients with schizophrenia who reduced their use of antipsychotics less than their use of other medications. This observation is moderately reassuring given that these two conditions likely are the most immediately sensitive to abrupt reductions in pharmacotherapy. The changes in RAD drug use among patients with RAD is also notable in that it greatly contrasts the overall pattern of RAD use, which declined by

19% immediately after the policy. Overall, the trend among all disease cohorts was a gradual decrease in the slope of utilization for both categories of drugs after the copays were introduced.

The 17% immediate decline in utilization of antidepressants among patients with depression is also striking. This was the largest decrease in utilization observed among the cohorts and also corresponded to an 18.5% increase in office visits for these patients ($p= 0.0922$). These findings potentially suggest that the reduction in medications (both antidepressants and non-antidepressants) may be related to the increase in office visits after the policy was implemented. While not definitive, the increase in office visits may represent an adverse unintended consequence of the copay policy and deserves further exploration.

While the dramatic absolute reduction in drugs of 17 % after the policy was implemented is, by itself, concerning, no evidence of unintended outcomes in terms of increased office visits, ED encounters, or hospitalizations was found overall. Significant decreases in therapeutic classes such as RAD are concerning given the immediate dependence of patients on these drugs. It is interesting to note that there was almost no immediate decline in the use of drug for RAD among patients with RAD. This finding perhaps suggests that the reduction in RAD drugs in the general population reflects more a decline in utilization among patients who may not have severe chronic respiratory disease. Similar line of reasoning could apply to the differences in utilization occurring overall compared to utilization among those with documented disease.

The method in which the various disease cohorts were selected merits discussion. Patients were selected if they had at least 1 medical encounter for their disease every 6 month during the 24

month cohort analysis. Thus, one could argue that these patients had regular contact with the health care system and had a high degree of comorbidity, which is reflected by a 10 fold higher Charlson Index among cohort members compared to the general population. Because these patients, by definition, had frequent contact with the health care system, it could also be argued that their condition was potentially better managed than a patient who had only one or two encounters during the entire study period. With the exception of drugs for depression, drug specific utilization changes, as shown in table 9 and 12, were at least 2 fold greater in the overall population compared to the cohort of patients with known disease. This finding potentially supports the contention that these patients were better managed through the policy than users in the overall population.

This research is consistent with other studies showing significant relationships between cost-sharing for prescriptions drugs and overall utilization of prescription drugs. In the only other comparable Medicaid copayment study published, Nelson et al, observed a significant 0.28 prescription per month immediate decline in utilization.[7] While the authors do not provide what percentage of the predicted utilization given no policy, this estimate is numerically of the same level of magnitude compared to the figure from our analysis. Also, similar to another analysis of the same data by Reeder et al , we found that the change in utilization differed dramatically depending on which therapeutic class was evaluated.[8] In an evaluation examining the impact of several cost-sharing policies on clients enrolled in the Oregon Health Plan receiving the expansion benefit package (OHP Standard), Carlson et al reported 46% of patients responding to survey indicated not purchasing needed medications because of cost-sharing.[36]

Several limitations and alternative explanations for the findings require discussion. First, this study is a retrospective, observational analysis of temporal changes in utilization coincident with a policy change. A control group of patients not exposed to this policy was not available at the time of this analysis. While, time trend analyses are capable of controlling, to some extent, secular trends in utilization it is impossible to completely exclude any other unknown confounders which may have been temporally related to the policy adoption. The relative stability of our patient demographics and the fact that the findings were generally robust to statistical adjustment for population changes suggest that these were not responsible for the results. Copays were introduced, not only for prescription drugs, but also for outpatient services, such as office visits, home visits, and outpatient hospital services. Therefore, it is conceivable that any unintended increase in office visits due to the prescription drug policy could potentially have been mitigated by the copay for an office visit. Anecdotal reports by providers suggest that these copays were not enforced; however, a formal evaluation of this does not exist. Emergency room visits were exempt from the copay policy. Therefore it seems unlikely that copays for medical services masked the unintended consequence attributable to the drug policy.

During the period of this analysis, Oregon's Preferred Drug Plan (PDL) was also implemented. The PDL was only actively enforced for 4 drug classes for a total of 5 months. In May of 2003, the PDL enforcement for proton pump inhibitors, long-acting opioids, NSAIDs and statins was initiated. From May 2003 to the end of September 2003, providers prescribing non-preferred agents from these classes were required to call the State's pharmacy benefit manager and listen to an educational message about the prescribed class. To avoid confusing the impact of this

policy with the cost sharing policy, these medication classes were eliminated from this study. No other significant policies were implemented during the study period.

This study used aggregated estimates of prescription drug and medical service utilization and therefore is classified as an ecologic study and subject to all of the associated limitations.[37] The unit of analysis was not individual patients and therefore it is very possible that adverse outcomes occurring to an individual were missed in the population level analysis. Overall, our data support no increase in unintended consequences secondary to the prescription.

This study used medical and pharmacy reimbursement claims to evaluate the clinical impacts of the cost-sharing policy. Automated claims are not typically collected for research purposes and therefore problems with coding accuracy may introduce both systematic and random error into this study. The validity of Medicaid pharmacy data is generally believed to be quite good. Agreement between claims for paid prescriptions and what actually transpired clinically has been documented to be high.[21, 38-41] The validity of medical encounter data has been studied less.[42] However, misclassifications of drug and health encounter claims are likely to be random with respect to the outcomes in this study. This occurrence would only bias the results towards the null hypothesis.

Medicaid is primarily composed of an economically disadvantaged and vulnerable population. Thus, the findings of this study may not be able to be extrapolated beyond this population. This may be especially true when examining the extent to which patients can absorb increases in the costs of their medications. The results of this study would most appropriately be applied to other

state Medicaid programs or international health systems for low-income individuals. Medicaid is currently one of the largest purchaser of health care in the country, so despite a limitation of external validity, the results of this study are still widely applicable. We also restricted our analysis to Medicaid patients who were not enrolled in a capitated managed care plan. Roughly 75% of OHP clients are enrolled in a fully-capitated managed care program. Patients who enroll in manage care typically have less comorbidity, are younger, and more likely to live in an urban area compared to patients who receive FFS benefits.[43] The validity of these findings among patients receiving managed care benefits is unclear. Nationally, 63% of the 45 million Medicaid clients are enrolled in a managed care program.[44] This still leaves a sizable population who are likely demographically similar to our study population. Finally, we restricted our analysis to Medicaid patients receiving the OHP Plus benefit package. Because the OHP Standard package was offered to those clients who would have not qualified via traditional, federally mandated, Medicaid eligibility rules, our study population is likely very similar to other state Medicaid FFS populations.

The results of this study were generally similar to the early studies of Nelson and Reeder.[7, 8] With the exception of sedative hypnotics and analgesics, their study noted significant declines in the use of all other studied drug classes, including cardiovascular and antidepressants.[8] Similarly, this study found reductions in the use of all evaluated medication classes. Among those patients with a defined diagnosis, these declines were generally less severe for drugs used for the condition than products not directly used to treat the condition. The results of this study differed from those found by Tamblyn et al of an elderly and welfare population in the province of Quebec. The introduction of a 25% coinsurance policy was associated with a 16% reduction in

overall drug use among adult welfare recipients. However, their policy was also associated with increases the monthly rate of adverse events (hospitalization, long-term care admission, or emergency department visits) and emergency department visits. Another Canadian study of elderly patients with rheumatoid arthritis has suggested that cost-sharing is also associated more physician office visits and hospitalizations.[45] This study does not provide evidence supporting that the copay policy lead to increases in the use of the emergency department, office visits, or hospitalizations, however the cost-sharing policy in Oregon was significantly less than the cost-sharing policies in both of these Canadian studies.

FUTURE DIRECTION AND CONCLUSIONS

Several unanticipated limitations with the current study could potentially be addressed in future studies using the same or similar datasets. While it is unlikely that the changes observed in this study assumed to be attributable to the policy were, in fact, secondary to secular changes in utilization, the inclusion of a similar Medicaid population as a control group would more definitely rule this out.[20] A control population could be obtained from another state FFS Medicaid program or potentially from one or several of the capitated managed care plans in Oregon. However, while the later option would be logistically less difficult to obtain it might present problems because of baseline population differences. If another state's Medicaid program were selected, the regional differences between the states and their population would need to be considered. Another potential improvement to this study would be to do undertake a cohort analysis where the unit of analysis was the individual, rather than monthly aggregate utilization levels over time. This change would better quantify the experience to the average population member and perhaps enhance the sensitivity to detect adverse unintended consequences. Finally, using the existing dataset, it would also be possible to explore the impact the copay policy on other prescription drug related outcomes such as drug therapy compliance. Assessing drug adherence would likely be more applicable to the individual patient than the current measure of aggregate utilization PMPM.

Much of the research on evaluating the impact of cost-sharing, and most other drug policies, have relied on administrative claims to quantify on health using surrogate markers such as volume of prescription drugs, ED visits, and hospitalizations.[46, 47] There have been no studies to date attempting to examine the impact of cost-sharing, of any type, on true health outcomes or

quality of life. Unfortunately, outside of prospective experimental research, these types of outcomes are difficult to quantify because most health care systems do not have readily available clinical databases. Notable exceptions to this are the Department of Veterans Affairs and managed care organizations such as Kaiser Permanente where a closed system style of care and advanced electronic medical record system may allow more detailed evaluation of unintended policy effects. Future research should directed at evaluating the impact of cost-sharing and copays on clinical and, where possible, humanistic outcomes.

This study is consistent with previous research in that cost-sharing, specifically copays, for prescription drugs is related to an immediate and significant decline in the utilization and costs of prescription drugs in a Medicaid program. The largest declines studied occurred in the RAD depression therapeutic classes however, significant decreases were also observed in all of the studied therapeutic areas. Among patients with diagnoses for specific diseases the level of decrease was generally higher for drugs not used to treat the condition. Especially concerning is the finding that patients with depression demonstrated the largest decrease in the use of antidepressants and non-antidepressants drugs while simultaneously exhibiting a nearly significant increase in office visits. While many of the observed declines are clinically concerning, there was no evidence suggesting that the copay policy was associated with increases in health service utilization such as ED encounters, hospitalizations, or office visits overall.

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TABLES

Table 1: Inclusion Exclusion Criteria

Category	Criteria Description	Data Source (Field/Table)
Inclusions		
Program Eligibility Categories (PERC codes)	Temporary Assistance to Needy Families (TANF)	Pharmacy and medical encounter data / CodeRptEligProg
	Aid to Blind/Disabled (AB/AD)	
	Old Age Assistance	
Exclusions		
Long Term Care	Nursing Home Flag Community-based facility	medical encounter data / CodeTypeRecClm medical encounter data / proccode
Native American	Native American/Alaskan	Pharmacy and medical encounter data/ CodeInfoAsst1-CodeInfoAsst7 Pharmacy and medical encounter data/ race
Age <19		Pharmacy and medical encounter data/age
Drugs filled with Mailorder pharmacy	Mailorder pharmacy	Pharmacy/ NmbrIdProv
Drugs for: family planning Infant formulas		Pharmacy / therapeutic class

Table 2: Cohort Disease Definitions

Condition	Diagnoses	ICD-9 Code
Depression	Affective disorder	296xxx
	Adjustment reaction	309xxx
	Depressive disorders	311xxx
	Neurotic disorders	300xxx
Schizophrenia	Schizophrenic disorders	295.xxx
Reactive Airway Disease	Asthma	493.xxx
	Chronic airway obstruction, NEC	496.xxx
	Chronic bronchitis	491.xxx
	Emphysema	492.xxx
Cardiovascular Disease	Essential hypertension	401.xxx
Hypertension	Hypertensive heart disease	402.xxx
	Hypertensive renal disease	403.xxx
	Hypertensive heart/renal	404.xxx
	Secondary hypertension	405.xxx
Coronary Heart Disease	Ischemic heart disease	410.xxx – 414.9xx
	Cardiovascular disease, unspecified	429.2xx
	Heart disease, unspecified	429.9xx
Heart Failure	Heart Failure	428.xxx
Diabetes Mellitus	Diabetes mellitus	250.xxx

Table 3: Disease Specific Drugs

Disease	Drugs
Depression	Selective Serotonin Reuptake Inhibitors
	Venlafaxine, mirtazepine, bupropion, duloxetine, nefazadone
Schizophrenia	Atypical antipsychotics
	First generation antipsychotics (e.g. haloperidol)
Reactive Airway Disease	Inhaled beta-agonts (short acting, long-acting), combinations (advair)
	Inhaled corticosteroids
	Inhaled anticholinergics (i.e. ipratropium, tiotropium)
	Leukotriene modifiers (e.g. montelukast)
	Mast cell stabilizers (e.g. cromolyn)
	Theophylline
Heart Disease	Diuretics
	Angiotensin converting enzyme inhibitors/angiotensin receptor blockers
	Beta-Blockers
	Calcium channel blockers
	Alpha-adrenergic blockers (e.g. doxazosin)
	Misc. (i.e. clonidine, hydralazine, minoxidil)
	Digoxin
	Antiplatelet (aspirin, clopidagril)
	Aldosterone Antagonist (spironolactone, elperenone)
Diabetes Mellitus	Injected Insulin
	Sulfonylureas
	Non-sulfonylurea secretagogues (e.g. repaglinide)
	Metformin
	Alpha glucosidase inhibitors
	Thiazolidinediones
	Misc. injectables (i.e. pramlintide, exenatide)

Table 4: Medical Service Definitions

Encounter Type	Uniform Billing (UB) -92 Revenue Center Code	Current Procedural Terminology (CPT) Code	CPT descriptor	Diagnosis Related Group
Office Visit	Any	99201-99205 99211-99215 99241-99245	Office- new patient Office-established patient Office consultation	Null
Emergency Department	045x OR 0981	99281-99285 99288	Emer Dept. Services Othr Emer Services	Null
Hospitalization	Any	Any	Any	Not Null

Table 5: Adapted Carlson Comorbidity Index

Condition	International Classification of Disease – 9th Revision Clinical Modification	Weight
myocardial infarction	410, 411, 412	1
Heart failure	428	1
Peripheral vascular	4439, 4402	1
Dementia	290	1
Cerebrovascular	430-438	1
Chronic lung disease	490-496, 500-505, 506.4	1
Diabetes mellitus (DM)	2500, 250.7	1
Rheumatologic disease	714.0-714.2, 7100, 710.1, 710.4, 714.81, 725	1
Peptic ulcer disease	531-534	1
Mild liver disease	571.2, 571.3, 571.4, 571.5, 571.6	1
Severe liver disease	572.2-572.4, 572.8	2
Hemiplegia/paraplegia	344.1, 342	2
Renal disease	582, 583, 585, 586, 588	2
DM with complications	250.4-250.6	2
Cancer	140-165, 166-169, 174-195.8, 200-208.9	2
Cancer with metastasis	196-198	6
HIV	042	6

Table 6: Demographics of yearly enrollment

	2002 (n=53,297)		2003 (n=59,734)		2004 (n=62,183)	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Age	39.16	16.07	38.5	15.07	38.54	15.07
Charlson Index	0.31	0.97	0.32	0.98	0.28	0.92
	Count	**% total**	**Count**	**% total**	**Count**	**% total**
Eligibility						
ABAD	16278	30.5	18761	31.39	17441	28.04
OAA	5328	9.98	4637	7.76	4851	7.8
TANF	31763	59.52	36374	60.85	39906	64.16
Race						
White	44792	83.93	50022	83.69	51925	83.48
Hispanic	3508	6.57	4092	6.85	4594	7.39
Black	2622	4.91	3097	5.18	3158	5.08
Asian	2043	3.83	2151	3.6	2097	3.37
Unknown/Other	404	0.76	410	0.69	424	0.68
Sex						
Female	36304	68.12	40673	68.09	41995	67.54
Region						
Urban	28560	59.08	34907	58.81	34815	56.44

Table 7: Segmented regression of number of prescriptions dispensed per member per month

	Unadjusted				Adjusted*			
Segment	**Estimate**	**95 % CI**		**P-value**	**Estimate**	**95 % CI**		**P-value**
Pre-trend	0.0070	-0.0044	0.0184	0.2364	0.0041	-0.0074	0.0155	0.491
Segment change	-19.4%	-22.7%	-18.5%	<.0001	-17.2%	-20.7%	-13.6%	<.0001
Trend change	-0.0291	-0.0410	-0.0172	<.0001	-0.0108	-0.0351	0.0135	0.3894

*Adjusted for monthly changes in prevalence of black and urban

Table 8: Segmented regression of prescription drug cost per member per month

	Un-Adjusted				Adjusted*			
Segment	**Estimate**	**95 % CI**		**P-value**	**Estimate**	**95 % CI**		**P-value**
Pre-trend	0.5469	-0.3467	1.4405	0.2394	0.3416	-0.5510	1.2342	0.4044
Segment change	-12.2%	-17.5%	-6.9%	0.0003	-6.3%	-13.7%	-2.3%	0.0046
Trend change	-1.7918	-2.7348	-0.8488	0.0008	0.2012	-1.5920	1.9944	0.9722

*Adjusted for monthly changes in prevalence of black and urban

Table 9: Segmented regression of drug class specific prescription volume per 100 patients per month

	Un-Adjusted				Adjusted*			
Segment	**Estimate**	**95 % CI**		**P-value**	**Estimate**	**95 % CI**		**P-value**
Diabetes mellitus related Medications								
Pre-trend	0.0647	0.0002	0.1292	0.0583	0.0656	0.0035	0.1277	0.0473
Segment change	-14.3%	-18.9%	-9.7%	<.0001	-13.5%	-18.0%	-9.0%	<.0001
Trend change	-0.1267	-0.1945	-0.0589	0.0009	-0.1122	-0.1751	-0.0493	0.0016
Cardiovascular-related Medications								
Pre-trend	0.1419	-0.0598	0.3436	0.1776	0.1859	0.0209	0.3509	0.0354
Segment change	-13.2%	-18.1%	-8.3%	<.0001	-13.1%	-17.2%	-8.9%	<.0001
Trend change	-0.2267	-0.4390	-0.0144	0.04	-0.1707	-0.3377	-0.0037	0.0545
Reactive airway disease-related Medications								
Pre-trend	-0.0301	-0.0989	0.0387	0.3971	-0.0372	-0.0954	0.0210	0.2204
Segment change	-20.7%	-26.4%	-15.0%	<.0001	-18.7%	-23.7%	-13.8%	<.0001
Trend change	-0.0356	-0.1081	0.0369	0.3436	-0.0207	-0.0797	0.0383	0.4967
Depression-related Medications								
Pre-trend	0.2001	0.0997	0.3005	0.0005	0.1899	0.0868	0.2930	0.0011
Segment change	-20.1%	-23.8%	-16.4%	<.0001	-19.6%	-23.5%	-15.6%	<.0001
Trend change	-0.3511	-0.4560	-0.2462	<.0001	-0.3452	-0.4508	-0.2396	<.0001
Schizophrenia-related Medications								
Pre-trend	0.1458	0.0307	0.2609	0.0185	0.1142	0.0135	0.2149	0.0343
Segment change	-14.5%	-19.1%	-10.0%	<.0001	-12.4%	-16.5%	-8.4%	<.0001
Trend change	-0.2429	-0.3634	-0.1224	0.0004	-0.2238	-0.3255	-0.1221	0.0002

*DM, cardiovascular, RAD, Schizophrenia adjusted for TANF and black race; Depression adjusted for black race

Table 10: Segmented regression of medical service encounters per 100 patients per month for selected cohort outcomes

	Un-Adjusted				Adjusted*			
Segment	**Estimate**	**95 % CI**		**P-value**	**Estimate**	**95 % CI**		**P-value**
Emergency Department Encounters								
Pre-trend	-0.0362	-0.1375	0.0651	0.489	-0.0138	-0.1265	0.0989	0.8126
Segment change	-3.2%	-10.5%	4.0%	0.347	-0.8%	-8.8%	7.3%	0.8019
Trend change	0.0314	-0.0772	0.1400	0.5754	0.0323	-0.0875	0.1521	0.601
Hospitalizations								
Pre-trend	-0.0421	-0.0709	-0.0133	0.0074	No significant covariates			
Segment change	-1.4%	-10.9%	8.1%	0.5362				
Trend change	0.0389	0.0070	0.0708	0.0229				
Office Visits								
Pre-trend	-0.0719	-0.5907	0.4469	0.7876	No significant covariates			
Segment change	2.2%	-6.6%	11.0%	0.6211				
Trend change	-0.0171	-0.5696	0.5354	0.9521				

*Adjusted for age and sex

Table 11: Demographics of disease cohorts

	Diabetes Mellitus (n=1222)		Cardiovascular (n=519)		Reactive Airway Disease (n=451)		Depression (n=546)		Schizophrenia (n=602)	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Age	53.17	13.9	60.78	13.3	55.18	14.01	53.17	13.9	41.81	10.63
Charlson	3.05	2.13	2.21	2.36	2.43	2.12	0.39	0.95	0.45	1.00
	Count	**% total**	**Count**	**% total**	**Count**	**% total**	**Count**	**% total**	**Count**	**% total**
Eligibility										
ABAD	785	64.24	239	46.05	259	57.43	417	76.37	575	95.51
OAA	381	31.18	269	51.83	177	39.25	65	11.9	27	4.49
TANF	56	4.58	11	2.12	15	3.33	64	11.72	0	0
Race										
White	998	81.67	421	81.12	417	92.46	485	88.83	554	92.03
Hispanic	74	6.06	19	3.66	10	2.22	10	1.83	12	1.99
Black	39	3.19	21	4.05	5	1.11	8	1.47	22	3.65
Asian	102	8.35	53	10.21	16	3.55	4	0.73	11	1.83
Unknown/Other	9	0.74	5	0.96	3	0.67	39	7.14	3	0.5
Sex										
Female	834	68.25	314	60.5	311	68.96	401	73.44	224	37.21
Region										
Urban	664	55.89	290	58.23	208	47.38	211	61.7	436	74.91

Table 12: Segmented regression models of disease cohorts

Cohort	Coefficient	Disease-Specific	95 % CI		P-value	Non-disease specific	95 % CI		P-value	P-value for difference
Diabetes Mellitus										
	Pre-trend	0.0106	0.0008	0.0204	0.0477	0.0172	-0.0001	0.0345	0.0669	0.4641
	Segment Change	-7.2%	-16.0%	1.6%	0.3092	-11.6%	-18.4%	-4.9%	0.0107	0.0336
	Trend Change	-0.0262	-0.0405	-0.0119	0.0019	-0.0475	-0.0716	-0.0234	0.0011	0.1469
Cardiovascular										
	Pre-trend	0.0172	0.0035	0.0309	0.0229	0.0056	-0.0104	0.0215	0.5025	0.2986
	Segment Change	-3.4%	-13.5%	6.8%	0.7538	-2.3%	-10.6%	6.0%	0.7069	0.8375
	Trend Change	-0.0224	-0.0420	-0.0028	0.0379	-0.0128	-0.0353	0.0097	0.2776	0.5124
Reactive Airway Disease										
	Pre-trend	-0.0042	-0.0086	0.0002	0.0801	0.0114	-0.0073	0.0301	0.2462	0.0918
	Segment Change	-0.1%	-5.3%	5.1%	0.4375	-8.3%	-14.4%	-2.1%	0.0521	0.0323
	Trend Change	-0.0186	-0.0247	-0.0125	<.0001	-0.0529	-0.0788	-0.0270	0.0008	0.0136
Depression										
	Pre-trend	0.0059	0.0029	0.0088	0.0009	0.0246	0.0171	0.0321	<.0001	<.0001
	Segment Change	-17.3%	-26.1%	-8.4%	0.0032	-16.5%	-21.7%	-11.3%	<.0001	0.0007
	Trend Change	-0.0067	-0.0108	-0.0026	0.0047	-0.0433	-0.0537	-0.0329	<.0001	<.0001
Schizophrenia										
	Pre-trend	0.0088	-0.0014	0.0189	0.1063	0.0262	0.0135	0.0389	0.0007	0.0291
	Segment Change	-5.2%	-9.7%	-0.7%	0.0714	-15.2%	-20.7%	-9.8%	0.0002	0.0165
	Trend Change	-0.0178	-0.0317	-0.0039	0.0217	-0.0552	-0.0728	-0.0376	<.0001	0.0034

Table 12: Segmented regression of medical service encounters per 100 patients per month

Cohort / Segment	Estimate	95% CI		P-value
Diabetes Mellitus Office visits				
Pre-trend	0.35	-0.62	1.32	0.4834
Segment change	3.5%	-7.9%	14.9%	0.4301
Trend change	-0.90	-2.35	0.54	0.2355
Diabetes Mellitus ER encounters				
Pre-trend	0.17	-0.09	0.44	0.2182
Segment change	-3.1%	-22.7%	16.4%	0.8778
Trend change	-0.18	-0.59	0.22	0.385
Cardiovascular Office visits				
Pre-trend	0.88	0.03	1.72	0.0559
Segment change	3.3%	-7.3%	14.0%	0.3469
Trend change	-1.48	-2.67	-0.29	0.025
Reactive airway disease Office visits				
Pre-trend	0.45	-0.50	1.41	0.3656
Segment change	1.3%	-10.4%	12.9%	0.7692
Trend change	-0.40	-1.74	0.93	0.5606
Depression Office visits				
Pre-trend	0.32	-0.39	1.04	0.3881
Segment change	18.5%	-4.5%	41.4%	0.0922
Trend change	-0.69	-1.71	0.34	0.204

FIGURES

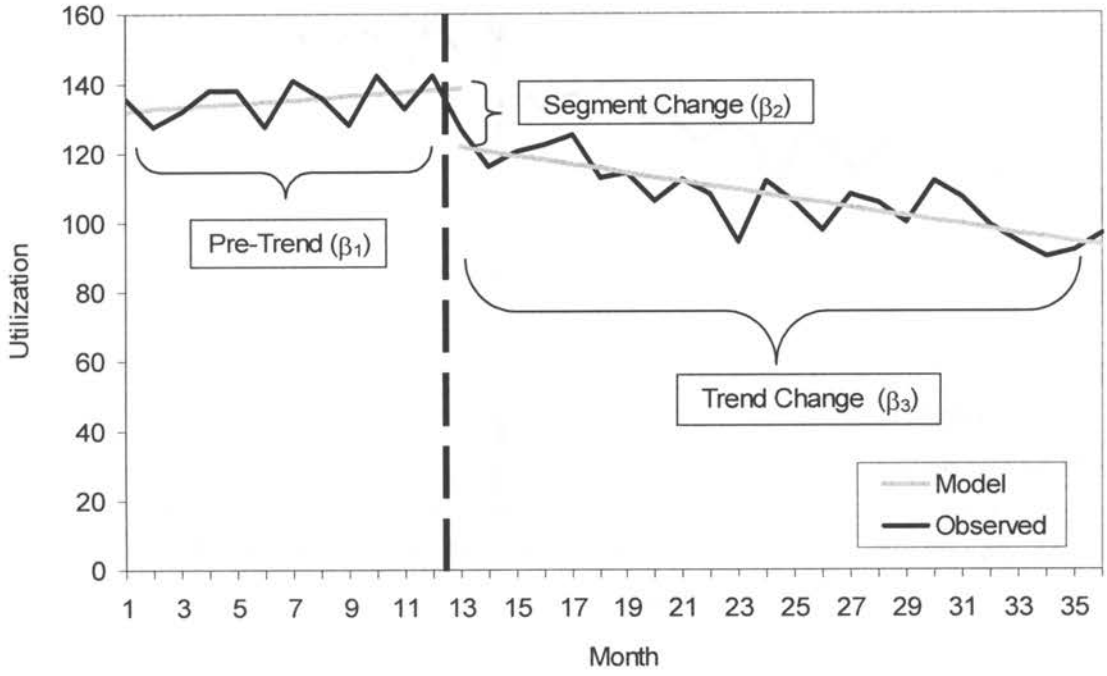

Figure 1: Features of a hypothetical segmented linear regression model $y = \beta_0 + \beta_1 + \beta_2 + \beta_3(x_t - 12)z_1 + \varepsilon$

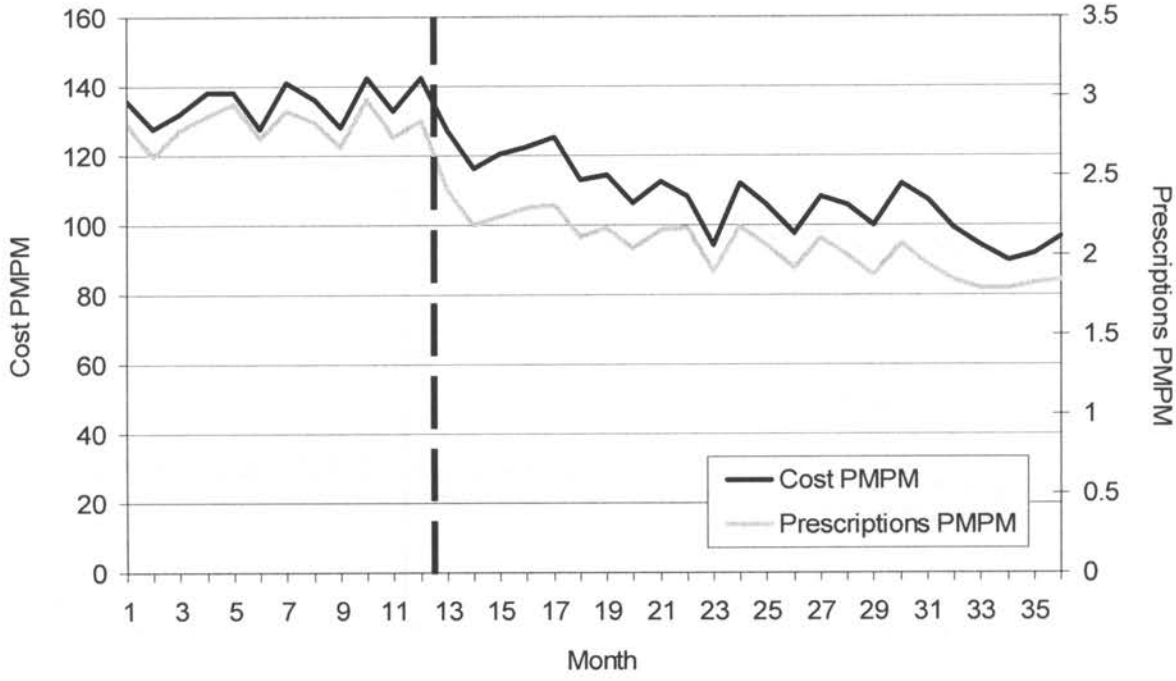

Figure 2: Prescriptions Dispensed and Cost per member per month (PMPM)

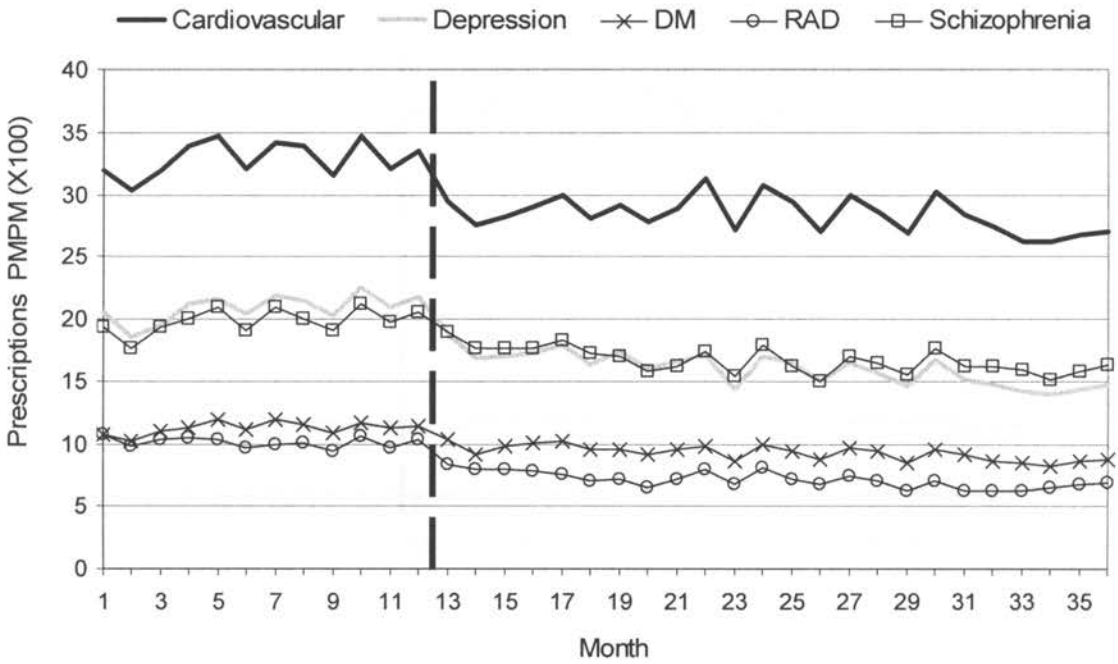

Figure 3: Drug class specific prescriptions dispensed per 100 members per month (PMPM(x100)). Diabetes mellitus = DM, Reactive airway disease = RAD.

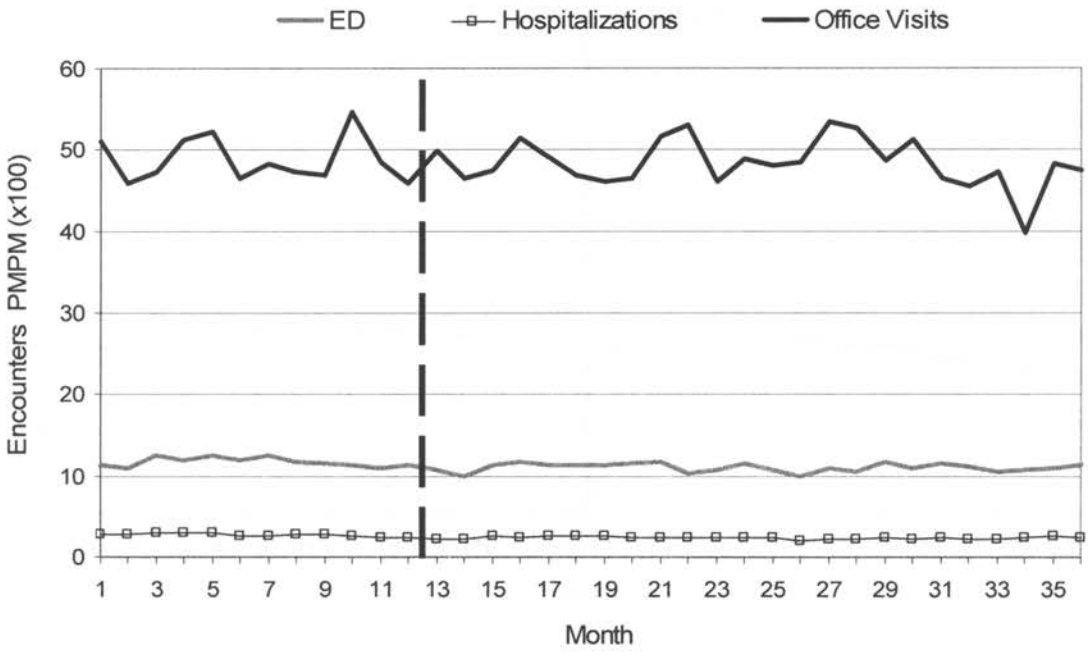

Figure 4: Medical Service Encounters per 100 members per month (PMPM (x100)).

Emergency Department = ED.

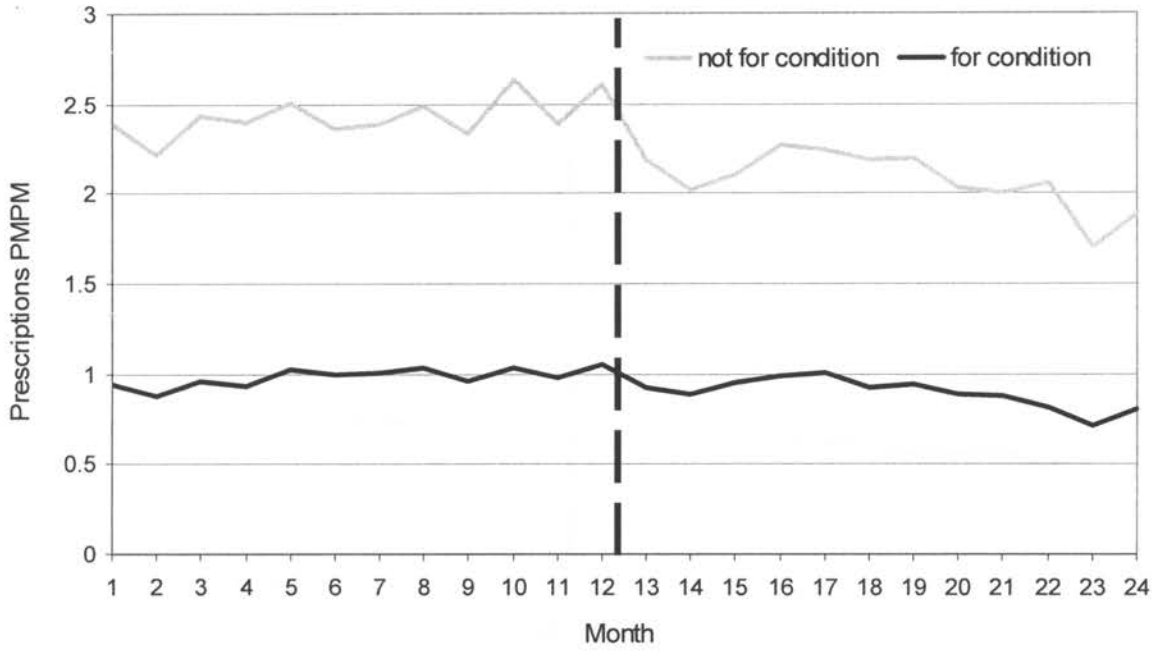

Figure 5: Prescriptions dispensed per member per month (PMPM) among subjects with diabetes mellitus.

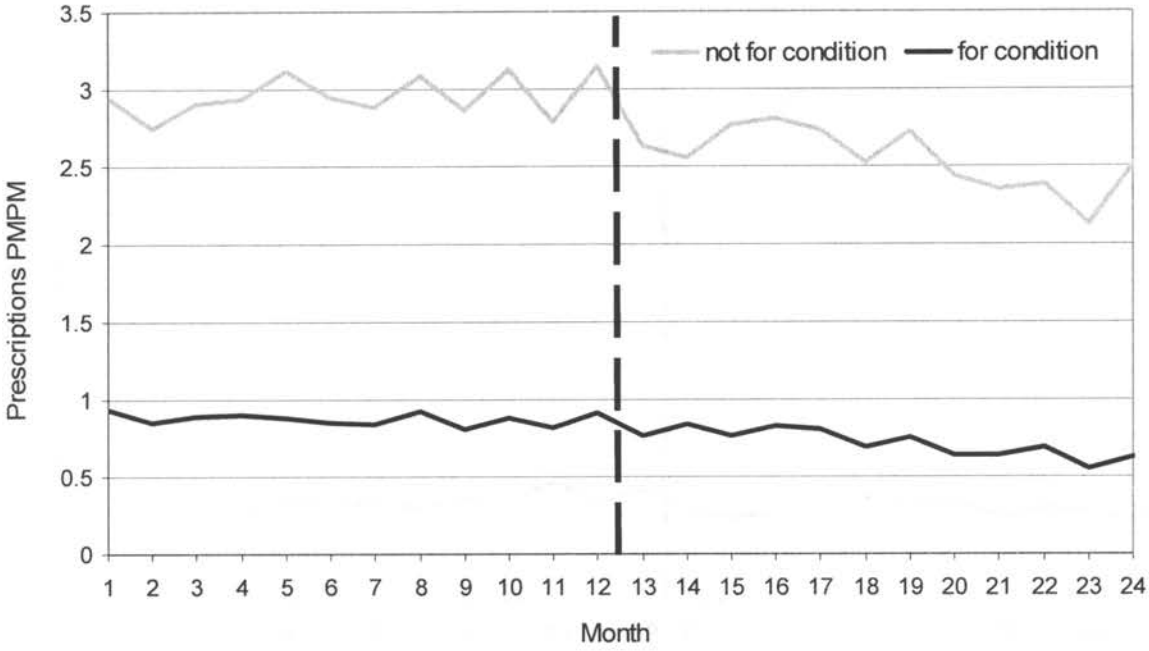

Figure 6: Prescriptions dispensed per member per month (PMPM) among subjects with reactive airway disease

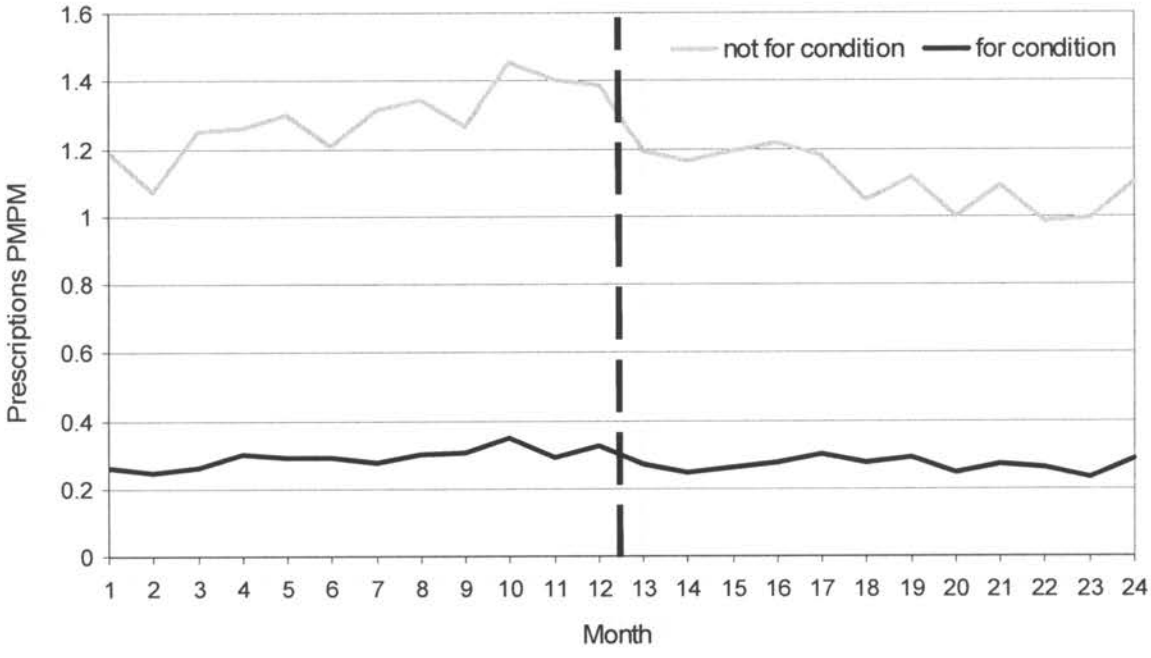

Figure 7: Prescriptions dispensed per member per month (PMPM) among subjects with depression

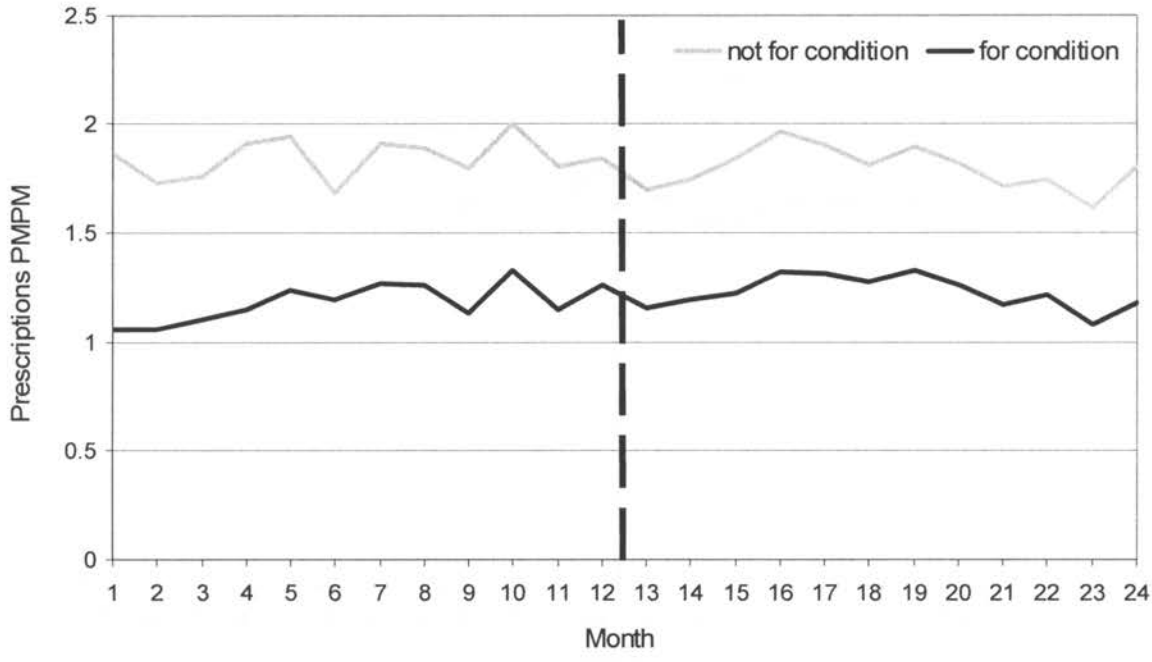

Figure 8: Prescriptions dispensed per member per month (PMPM) among subjects with cardiovascular disease

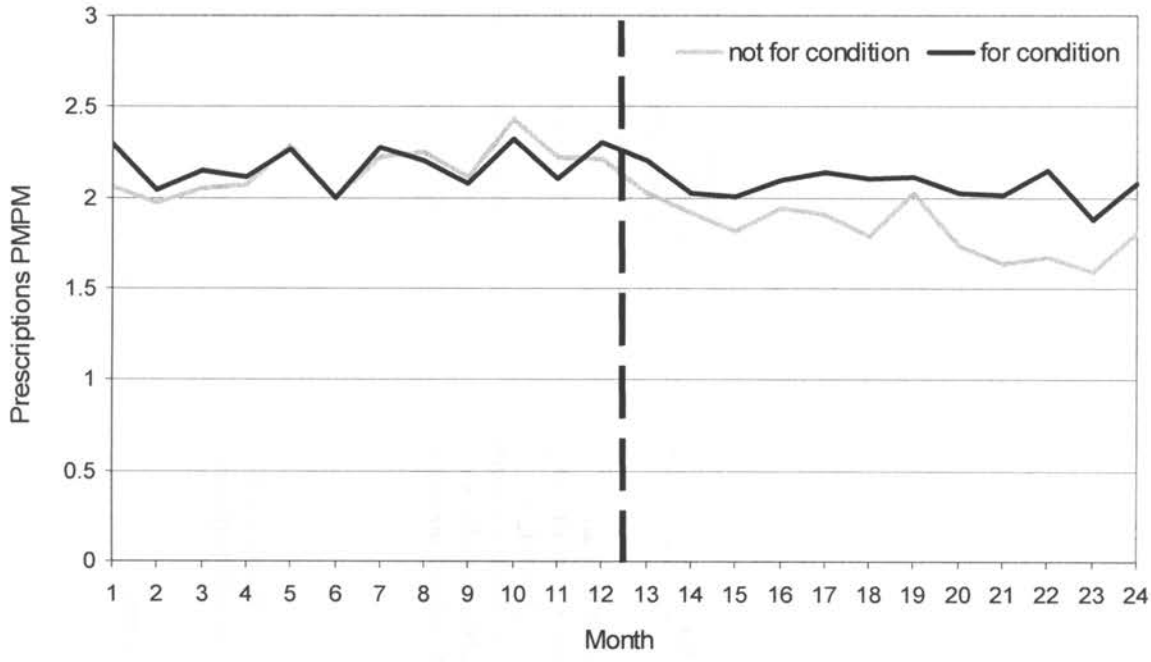

Figure 9: Prescriptions dispensed per member per month (PMPM) among subjects with schizophrenia.

APPENDIX

Appendix A: Summary of Medicaid Cost-Sharing Literature

Author (reference no.)	Date(s) of study	Study Population Data Source	N	Design	Outcomes	Results
Nelson AA, et al	1976-1979	Medicaid -South Carolina -Tenn (control) $0.50 Copay	17,811	-Pre/Post time series with control (Tenn.) -1 year pre/3 years post	-Rx dispensed/eligible/month -Cost/eligible/month	-Tx: significant decrease in rate and magnitude of utilization -Control: had reduction in rate but no change in magnitude
Reeder CE, et al -same study data as above	1976-1979	Medicaid -South Carolina $0.50 Copay	17,811	-Pre/Post time series -1 year pre/3 years post -10 AHFS therapeutic categories: adrenergics, analgesics, antihistamines, anti-infectives, CV, cholinergics, GI, diuretics, psychoactive, sed/hypnotics	-Cost/eligible/month for therapeutic categories (cost as utilization indice was used to "control" for prescribers increasing # in response to copay)	-Copay exert a differential effect on utilization by class -significant immediate ↓ for all except analgesics, sed/hypnot. -significant slope ↓ for CV, cholinergics, diurtics, psych -largest decline was for CV -no effect on sed/hypnotics and analgesics
Smith DG, et al	1989	Aggregated claims Nationwide employer based MCO -unit of analysis benefit plan	212 benefit plans	-Multiple linear regression Dependent –Claim and cost/member Independent-copay level, generic option, plan type, aver.age, etc…	-Rx price elasticity of demand	-unadjusted = -0.187 -adjusted = -0.098 $p<0.05$

<table>
<tr>
<td>Harris, BL et al</td>
<td>1982 - 1986</td>
<td>Claims

GHC Puget sound
-continuously eligible <65</td>
<td>Copay= 19,982
control= 23,164</td>
<td>longitudinal analysis with control arm
<table>
<tr><th></th><th>Tx</th><th>Control</th></tr>
<tr><td>BL</td><td>0</td><td>0</td></tr>
<tr><td>Yr1</td><td>$1.50/rx</td><td>0</td></tr>
<tr><td>Yr2</td><td>$3/rx</td><td>0</td></tr>
<tr><td>Yr3</td><td>$3/rx
OTC dc
$5 OV
$25 ER</td><td>0</td></tr>
</table>
ANCOVA model</td>
<td>Rx/pt
-aggregate
-subgroup of therapeutic class
-essential: antiHTN, CV, DM, thyroid
-discretionary: analgesics, NSAIDs, cough/cold, muscle relaxants

Cost/pt, drug cost/rx</td>
<td>Rx/Pt
<table>
<tr><th></th><th>YR1</th><th>YR2</th><th>YR3</th></tr>
<tr><td>agg</td><td>-10.7%</td><td>-10.6%</td><td>-12.0%</td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
<tr><td>disc.</td><td>-17.3%</td><td>-19.2%</td><td>-19.0%</td></tr>
<tr><td>esst.</td><td>-10.5%</td><td>-13.0%</td><td>-4.0%</td></tr>
</table></td>
</tr>
<tr>
<td>Leibowitz et al.
Rand HIE</td>
<td>1976
3 or 5 year</td>
<td>Claims

Families in 6 cities
-unit of analysis</td>
<td>3860</td>
<td>Random assignment to different insurance plans that varied amount of cost-sharing faced
arm 1: free care
arm 2: 25% coinsurance
arm 3: 50% coinsurance
arm 4: 95% coinsurance
arm 5: 95% coinsurance with annual per/pt deductible

ANCOVA model</td>
<td>-Ave drug expenditures
-# rx/person
-# Rx/person proportion from MD
-# Rx/person proportion generic from pharmacy</td>
<td>
<table>
<tr><th></th><th>$/patient</th><th>#/patient</th></tr>
<tr><td>free</td><td>$60.09</td><td>5.43</td></tr>
<tr><td>25%</td><td>$45.64</td><td>4.43</td></tr>
<tr><td>50%</td><td>$35.78</td><td>4.33</td></tr>
<tr><td>95%</td><td>$34.08</td><td>3.63</td></tr>
<tr><td>95%/dec</td><td>$44.07</td><td>4.30</td></tr>
</table>
-patients with less generous insurance were no more likely to purchase generic drugs, rather responded by reducing use
</td>
</tr>
</table>

<table>
<tr>
<td>Tamblyn R et al.</td>
<td>1995 - 1997</td>
<td>Claims

Quebec Rx benefit for 2 groups:
1)elderly
2)welfare recipients</td>
<td>120,000 welfare

120,000 elderly</td>
<td>9/1/1996 – 25% coninsurance
<u>Drug Utilization</u>
interrupted time-series of 3 years pre and 17 months post (53 monthly units)
-essential drugs
-nonessential drugs

ARIMA

<u>Adverse Events and ED visits</u>
2 Cohorts – regular recipients of Drugs
PrePolicy: 10 month period before coinsurance provided expected rate of AE (control)
PostPolicy: 10 month period during coinsurance provided actual rate of AE (active)

The difference in 2 cohorts used to estimate of impact

AE – COX model
ED – Poisson regression</td>
<td>-monthly daily drug use in aggregate
essential: medications that prevent deterioration in health or prolong life
nonessential: medications that may provide relief of Sx

-ED visits
-Adverse Events (1st occurrences of hospitalization, LTC, death)</td>
<td><u>Welfare Recipients</u>

-15.9% ↓ overall meds
-14.4% ↓ essential meds
-22.4% ↓ nonessential meds

The monthly rate of increase:
AE: +12.9 events per 10,000 person months
ED: +54.2 ED visits per 10,000 person months</td>
</tr>
<tr>
<td>Stuart B et al.</td>
<td>1992</td>
<td>Survey Data from nationally representative sample Medicaid who participated in Medicare Current Beneficiary Survey (MCBS)</td>
<td>1302</td>
<td>Cross-sectional survey of beneficiaries in Copay and non-copay states

Multivariate regression models
<u>Independent Variables:</u>
-copay state status
-other relevant state policies
-individual demographics
-health status</td>
<td>Associations between copay/noncopay states:

<u>Dependent Variables:</u>
-out of pocket costs (OPC)
-Number Rx filled
-reported health status</td>
<td>
<table>
<tr><th></th><th>Copay</th><th>no-Copay</th></tr>
<tr><td>OPC</td><td>68% of rx</td><td>26% of rx</td></tr>
<tr><td>no rx/year</td><td>19.6</td><td>24.6</td></tr>
<tr><td>Rx/year pts w/ excel. health</td><td>12.5</td><td>12.2</td></tr>
<tr><td>Rx/year pts w/ poor health</td><td>28.4</td><td>36.0</td></tr>
</table>
</td>
</tr>
</table>

<table>
<tr>
<td>Soumerai SB, et al</td>
<td>1980-84</td>
<td>Claims
Medicaid
-NH
-NJ (control)</td>
<td>10,734</td>
<td>Interrupted-time series (48 mths) with comparative control to investigate the impact of:
1) 3 drug Rx cap: 11 months
2) immediately replaced by $1 copay: 17 months
Pre Period 20 mths

Medicaid pts cont. enrolled for ≥ 10 months in each year of study
-pt with >3 rx/month and 1 Rx/quarter in yr 1 (n=860)</td>
<td><u>Dependent Variables:</u>
-Rx/month
-units dispensed/month
-drug costs/month

Secondary Outcomes:
-Essential drug use
-Non Essential drug use
-Expensive/Inexpensive drugs</td>
<td>
<table>
<tr><th></th><th>Pre</th><th>cap</th><th>copay</th></tr>
<tr><td>high use cohort</td><td>5.2 rx/pt</td><td>2.8 rx/pt</td><td>4.7 rx/pt</td></tr>
<tr><td>essn.</td><td>0.67</td><td>0.49</td><td>-</td></tr>
<tr><td>noness.</td><td>0.05</td><td>0.02</td><td>-</td></tr>
</table>
</td>
</tr>
<tr>
<td>Fahlman C, et al</td>
<td>1998</td>
<td>R.Ph. Survey
MD, PE, WV</td>
<td>539 rspnc. 36%</td>
<td>Survey of pharmacies
3 States where Medicaid copays are collected
Goal: determine the extent to which R.Ph waived Medicaid copays and document knowledge of copayment policies</td>
<td><u>44 questions, 6 domains</u>
-pharmacy characteristics
-pharmacist characteristics
-estimate of Medicaid Vol
-strategies to save client money
-circumstances where R.Ph would collect copays</td>
<td>
<table>
<tr><th>RPh. Medicaid Knldg.</th><th></th></tr>
<tr><td>good</td><td>30%</td></tr>
<tr><td>fair</td><td>44%</td></tr>
<tr><td>poor</td><td>26%</td></tr>
</table>
</td>
</tr>
<tr>
<td>Goldman DP, et al</td>
<td>1997 - 2000</td>
<td>US employee based health coverage (52 health plans)</td>
<td>528,969</td>
<td>-Prediction model to determine change in day supply when copayments doubled among general population and those with specific chronic disease
-Probit model based on Index of Plan Generosity (out of pocket costs of drugs adjusted for age, sex, income, ZIP, retired status, urbanicity, disease indicators</td>
<td>-% reduction in days supply by various therapeutic classes overall and within several chronic conditions
-conditions studied: allergic rhinitis, arthritis, DM, asthma, GI, dyslipidemia, HTN, depression</td>
<td>-General Pop:
-45% ↓ NSAIDSs, 44% ↓ antihistamines, 26% antiHTN
-Antidepressants
-Depressed pts: ↓ 8%
-Overall : ↓ 26%
-AntiHTN Drugs
-HTN pts ↓10%
-Overall ↓ 26%
-DM Drugs
-DM pts ↓ 23%
-overall ↓ 25%</td>
</tr>
</table>

Roemer MI, et al Medi-Cal copay experiment	1971-1972	Claims California Medicaid	sample of AFDC in 3 counties tx=10,687 control = 29,975	Copay applied to clients with additional financial resources. office visits = $1 (1st 2/month) Rx=$0.50 (1st 2/month) Pre (6 months before) post (12 months after) comparison with control series of non-copay Medi-Cal clients *analysis confounded by implementation of PA for services and rx 6 months prior to copay activation	quarterly rates: MD visits UA tests Pap smear Rx dispensed hospitalizations	 7% less NA- qualitatively lower NA- qualitatively lower NA- qualitatively lower 6% higher -the results of this study suggest that utilization of medical services, Rx are related to cost-sharing and may increase hospitalizations -however, results only based on 6 data points making it difficult to isolate random fluctuations and seasonality

Appendix B: Multivariable Modeling Details

Variable Descriptions:

Variable	Description
ABAD	% Adult Blind/ Adult Disabled
TANF	% Temporary Assistance for Needy Families
W	% White
B	% Black
H	% Hispanic
F	% Female
urban	% Urban Residence
AGE	age in years
CHARLSON	Charlson Comorbidity Index
trend	Initial monthly trend (month number)
seg1	period indicator dummy variable
trend1	Monthly trend after policy (month number -12)*dummy variable

initial covariate correlation matrices (Pearson / Spearman)

Pearson Correlation Coefficients, N = 36 Prob > |r| under H0: Rho=0									
	ABAD	TANF	W	B	H	F	urban	AGE	CHARLSON
ABAD ABAD	1.00000	-0.90222 <.0001	-0.05359 0.7562	0.20396 0.2328	-0.76680 <.0001	0.51127 0.0014	0.86667 <.0001	0.48447 0.0028	-0.24368 0.1521
TANF TANF	-0.90222 <.0001	1.00000	-0.00012 0.9995	-0.04446 0.7968	0.78457 <.0001	-0.41646 0.0115	-0.81353 <.0001	-0.63901 <.0001	0.28467 0.0924
W W	-0.05359 0.7562	-0.00012 0.9995	1.00000	-0.74988 <.0001	-0.12307 0.4745	-0.46410 0.0044	-0.19679 0.2500	0.02294 0.8943	0.22073 0.1958
B B	0.20396 0.2328	-0.04446 0.7968	-0.74988 <.0001	1.00000	-0.18428 0.2820	0.63209 <.0001	0.20646 0.2270	-0.15172 0.3771	-0.37355 0.0248
H H	-0.76680 <.0001	0.78457 <.0001	-0.12307 0.4745	-0.18428 0.2820	1.00000	-0.64770 <.0001	-0.82037 <.0001	-0.53648 0.0007	0.37135 0.0258
F F	0.51127 0.0014	-0.41646 0.0115	-0.46410 0.0044	0.63209 <.0001	-0.64770 <.0001	1.00000	0.66626 <.0001	0.20174 0.2380	-0.32494 0.0532
urban urban	0.86667 <.0001	-0.81353 <.0001	-0.19679 0.2500	0.20646 0.2270	-0.82037 <.0001	0.66626 <.0001	1.00000	0.63908 <.0001	-0.23985 0.1588
AGE AGE	0.48447 0.0028	-0.63901 <.0001	0.02294 0.8943	-0.15172 0.3771	-0.53648 0.0007	0.20174 0.2380	0.63908 <.0001	1.00000	-0.16360 0.3404
CHARLSON CHARLSON	-0.24368 0.1521	0.28467 0.0924	0.22073 0.1958	-0.37355 0.0248	0.37135 0.0258	-0.32494 0.0532	-0.23985 0.1588	-0.16360 0.3404	1.00000

Spearman Correlation Coefficients, N = 36 Prob > |r| under H0: Rho=0									
	ABAD	TANF	W	B	H	F	urban	AGE	CHARLSON
ABAD ABAD	1.00000	-0.81133 <.0001	0.09807 0.5693	0.12870 0.4544	-0.69215 <.0001	0.51017 0.0015	0.77941 <.0001	0.45307 0.0055	-0.21647 0.2048
TANF TANF	-0.81133 <.0001	1.00000	-0.11789 0.4935	-0.13616 0.4284	0.77349 <.0001	-0.45174 0.0057	-0.83990 <.0001	-0.67442 <.0001	0.28726 0.0894
W W	0.09807 0.5693	-0.11789 0.4935	1.00000	-0.56448 0.0003	-0.21905 0.1993	-0.26795 0.1141	-0.01673 0.9228	0.15583 0.3641	0.17503 0.3072
B B	0.12870 0.4544	-0.13616 0.4284	-0.56448 0.0003	1.00000	-0.14234 0.4076	0.30862 0.0670	0.18095 0.2909	-0.07745 0.6534	-0.24144 0.1560
H H	-0.69215 <.0001	0.77349 <.0001	-0.21905 0.1993	-0.14234 0.4076	1.00000	-0.70940 <.0001	-0.84093 <.0001	-0.58216 0.0002	0.32819 0.0507
F F	0.51017 0.0015	-0.45174 0.0057	-0.26795 0.1141	0.30862 0.0670	-0.70940 <.0001	1.00000	0.69858 <.0001	0.28190 0.0958	-0.36216 0.0300
urban urban	0.77941 <.0001	-0.83990 <.0001	-0.01673 0.9228	0.18095 0.2909	-0.84093 <.0001	0.69858 <.0001	1.00000	0.73798 <.0001	-0.24015 0.1583
AGE AGE	0.45307 0.0055	-0.67442 <.0001	0.15583 0.3641	-0.07745 0.6534	-0.58216 0.0002	0.28190 0.0958	0.73798 <.0001	1.00000	-0.10524 0.5413
CHARLSON CHARLSON	-0.21647 0.2048	0.28726 0.0894	0.17503 0.3072	-0.24144 0.1560	0.32819 0.0507	-0.36216 0.0300	-0.24015 0.1583	-0.10524 0.5413	1.00000

Model 1: Prescriptions per member per month (PMPM) best subsets regression

Number in Model	C(p)	R-Square	AIC	Variables in Model
6	4.8418	0.9363	-152.8635	ABAD TANF B F urban AGE
7	6.5185	0.9371	-151.2996	ABAD TANF B F urban AGE CHARLSON
7	6.7327	0.9366	-151.0100	ABAD TANF B H F urban AGE
6	6.8077	0.9316	-150.3189	W B H F urban AGE
7	6.8195	0.9364	-150.8934	ABAD TANF W B F urban AGE
7	8.0506	0.9334	-149.2777	W B H F urban AGE CHARLSON
8	8.2724	0.9377	-149.6353	ABAD TANF B H F urban AGE CHARLSON
8	8.4617	0.9372	-149.3769	ABAD TANF W B F urban AGE CHARLSON
6	8.5602	0.9275	-148.1929	ABAD TANF W F urban AGE
8	8.5998	0.9369	-149.1894	ABAD TANF W B H F urban AGE
7	8.6498	0.9320	-148.5167	TANF W B H F urban AGE
7	8.7090	0.9319	-148.4424	ABAD W B H F urban AGE
5	8.7466	0.9223	-147.7053	ABAD TANF W urban AGE
7	8.9534	0.9313	-148.1373	ABAD TANF W H F urban AGE
5	9.0165	0.9217	-147.4098	W B H urban AGE
5	9.0256	0.9216	-147.3998	ABAD TANF B urban AGE
6	9.1504	0.9261	-147.5043	W B H F AGE CHARLSON
7	9.1516	0.9308	-147.8917	ABAD TANF W F urban AGE CHARLSON
5	9.2113	0.9212	-147.1980	W B H F AGE
4	9.3334	0.9162	-146.9682	B F urban AGE
6	9.4157	0.9254	-147.1990	ABAD TANF B H urban AGE
6	9.4432	0.9254	-147.1674	ABAD W B H F AGE
6	9.6130	0.9250	-146.9736	W B H urban AGE CHARLSON
5	9.6821	0.9201	-146.6912	TANF B F urban AGE
8	9.8619	0.9339	-147.5207	TANF W B H F urban AGE CHARLSON
7	9.9150	0.9290	-146.9610	ABAD W B H F AGE CHARLSON
8	9.9883	0.9336	-147.3577	ABAD W B H F urban AGE CHARLSON
6	9.9896	0.9241	-146.5473	ABAD W B H urban AGE
9	10.0000	0.9383	-148.0106	ABAD TANF W B H F urban AGE CHARLSON
6	10.0732	0.9239	-146.4533	ABAD TANF W urban AGE CHARLSON

Thirty best models indicate best models contain: ABAD TANF B F urban AGE. Minor variations in R-sq when Charlson added, but AID and Cp are in complete agreement.

proc autoreg data=rx_utiliz dwprob nlag=1;;
model rx_pmpm = trend seg1 trend1 ABAD TANF B F urban AGE;
run;

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	-9.9671	5.1188	-1.95	0.0628	
trend	1	0.003935	0.007348	0.54	0.5970	trend
seg1	1	-0.3655	0.0850	-4.30	0.0002	seg1
trend1	1	0.001565	0.0119	0.13	0.8967	trend1
ABAD	1	1.7464	5.0447	0.35	0.7321	ABAD
TANF	1	-2.7537	3.5179	-0.78	0.4411	TANF
B	1	-31.5508	9.7592	-3.23	0.0034	B
F	1	14.3809	6.8632	2.10	0.0464	F
urban	1	6.1566	3.7742	1.63	0.1154	urban
AGE	1	0.0259	0.0147	1.76	0.0901	AGE

Removed variables not significant at the 0.25 level and those variables with significant multicollinearity (pearson or spearman <0.05), retaining those with stronger associations to dummy variables (ie dropped female variable because it was strongly associated with black variable however black was more significant in the above model).

Model reduced to:

proc autoreg data=rx_utiliz;
model rx_pmpm = trend seg1 trend1 B urban age/ dwprob nlag=1;
run;

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	-1.1658	2.3086	-0.50	0.6175
trend	1	0.008817	0.007217	1.22	0.2320
seg1	1	-0.4553	0.0537	-8.47	<.0001
trend1	1	-0.0119	0.0123	-0.97	0.3381
B	1	-12.8555	6.3695	-2.02	0.0532
urban	1	6.1022	3.4579	1.76	0.0885
AGE	1	0.0160	0.0147	1.09	0.2860

We then dropped the variable age to reach our final model of

proc autoreg data=rx_utiliz;
model rx_pmpm = trend seg1 trend1 B urban / dwprob nlag=1;
run;

Model 2: Cost PMPM

Number in Model	C(p)	R-Square	AIC	Variables in Model
5	2.3113	0.9111	123.5837	W B F urban AGE
4	2.4653	0.9039	124.4164	B F urban AGE
5	3.0274	0.9087	124.5503	B H F urban AGE
4	3.9044	0.8990	126.1918	W B F urban
5	4.0415	0.9053	125.8764	B F urban AGE CHARLSON
6	4.1000	0.9118	125.2933	W B F urban AGE CHARLSON
5	4.2427	0.9046	126.1337	ABAD B F urban AGE
6	4.2678	0.9113	125.5240	ABAD W B F urban AGE
6	4.2756	0.9112	125.5348	TANF W B F urban AGE
6	4.3113	0.9111	125.5837	W B H F urban AGE
5	4.4411	0.9039	126.3858	TANF B F urban AGE
3	4.7846	0.8893	127.5022	B F urban
6	4.8474	0.9093	126.3098	TANF B H F urban AGE
6	4.9546	0.9090	126.4533	B H F urban AGE CHARLSON
6	5.0238	0.9087	126.5455	ABAD B H F urban AGE
5	5.5138	0.9003	127.7185	W B H F urban
5	5.5842	0.9001	127.8044	TANF W B F urban
4	5.8410	0.8925	128.4508	ABAD B F urban
4	5.8432	0.8924	128.4533	B H F urban
5	5.8584	0.8991	128.1364	ABAD W B F urban
6	5.8780	0.9058	127.6659	ABAD B F urban AGE CHARLSON
5	5.8925	0.8990	128.1776	W B F urban CHARLSON
7	6.0138	0.9121	127.1742	TANF W B F urban AGE CHARLSON
6	6.0415	0.9053	127.8764	TANF B F urban AGE CHARLSON
7	6.0454	0.9120	127.2179	ABAD W B F urban AGE CHARLSON
7	6.0620	0.9120	127.2409	W B H F urban AGE CHARLSON
6	6.1354	0.9050	127.9966	ABAD TANF B F urban AGE
7	6.2658	0.9113	127.5213	ABAD TANF W B F urban AGE
7	6.2663	0.9113	127.5220	TANF W B H F urban AGE
7	6.2677	0.9113	127.5239	ABAD W B H F urban AGE

Again, all three measures nearly universally suggest the variables W B F urban AGE are the top choices.
Initial model evaluated was:

proc autoreg data=rx_utiliz;
model cost_pmpm = trend seg1 trend1 W B F urban AGE/ dwprob nlag=1;
run;

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|	Variable Label
Intercept	1	77.3419	556.9727	0.14	0.8906	
trend	1	0.2227	0.5910	0.38	0.7093	trend
seg1	1	-6.8742	4.9081	-1.40	0.1727	seg1
trend1	1	0.3020	0.9401	0.32	0.7505	trend1
W	1	-770.0611	545.8973	-1.41	0.1698	W
B	1	-2545	784.6300	-3.24	0.0031	B
F	1	694.2021	442.4718	1.57	0.1283	F
urban	1	538.2810	245.6825	2.19	0.0373	urban
AGE	1	0.5606	0.9934	0.56	0.5772	AGE

Under this model we drop the variables W because it is highly correlated with B, F and AGE which are both highly correlated with urban to get our final model of

proc autoreg data=rx_utiliz;
model cost_pmpm = trend seg1 trend1 B urban / dwprob nlag=1;
run;

The finding that same variables were selected for both models is not surprising given the relative symmetry of the two outcome variables (Rx PMPM and Cost PMPM)

Model 3 -7: Models evaluating individual drug classes

Best subsets for each drug class

Number in Model	C(p)	R-Square	AIC	Variables in Model
DM				
5	4.9757	0.8778	-58.4988	TANF B F urban AGE
4	5.9256	0.8654	-57.0087	B F urban AGE
6	6.0367	0.8818	-57.6849	TANF B F urban AGE CHARLSON
4	6.0988	0.8646	-56.8139	TANF B F AGE
6	6.1528	0.8813	-57.5361	ABAD W B H F AGE
7	6.2045	0.8895	-58.1179	ABAD W B H F AGE CHARLSON
6	6.3519	0.8804	-57.2823	W B H F AGE CHARLSON
6	6.3661	0.8804	-57.2644	ABAD TANF B F urban AGE
7	6.3786	0.8888	-57.8794	TANF W B H F AGE CHARLSON
5	6.5804	0.8711	-56.5585	TANF B F AGE CHARLSON
6	6.8211	0.8785	-56.6915	TANF W B F urban AGE
CAD				
6	5.0649	0.801	22.8514	ABAD TANF B F AGE CHARLSON
5	5.1164	0.786	23.4817	ABAD TANF B F AGE
5	5.8444	0.7806	24.3708	ABAD TANF B F urban
4	6.0009	0.7648	24.8824	TANF B F AGE
6	6.0661	0.7937	24.1591	ABAD TANF B F urban CHARLSON
6	6.2948	0.792	24.4513	ABAD TANF B F urban AGE
7	6.3481	0.8063	23.8851	ABAD TANF B F urban AGE CHARLSON
6	6.4472	0.7909	24.6446	ABAD TANF W B F AGE
5	6.6032	0.775	25.2747	TANF W B F AGE
7	6.7024	0.8037	24.366	ABAD TANF W B F AGE CHARLSON
RAD				
5	2.2992	0.9229	-49.9394	ABAD TANF W urban AGE
5	3.1621	0.9204	-48.7771	ABAD TANF B urban AGE
4	3.2746	0.9142	-48.0808	ABAD TANF urban AGE
6	4.1191	0.9234	-48.1866	ABAD TANF W urban AGE CHARLSON
6	4.256	0.923	-47.9985	ABAD TANF W B urban AGE
6	4.2801	0.923	-47.9655	ABAD TANF B H urban AGE
6	4.2889	0.9229	-47.9534	ABAD TANF W H urban AGE
6	4.2894	0.9229	-47.9527	ABAD TANF W F urban AGE
5	4.6199	0.9161	-46.895	ABAD TANF urban AGE CHARLSON
5	4.678	0.9159	-46.822	ABAD TANF H urban AGE

Depression				
6	4.7695	0.8939	2.1876	ABAD TANF B F urban AGE
5	4.9028	0.8854	2.948	ABAD TANF B F urban
4	5.4158	0.8755	3.9495	B F urban AGE
6	5.9674	0.8891	3.7636	W B H F urban AGE
5	6.0463	0.8809	4.3448	TANF B F urban AGE
7	6.3504	0.8955	3.6197	ABAD TANF B F urban AGE CHARLSON
6	6.571	0.8867	4.5323	ABAD TANF B F urban CHARLSON
7	6.6928	0.8942	4.0844	ABAD TANF B H F urban AGE
7	6.7412	0.894	4.1495	ABAD TANF W B F urban AGE
6	6.8	0.8858	4.8197	ABAD TANF B H F urban
antipsych				
4	2.9201	0.8203	-9.4988	B F urban AGE
5	4.0412	0.8258	-8.6098	ABAD TANF B F urban
4	4.0985	0.813	-8.061	ABAD TANF B urban
5	4.2356	0.8246	-8.3611	B H F urban AGE
4	4.2704	0.8119	-7.8559	ABAD TANF W urban
4	4.275	0.8119	-7.8505	ABAD B H urban
3	4.4146	0.7986	-7.3921	B F urban
5	4.4617	0.8232	-8.0739	ABAD TANF B H urban
5	4.664	0.8219	-7.8189	ABAD B F urban AGE
5	4.7227	0.8216	-7.7453	ABAD TANF W B urban

From table above, it can be observed that AIC and Cp are in complete agreement. Minor deviations in R-squared occurred for some of the models therefore AIC and Cp were the primary measures used for model selection.

Individual Regression models of specific drug classes

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
DM					
Intercept	1	-46.7557	21.9559	-2.13	0.0428
trend	1	0.0572	0.0382	1.5	0.1465
seg1	1	-0.7279	0.3461	-2.1	0.0453
trend1	1	0.0528	0.0653	0.81	0.4261
TANF	1	-27.4479	9.8682	-2.78	0.0099
B	1	-150.034	48.3529	-3.1	0.0046
F	1	68.5917	32.7405	2.1	0.0461
urban	1	40.6031	17.5105	2.32	0.0285
AGE	1	0.1198	0.0709	1.69	0.1031
CAD					
Intercept	1	-102.848	73.1173	-1.41	0.1719
trend	1	-0.0144	0.1042	-0.14	0.8909
seg1	1	-2.7388	1.1393	-2.4	0.024
trend1	1	0.1334	0.1394	0.96	0.3477
TANF	1	-100.399	40.538	-2.48	0.0204
ABAD	1	29.5972	64.965	0.46	0.6526
B	1	-323.265	135.7973	-2.38	0.0252
F	1	254.8209	93.5823	2.72	0.0116
AGE	1	0.0702	0.2022	0.35	0.7315
CHARLSON	1	3.6381	1.6386	2.22	0.0357
RAD					
Intercept	1	-13.5237	24.27	-0.56	0.5821
trend	1	0.0249	0.0322	0.77	0.4466
seg1	1	-1.152	0.3343	-3.45	0.0019
trend1	1	-0.067	0.0481	-1.39	0.1758
TANF	1	-33.3972	16.2925	-2.05	0.0506
ABAD	1	-44.0307	23.4745	-1.88	0.072
W	1	44.0639	25.1232	1.75	0.0912
urban	1	14.6484	16.2607	0.9	0.3759
AGE	1	0.2228	0.062	3.59	0.0013

Antidepressants					
Intercept	1	-74.0571	52.1938	-1.42	0.1683
trend	1	0.1616	0.0769	2.1	0.0458
seg1	1	-3.0566	0.844	-3.62	0.0013
trend1	1	-0.0634	0.1262	-0.5	0.6197
TANF	1	-28.5375	36.3765	-0.78	0.4401
ABAD	1	11.3518	51.737	0.22	0.8281
B	1	-224.171	98.4172	-2.28	0.0316
F	1	106.3964	67.6831	1.57	0.1285
urban	1	58.0081	38.2064	1.52	0.1415
AGE	1	0.1088	0.1468	0.74	0.4654
Antipsychotics					
Intercept	1	-68.9805	73.4095	-0.94	0.3567
trend	1	0.0585	0.0678	0.86	0.3966
seg1	1	-1.7879	0.6726	-2.66	0.0138
trend1	1	0.2067	0.1243	1.66	0.1094
TANF	1	-21.4662	31.4258	-0.68	0.5011
ABAD	1	21.0394	48.6713	0.43	0.6694
W	1	-3.6771	78.6289	-0.05	0.9631
B	1	-298.305	106.4091	-2.8	0.0099
F	1	63.4248	55.8058	1.14	0.267
urban	1	98.7658	33.6929	2.93	0.0073
CHARLSON	1	1.4245	1.1042	1.29	0.2093

Again, variables were dropped if they were not significant at the 0.25 level or if they were had significant multicollinearlity with another covariate. The final models were produced using this procedure.

Models 8-10; Models of health outcomes (emergency department (ED), office, hospital)

ED				
Number in Model	C(p)	R-Square	AIC	Variables in Model
2	-0.3215	0.3245	-43.2968	F AGE
2	-0.0255	0.3177	-42.9395	H AGE
3	0.3696	0.3543	-42.9206	W F AGE
1	0.4821	0.2606	-42.0472	H
3	0.5463	0.3502	-42.697	TANF H AGE
3	0.9435	0.3412	-42.1995	H F AGE
3	1.5192	0.3281	-41.4905	F AGE CHARLSON
3	1.5585	0.3272	-41.4426	F urban AGE
3	1.5704	0.3269	-41.4281	TANF F AGE
3	1.5779	0.3268	-41.419	B F AGE
hospital				
Number in Model	C(p)	R-Square	AIC	Variables in Model
2	-2.4057	0.5933	-130.8843	AGE CHARLSON
3	-1.4653	0.6089	-130.2938	urban AGE CHARLSON
3	-1.3463	0.6072	-130.1328	ABAD AGE CHARLSON
3	-1.1307	0.604	-129.8427	TANF AGE CHARLSON
3	-0.9085	0.6007	-129.5462	F AGE CHARLSON
3	-0.6638	0.5971	-129.2225	H AGE CHARLSON
3	-0.4754	0.5943	-128.9752	W AGE CHARLSON
3	-0.4228	0.5936	-128.9066	B AGE CHARLSON
1	0.1488	0.5262	-127.3847	AGE
2	0.2073	0.5548	-127.6272	urban AGE
office				
Number in Model	C(p)	R-Square	AIC	Variables in Model
3	0.9147	0.2974	70.7329	TANF H F
2	1.0647	0.2452	71.315	TANF H
4	1.2666	0.3374	70.6202	TANF B H F
4	1.678	0.3275	71.1593	TANF W H F
4	2.0491	0.3184	71.6388	TANF H F charlson
3	2.2474	0.265	72.3552	TANF H charlson
4	2.5099	0.3072	72.2254	TANF H F age
5	2.6952	0.3513	71.8578	TANF B H F charlson
4	2.7789	0.3007	72.5635	ABAD TANF H F
2	2.7941	0.2031	73.2653	age charlson

Selection of models occurs as discussed above.

Model containing sex (F) and AGE with ER as dependent resulted in significance for both variables with no multicollinearity, thus both were retained in the final model.

Model containing Age and Charlson with Hospital as dependent produced no significant beta coefficients for these covariates. Both variables were dropped.

In the office model, TANF is highly associated with both H and sex (F). Thus, only H was retained, because it was the most significant in the full model. However, once TANF and F were dropped, H lost statistical significance and was dropped. Thus, no covariates were statistically significant.