THE IMPACT OF A VALUE-BASED INSURANCE DESIGN ON THOSE WITH MULTIPLE CHRONIC CONDITIONS.

by

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Abstract

Background: Value-based insurance designs establish cost-sharing levels to promote services perceived to be high value from the health insurer or policy maker's perspective. However, it is unclear how people with multiple chronic conditions will react to changes in insurance design because they may not be willing or able to switch to lower cost prescription drugs. These individuals are the heaviest consumers of prescription drugs and may be more susceptible to short term complications from poorly managed conditions or from drug/drug interactions. This dissertation evaluates how adults with multiple chronic conditions respond to a change in insurance benefit design.

Methods: Data consists of drug and medical claims from Maryland's high-risk pool for the years 2007-2011. High-risk pools offer insurance to those with preexisting conditions who were denied coverage on the individual market and who do not have access to employer-based insurance. An interrupted time series design with individual-level data exploits a co-pay change in 2010 that raised copayments on brand name medications while decreasing copayments on generic drugs. Outcomes include drug utilization, medical service utilization, drug and medical spending, generic substitution and whether the policy impacted medication adherence.

Results: The copayment policy change had a statistically significant impact on those with increasing numbers of chronic conditions, but the magnitudes are small. The use of both

brand and generic drugs increased less than one drug fill per quarter across all numbers of chronic conditions following the policy change. The financial impact was greatest for those with the most chronic conditions—an over $150 increase in quarterly out-of-pocket spending for those with 10 or more chronic conditions. The use of generics increased for antidepressant drugs and decreased for hypertensive drugs. Overall, adherence levels remained unchanged.

Conclusions: This study finds little impact on the use of prescription drugs following a value-based insurance design initiative. Most of the impact is seen in those with the highest number of conditions who use more services and they experienced increased financial burden. Other insurance benefit design tools may be more effective in this population.

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1 Introduction, background and study rationale

1.1 Introduction

The typical person with five or more chronic conditions fills over 50 prescriptions per year (Anderson 2010). Managing spending in this group is key, since individuals with multiple chronic conditions typically have worse health outcomes and higher spending levels (Anderson 2005; Wolff, Starfield, and Anderson 2002; Hwang et al. 2001; Paez, Zhao, and Hwang 2009; Anderson 2010). Five diseases—cancer, asthma, chronic obstructive pulmonary disease, high cholesterol, diabetes and psychosis/bipolar disorder—accounted for one third of the 320 billion spent on medications in the US last year (IMS Institute for Health Informatics 2012). Many Americans have more than one of these chronic conditions and people with multiple chronic conditions have higher out-of-pocket burdens and take more medications (Paez, Zhao, and Hwang 2009). Those with more chronic conditions often report problems accessing medication due to cost and have worse health outcomes (Heisler et al. 2004).

Despite the importance of medications for improving health outcomes, cost sharing on drugs has long been used as a mechanism to control pharmacy spending in insurance plans. Studies have recognized that increasing co-pays can reduce compliance with medications, (Goldman, Joyce, and Zheng 2007a) and these arrangements often criticized for being 'penny wise and pound foolish' (Chandra, Gruber, and McKnight 2010).

When faced with an increase in prices, studies suggest that those with multimorbidites may reduce the use of some drug classes more than others. This may result in downstream health effects. More recently, Chandra, Gruber and McKnight found the probability of any hospital visit increased by 6 percent in the post-period after the co-pay increases (Chandra, Gruber, and McKnight 2010). Mojtabai and Olfson (2003) used the Health and Retirement Survey to perform a similar analysis for Medicare enrollees. The authors found that those with more cost-related non-adherence were more likely to have more hospitalizations for several chronic conditions (Mojtabai and Olfson 2003).

On the other hand, those who are already sick might treat medical care as a necessity and therefore will not reduce or change utilization when prices increase. Remler and Atherly (2003) found that people with chronic health conditions are less price sensitive than their healthier counterparts (Remler and Atherly 2003). Goldman et al. (2004) classified patients according to an index condition and estimated their use of the primary condition's drugs and then, for all other drugs (Goldman et al. 2004). Goldman and colleagues described general price insensitivity for the index condition drug, and higher price sensitivity for all other classes of drugs. The limitation of this analysis is that the authors are assigning patients to the index diseases, when they in fact might have multiple conditions which patients view as equally important.

The downstream consequences may be of particular concern for insurers and payers for populations with large numbers of high-risk individuals. There is little in the literature to guide policymakers on the impact of value-based insurance design on those with multiple

chronic conditions. Most of the studies of value-based initiatives have used employer-based populations, with mostly healthy adults or adults suffering from only one chronic condition (e.g.: Gibson, McLaughlin, and Smith 2005). State and federal policy makers, however, have acute interest in understanding the utilization of the new enrollees in the health insurance exchanges and their responses to changes in cost sharing, because those with pre-existing conditions are now included in the exchanges.

Studies of high-risk pool enrollees may inform us about the behavior of exchange enrollees who will be the heaviest users of medical services. High-risk pools provide coverage for individuals in many states who attempted to purchase coverage on the individual market, but who were denied coverage because of a preexisting condition. Offering coverage since 2002, Maryland has the country's fourth largest high-risk pool (Kaiser State Health Facts 2011). While policy makers hope young healthy adults will enter the exchanges to lower the overall risk level, managing the spending of those at the upper risk levels will be key to maintaining affordable premiums.

1.2 Background

This section will discuss the theoretical background on cost sharing in health insurance followed by several sections on the empirical evidence about consumer reactions to value-based insurance designs, particularly for prescription drugs. The empirical sections cover the impacts on drug utilization, changes in adherence, whether there are offset effects from changes in utilization or adherence, whether value based designs generate

cost savings for insurers and how those with multi morbidities may behave differently than the previous empirical studies have shown.

1.2.1 Theoretical background on cost sharing in health insurance

The demand for medical care is commonly described as a derived demand for health. Michael Grossman articulated this in his 1972 seminal work, "On the concept of health capital and the demand for health." Health is valued for its consumption properties because individuals dislike being ill (Grossman 1972). Health is also valued for its investment properties since health will affect the total time one can spend in the labor markets or in leisure time. Grossman's model treats health as a capital stock that improves with investment and depreciates over time.

The model has additional relevant insights for this study. One is that the demand for medical care increases with income and age. Demand for pharmaceuticals, for example, would increase with income since a person could substitute medical technologies for time consuming activities, such as going to the gym. Drugs such as high blood pressure medications could allow for additional leisure activities. Those with more education are also more efficient producers of health. Those with more education also have different rates of time preference, and tend to value the future more (Fuchs 1974). Therefore, it is no surprise that education is highly correlated with adherence to treatment regimens. As we age, we are also more likely to have illnesses needing more inputs to stem the rate of depreciation. Therefore, older people are more willing to use medical care to maintain their existing stocks of health (Grossman 1972).

Health insurance complicates the picture. Insurance creates an *ex-post* moral hazard problem: because they face lower prices, individuals have the incentive to consume more medical services (Pauly 1968; Cutler and Zeckhauser 2000). The essential tradeoff for health insurance is to avoid risk associated with uncertain outcomes, while combating the increased use of services with insurance when faced with prices to patients that are lower than they would be without insurance.

Forcing patients to face a greater proportion of the full price of services is one way to curb moral hazard. Cost sharing, coinsurance and deductibles are all facets of demand-side controls on the use of health services. Pauly and Held in their 1990 article discuss how increased cost-sharing should be applied to those services with higher price elasticities of demand—when the moral hazard is high under insurance contracts (Pauly and Held 1990). If moral hazard is low it is better not to insure this service since people will consume it regardless of insurance coverage. Increasing cost sharing is viewed as a way to reduce the excess utilization for insured patients.

Since the Pauly and Held article, other economists have argued that some goods may be substitutes. In the context of insurance, it may be beneficial to reduce risk sharing on some goods where the probability of use is certain, such as prescription drugs, if it lowers the demand for more expensive substitutes such as hospital visits (Goldman and Philipson 2007). Newhouse (2006) reviews the essential framework for placing the incentives within health insurance plans. He finds that those who are non-adherent to

their treatment regimens may cause fiscal externalities to their insurance pools. Improving adherence through lowering costs on drugs would be beneficial, since lower downstream costs might reduce spending for everyone (Newhouse 2006).

In summary, the demand for prescription drugs is a derived demand for health. Health insurance can increase moral hazard leading to a higher use of prescription drugs than otherwise would be seen if patients had to pay the full price. However, in recent years, research has shown that some types of cost sharing are "penny wise and pound foolish." As a result, subsidizing prescription drugs for chronic maintenance medications may be beneficial for those with multi-morbidities if this prevents the development of further conditions or adverse health effects that would increase spending for the pool as a whole.

1.2.2 Impacts on utilization

As health insurance in the US spread following World War II, many economists wondered whether the health insurance was inducing those with insurance to spend more on medical care than necessary. Previous studies to estimate the demand for medical care under insurance suffered from concerns about the endogeneity of health insurance, where those who are sicker may be more likely to purchase health insurance, therefore biasing the estimates of the demand for medical care (Zweifel and Manning 2000). The RAND Health Insurance Experiment (HIE) used a randomized controlled trial design to study how consumers reacted to changes in cost-sharing and found that increased cost sharing led to reductions in use of all types of care (Manning et al. 1987). Substantial literature since the RAND HIE has indicated that increased cost sharing for prescription drugs reduces demand, lowers adherence and in contrast to the RAND findings, can have

adverse health effects. Since then, many empirical studies have been conducted to estimate the impact of cost sharing on the use of a variety of medical services. Goldman et al. (2007) summarized the findings for pharmaceuticals through a systematic review of cost-sharing studies. The overall conclusion from the 132 studies is that cost-containment policies generally reduce the utilization of drugs and lower drug expenditures (Goldman, Joyce, and Zheng 2007a).

Generally, the design and resulting impact of these value-based strategies is to increase adherence of generic drugs and lower the utilization of expensive brand name drugs. The Goldman et al. study reviewed a variety of different value-based strategies in pharmaceuticals. Across these studies, the authors found price elasticities of demand ranging from -0.2 to -0.6 (Goldman, Joyce, and Zheng 2007b). This means for a 10% increase in price, the utilization of the drugs dropped between 2%-6%. The variation in the elasticities depended on whether the study examined total use, use by tier or by class, such as statins or antidepressants. In general, drugs perceived as 'less essential,' such as anti-inflammatories, had higher elasticities. Sen et al. (2012) evaluated a copayment increase for drugs and other services in the Alabama children's health insurance program and found significant reductions in the use of drugs and other medical services such as outpatient visits.

1.2.3 Adherence

Simply examining overall numbers of drugs filled may miss important behavior changes when the prices change. Adherence is a more granular measure of utilization, designed to capture how well someone is taking the medications they are prescribed. The link

between cost sharing and other health outcomes is thought to be through increased adherence. If a person is taking medication as prescribed, this should prevent downstream complications. However, because only about 50% of those taking medications are taking them as prescribed in the US and other highly developed countries, there is considerable concern about the health impact of non adherence (World Health Organization 2003; Osterberg and Blaschke 2005).

Many factors can affect whether patients adhere to recommended medication regimens including the cost to the patient (copay or coinsurance), perceived and real side effects, personal characteristics or prescriber behavior (Piette, Heisler, and Wagner 2004; Piette et al. 2006). Lower adherence is associated with higher mortality and increased incidence of further health complications in chronic diseases (Horwitz et al. 1990; Sokol et al. 2005; Ho, Bryson, and Rumsfeld 2009). Increased adherence has also been associated with lower medical spending (Stuart et al. 2011).

As such, many investigators have begun using value-based insurance design to incentivize patients to improve their adherence to medications. In a recent trial of a value-based design, Choudhry et al. 2011 found that eliminating cost sharing for patients after a heart attack improved adherence between 2 and 6 percentage points, but had no significant differences in overall spending (Choudhry, Avorn, et al. 2011). Maciejewski et al. (2010) examined reductions in co-pays for four classes of drugs and found adherence improved between 2 and 4 percentage points. The authors did not, however, find any savings overall (Maciejewski et al. 2010), which could be the result of the short

time frame of they study. The modest improvement in adherence is corroborated in other studies lowering copayments for individual classes of chronic disease medications (Farley 2012; Gibson et al. 2011; Roebuck et al. 2011).

1.2.4 Offset effects

The elderly, a group that consists of a large number of individuals with more than one chronic illness, may provide some insight into the nature of response to cost sharing among individuals with multiple morbidities. The papers in this area do generally find there are downstream health impacts from increased levels of cost sharing.

Chandra et al. (2010) focused explicitly on the question of whether increased cost sharing for drugs resulted in increased hospitalizations because patients were not taking their recommended medications. The probability of any hospital visit increased by 6 percent in the post-period after the co-pay increases for those with the highest comorbidity burdens (Chandra, Gruber, and McKnight 2010). Mojtabai and Olfson (2003) used the Health and Retirement Survey to analyze whether prescription drug coverage was associated with health outcomes. Those with less coverage (and more cost-related non-adherence) were more likely to report hospitalizations for several chronic conditions (Mojtabai and Olfson 2003). Basu and colleagues examined the implementation of Part D to assess the impact of cost sharing on the dual-eligible population. The authors found that Part D had no impact on costs or utilization of prescriptions (Basu, Yin, and Alexander 2010). A different study analyzing the impact of Part D on Medicare enrollees did find a significant increase in drug utilization as seniors' out-of-pocket costs decreased,

but found no offset effects on emergency department or hospital inpatient utilization (Liu et al. 2011).

While there have been some findings of adverse consequences of increased cost sharing in the elderly populations, these findings have not been replicated in employer pools or Medicaid populations, and it is unclear how high-risk pool adults under age 65 may react to a value-based design. For example, Motheral and Fairman (2001) found no effects of co-pay increases on the generic fill rates or utilization of health services. Using time series methods, this study looked at two employer groups, one of which moved to a three-tiered design while the other kept their same two-tiered design (Motheral and Fairman 2001). While overall drug costs dropped, they found no changes in utilization of physician visits, inpatient admissions or emergency room use. Another study with longer follow-up period of two years found no differences between the treatment and control groups in terms of continuation of chronic maintenance medications or on utilization of other medical services (Fairman, Motheral, and Henderson 2003).

Others have studied different populations. In a study of changes to North Carolina's Medicaid program, Domino et al. (2011) did not find 'spillover' effects in changes to outpatient, inpatient or emergency department visits in their study of a new copayment requirement for North Carolina Medicaid enrollees. The authors used a difference-in-difference design with Georgia Medicaid enrollees as a comparison group. They examined six chronic condition classes of drugs: anti-diabetics, anti-hypertensives, lipid-lowering agents, seizure medications, antidepressants and antipsychotics since these

conditions have the greatest potential to impact the use of other health services. The authors found reductions in adherence for the North Carolina residents under the policy, but again, no spillover effects (Domino et al. 2011).

An older analysis of a change in copayments in New Hampshire Medicaid found significant offset effects. This study focused on those with serious and persistent mental illness. Soumerai et al. (1994) examined a limit on the number of prescription drugs enacted in the New Hampshire Medicaid program and its effect on patients with schizophrenia. The authors found that the use of drugs dropped during the drug limit period and visits to the Community Mental Health Centers increased (Soumerai et al. 1994). Hospitalizations increased from 3.4 per patient per month before to 4.6 after the cap.

1.2.5 Spending Reductions

While most evaluations of value-based insurance design have shown some impact on service utilization and certain health outcomes, there is still little evidence that they produce any overall savings for insurers, regardless of populations studied. Lee et al. (2013) conducted an extensive literature review and found mixed results on spending reductions for insurers or employers, leading the authors to conclude that there is no empirical evidence on whether value-based designs actually reduce spending for insurers (Lee et al. 2013).

Older studies such as Gibson et al. (2005), find similar results. Gibson and colleagues used a time-series methodology to look at how the demand for drugs might change over

time after a co-pay increase. While there were savings initially, these savings diminished over time (Gibson, McLaughlin, and Smith 2005). Wallace et al. (2008) used a change in Medicaid policy in Oregon to test whether increased cost sharing reduced spending by the Medicaid plan. While they did not explicitly test for changes in adherence, the authors found that increases in co-pays reduced drug expenditures, but increased expenditures for hospital outpatient and inpatient services (Wallace et al. 2008). The net effect resulted in no significant change in total Medicaid expenditures, but the implication is that the reduced cost sharing led to lower adherence and resulted in more adverse health outcomes.

In contrast to these studies, one recent study of a value-based design in a large employer showed some evidence of cost savings (Gibson et al. 2011). However, the cost savings were seen in the group that also had a disease management program, which makes disentangling the effects of the co-pays versus the extra patient monitoring and education more difficult.

1.2.6 Generic substitution

Generic use has grown substantially in the US over the last three decades and now accounts for 86% of all prescriptions filled (IMS Institute for Healthcare Informatics 2014). The savings to health insurers and patients can be substantial from increased generic substitution. One study estimated the savings on just three drugs could be 100 million dollars for state Medicaid programs (Shrank et al. 2010). Another study estimated the savings to Medicare's Part D program could be a billion dollars for every ten percent increase in the use of generics (Hoadley et al. 2012). Using employer data, Liberman and

Roebuck found that a one-percent increase in the use of generics could lower plan expenditures for pharmaceuticals by 2.5 percent (Liberman and Roebuck 2010).

While the overall use of generics has increased, the generic use rate across particular drug classes varies. The Office of the Inspector General used the Medicare Part D program to examine the generic substitution rate (number of generic fills/total number of generic + multisource brand fills) across several drug classes in Part D plans (Office of Inspector General 2007). Generics account for between 75-98 percent of diuretic prescriptions, but only 33-77 percent of diabetic therapies when the generics are available. The report hypothesized that some plans have more single-source brand name drugs on the forumulary, which limits the opportunity for generic drugs substitution, since these drugs have no generic substitutes.

Value-based insurance design has been used to increase generic usage through lower copayments on generic drugs, higher copayments for brand name drugs, or some combination of the two. However, not all patients use generic drugs when they are available. While the Food and Drug Administration requires that all generic drugs have the same active molecule, in practice, there are disputes as to whether the generic versions are exactly bioequivalent. Some drugs may have different inert ingredients to which some individuals may be allergic. Other generic drugs are different, older compounds with expired patents.

This seems to be a particular concern in drugs for mental health conditions. West et al. (2012) found that the Medicare Part D benefit designs could limit patients' access to particular drugs within the mental health classes. The authors found that 68% of dual eligibles who were forced to switch medications experienced adverse events versus 40% in the control group (Huskamp et al. 2009; West et al. 2012). However, from these studies, it is not clear if patients switching to a different molecule in the same drug class caused the increase in adverse events or if they experienced delays accessing different medications.

Perception also plays a role. Shrank and colleagues conducted a patient survey on attitudes towards generic usage. The authors found that while 70 percent of respondents said the generics were a better value, only 38 percent agreed that they would rather take generics (Shrank et al. 2009). Physicians may also impact generic usage if they do not realize the variation in out-of-pocket costs each patient faces for various medications (Shrank, Liberman, et al. 2011). Harmful drug interactions may also be a concern, though much of this research has been conducted in elderly populations (Ballentine 2008). Those on complex medication regimens may be unwilling to alter their prescriptions even with substantial copay increases for fear of setting off an adverse reaction.

1.2.7 VBID and those with multiple morbidities

There have been many studies examining the impact of cost sharing in the use of services. However, the effect of value-based insurance design has not extensively been explored among those with multiple chronic conditions, especially among those under age 65.

Most studies have been conducted primarily in large employer pools, elderly populations or in some instances, Medicaid (e.g., Gibson, McLaughlin, and Smith 2005; Chandra, Gruber, and McKnight 2010; Sen et al. 2012).

It is important to determine separately the effects for those with multiple chronic conditions, as they may be more susceptible to short-term complications from poorly managed conditions. Individuals with multiple chronic conditions are both heavy utilizers of prescription drugs and have high out of pocket spending (Paez, Zhao, and Hwang 2009). As such, Remler and Atherley (2003) predict those with more chronic diseases may be less likely to change their utilization in response to changes in benefit packages. The authors explain that for sicker individuals, health care is a necessity and they are, therefore, less responsive to changes in price.

One recent study examined the impact of increase cost sharing on Veteran's Affairs enrollees and found that those with lower disease burden, measured with a comorbidity score, were more likely to reduce medication usage following an increase in drug copayments (P. S. Wang et al. 2010). Goldman et al. (2006) examined the impact of lowering copayments for cholesterol-lowering drugs and found a decrease in emergency department utilization among the higher-risk disease groups, the lower copayments increased adherence to medications more than in the low-risk disease group (Goldman, Joyce, and Karaca-Mandic 2006).

The existing literature on cost sharing does not directly inform how benefit designs will affect a younger multimorbid population (Boyd and Fortin 2010). If co-pays are increased, multi-morbid patients could reduce the total amount of medications or reduce the use of specific types of medications they consume. Those with multiple chronic conditions may have lower adherence if their regimens contain too many different drugs or the drug regimens are too complicated to follow (LeRoy et al. 2014). The increase in copayments could exacerbate this process. They could substitute one type of medication for another, substitute a cheaper drug for a more expensive alternative or place priority on taking some medications over others (Berkowitz, Gerstenblith, and Anderson 2007).

The different populations used in the variety of studies cited here may account for the heterogeneity of findings. Table 1.3.1 highlights some of these studies discussed previously. Employer populations, with a larger distribution of healthier adults may show greater impacts on drug utilization than sicker populations faced with the same cost sharing. Studies using Medicaid populations may find greater effects of copayment change as these populations are low-income and are likely to be more sensitive to price changes. Elderly populations may have income constraints as well as other unmeasured health problems, such as frailty, which may lead to the increased offset effects. Across studies, the benefit design changes also differed, ranging from changing the number of tiers in a formulary, to changing the copayments within the tiers, to adding benefits altogether. The heterogeneity of the findings leaves the impact on younger, multimorbid adults uncertain.

[Table 1.3.1: Heterogeneity of populations, interventions and effects across selected studies.]

1.2.7 Multimorbid adults in high-risk pools

High-risk pools provide a unique view into a working-age population with one or more chronic diseases who are outside of employer-based coverage. Despite this, there has been little study of these pools, largely because the pools are state-run and largely state funded. The few studies or reports on high risk pools have given descriptive overviews of Minnesota's high risk pool (Zellner, Haugen, and Dowd 1993), the adequacy of high-risk pool benefits for the disabled in Kansas (Hall and Moore 2008), or described in broad overview the high-risk pool system (Achman, Chollet, and Fund 2001).

Thirty-five states have high-risk pools outside of the federal program enacted as part of health reform (NASCHIP 2012). Most high-risk pool enrollees will join the health insurance exchanges in 2014-2015, as the high-risk pools in most states cease operations (111th Congress). Maryland has the country's fourth largest high-risk pool (Kaiser State Health Facts 2011). Since inception in 2002, Maryland's pool has used funds from a statewide hospital tax to subsidize health insurance premiums for individuals with preexisting conditions. In order to qualify for this insurance, the person must have attempted to purchase coverage on the private individual market and be denied because of a pre-existing medical condition.

Premiums for the high-risk pool are generally set at about 125% of the average premium in Maryland's individual market. For the average individual in 2012, the premium was about $500 per month. These high-risk pool enrollees do not have the option to enroll in

other government programs because they make too much money to qualify for Medicaid, or are younger than the Medicare eligibility age of 65.

1.3 Objective

The objective of this study is to assess the impact of changing copayment rates for prescriptions on drug use, spending and utilization of other medical care for working age adults with multiple chronic conditions.

High-risk pools insure the uninsurable on the private, individual health insurance market. To be eligible for the pool, the enrollees must have a pre-existing medical condition. As a result the pools have a large number of working-aged adults with multiple chronic conditions. A discrete policy change in co-pay rates in Maryland's high-risk pool will be used in a interrupted time series design to evaluate the changes in demand for prescription drugs, other medical services and costs. In July 2010, MHIP restructured its pharmacy benefit program. The pool lowered copayments on generic drugs and raised them on preferred and non-preferred brands. In this year, the pool also created a specialty or fourth tier. Copayments for a given drug are based on both the generic/brand status of the drug but also the tier in which it was placed. Copayments for generics were dropped as much as 50% ($5) while the copayments for the specialty tier increase by as much as two thirds ($78).

Many prescription drugs are considered 'high value' since they can prevent costly downstream complications, and are cheaper than many other surgical or other such

interventions (Fendrick and Chernew 2009). With no clear consensus in the literature surrounding the impact of VBID on those with multiple chronic conditions, the effects of the policy change on utilization could result in either a decrease or no change in the use of prescription drugs. Therefore, the a priori impact on the use of other services is unclear, as are the impacts on downstream complications. This dissertation has three specific aims.

Aim 1.1: To assess change in demand for drugs in individuals stratified by their number of chronic conditions

Null Hypothesis 1.1: No change in drug utilization following the co-pay change.

Aim 1.2: To quantify the change in utilization of hospitalizations, emergency department and physician visits stratified by numbers of chronic conditions.

Null Hypothesis 1.2: No change in the use of other medical service use following the co-pay change.

Aim 1.3: To analyze changes in MHIP plan health expenditures with patients stratified by numbers of chronic conditions.

Null Hypothesis 1.3: No change in plan expenditures for prescription drugs or medical services following the policy change.

Aim 2: To analyze whether the copayment change shifts the utilization of generic drugs in particular drug classes.

Null Hypothesis 2.1: No change in the generic utilization rate in particular drug classes.

Aim 3: To examine whether adherence changes with the copayment change among those with both mental health and chronic medical conditions

Null Hypothesis 3.1: No change in adherence for particular drug classes following the copayment change.

The data used for this analysis are pharmacy and medical claims from the Maryland Health Insurance Plan for the years 2007 to 2012. The sample is limited to those 18-64 and those who are continuously eligible for one year before and after the policy change. The three papers comprising this dissertation use an interrupted time series analysis, with the added benefit of individual-level data. Statistical models attempt to control for the

correlation in observations within an individual over time. This is one of the stronger quasi-experimental designs to use with observational data and no control group. The assumption is that in the absence of the policy change, the preexisting trend in utilization would stay the same. A control group would allow for a difference-in-difference study design, but there were no adequate control groups for this high-risk pool.

Chapter 2 will examine the impact of the policy change on the numbers of drugs filled, outpatient, inpatient and spending. Chapter 3 will examine how the policy impacted the use of generic drugs. Chapter 4 will examine the policy's impact on adherence to medications among those with both a mental health condition and a physical comorbidity. Chapter 5 provides a conclusion and policy recommendations. Tables and figures will follow in each chapter. References for the entire document are in Chapter 6.

Table 1.3.1: Heterogeneity of populations, interventions and effects across selected studies.

Authors	Sample	Type of policy evaluated	Method	Impact on drug utilization/adherence	Offset effects	Spending effects
Chandra, Gruber & McKnight (2010)	2000-2003 Calpers claims, which provided supplemental benefits to retired civil service employees	Increased drug copayments	Difference-in-Difference	(-) drug usage	(+) inpatient, (-) outpatient visits	
Choudhry et al. (2011)	Aetna enrollees with heart attack	Reduced drug copayments.	Randomized controlled trial	(+) drug adherence	(/) major vascular events or revascularization.	(/) total spending
Domino et al. (2011)	North Carolina and Georga Medicaid claims, 2000-2002.	Increased drug copayments, reduced days supplied.	Difference-in-Difference-in-Difference.	(-) drug adherence		(-) total spending
Fairman, Motheral & Henderson (2003)	Midwest preferred provider organization database, 1997-2000.	Moving to 3-tier formulary (increasing copayments).	Logistic regression to predict utilization in the post period.	(/) drug adherence.	(/) office visits, inpatient, ED visits.	(-) net plan drug spending
Gibson et al. (2011)	Single firm in Thomson Reuters Advantage Suite, 2005-2008.	Reduced drug copayments, disease management for diabetics.	Matched control group, GEE for use in each quarter.	(+) drug adherence		(/) drug and overall spending
Gibson, McLaughlin & Smith (2005)	Selected Two large firms from Medstat MarketScan database, 1995-1998.	Increased drug copayments	Difference-in-Difference	(-) drug usage		(-) drug spending
Goldman, Joyce, Escarcee et al. (2004	Employer data, 1997-2000.	Increased drug copayments	Two-part models assesing copayment level on usage.	(-) drug usage		
Huskamp et al. (2003)	Data on two employers from Medco Health Solutions, 1999-2001.	Moving to 3-tier formulary (increasing copayments).	Difference-in-Difference	(-) drug usage		(-) net plan drug spending, (+) enrollee spending.
Maciejewski et al. (2010)	Blue Cross Blue Shield of North Carolina,	Reduced drug copayments.	Difference-in-Difference	(+) drug adherence		

2007-2008.

Motheral & Fairman (2001)	Midwest preferred provider organization database, 1997-1999.	Increased drug copayments	Segmented time series	(/) drug usage	(/) office visits, inpatient, ED visits.	(-) total spending
Wallace et al. (2008)	Adult Medicaid beneficiaries in Oregon from 2001-2004	Increased drug and medical service copayments	Matched control group, difference-in-difference.	(-) drug usage	(+) inpatient, hospital outpatient, (-) outpatient, ED visits	(-) drug spending, (/) total spending
Wang et al. (2011)	Veterans Administration claims, 2001-2003.	Increased drug copayments	Matched control group, GEE for use.	(-) drug adherence for low health risk group, (/) drug adherence, high risk health group.		

2 Value-based insurance design: Differential impact for those with multiple chronic conditions?

2.1 Abstract

Background: Value-based insurance designs change the level of cost sharing to promote services perceived to be high value from the insurer or policy maker's perspective. For example, many insurers and employer groups have begun lowering cost sharing on generic drugs to increase their utilization, and increasing copayments for on all or some brand name drugs. However, it is unclear how people with multiple chronic conditions react to value based insurance design because they may not be willing or able to switch to lower cost alternatives. The behavior of these individuals is important because they are the heaviest consumers of prescription drugs and medical services and may be more susceptible to short term complications from poorly managed conditions. It is not known how working-aged adults with multiple chronic conditions may react to cost sharing changes, and these individuals will make up a significant portion of the health insurance exchange enrollees.

Objective: This paper evaluates how adults with multiple chronic conditions respond to a change in value-based insurance design that increased copayments on brand name drugs while decreasing copayments on generics.

Data: Data consists of drug and medical claims from Maryland's high-risk pool for the years 2007-2011. High-risk pools offer insurance to those with preexisting conditions who were denied coverage on the individual market and who do not have access to employer-based insurance. The sample was restricted to those aged 18-64 and who were continuously enrolled for one-year period before and after the policy change.

Methods: An interrupted time series design with individual-level data exploits a 2010 co-pay change that raised copayments on preferred brands, non-preferred brands and specialty medications while decreasing generic copayments. Total medical and drug spending are assessed, as well as the use of outpatient, emergency department and inpatient services. Spending to both plan and the patient are assessed. Although the insurer might reduce spending on a value-based design, consumers may end up paying more if they are unwilling or unable to switch to lower cost alternatives.

Results: The copayment policy change has a statistically significant impact on those with chronic conditions, but the magnitudes are small. The overall number of drug fills increases in the post-period, and increases less than on fill per quarter for those with less than 8 chronic conditions. While the use of generics increased, the use of brand name drugs decrease. Because they are the heaviest users of prescription drugs, people with multiple chronic conditions have much higher total out of pocket payments as the result of the benefit design change.

Outpatient visits increased by less than one visit per quarter in the post period, while emergency department visits remained fairly constant. However, these could also reflect temporary changes in service utilization at the start of a new plan year. Inpatient visits, including those for ambulatory care sensitive conditions and 30-day readmissions, decreased after the policy change. Prescription drugs spending increased in the post period while the medical and total spending was not significantly impacted.

Conclusions: This study finds little impact on the use of prescription drugs after a value-based insurance design initiative. Most of the financial impact is seen in those with the highest number of chronic conditions. As a result, an out of pocket maximum should be considered. Without a control group, it is impossible to know whether these are unique to the pool or represent general utilization trends. More research is needed on working-aged adults with multiple chronic conditions and how they respond to cost sharing in order to confirm results. As these individuals with chronic conditions enter the exchanges, this will be an important group to follow.

2.2 Introduction

Value-based insurance design uses targeted cost sharing to encourage the use of high value services. High values services from a health plan's perspective are those showing great clinical benefit for the lowest level of spending. By altering the level of copayments or coinsurance, it is possible to discourage the overutilization of certain services by signaling to patients that certain services are high value, while still allowing patients their freedom of choice (Fendrick et al. 2001a). However, those with multiple morbidities may be forced to pay higher copayments and therefore higher out of pocket

payments if they have large numbers of needed services or are unable to switch to lower cost alternatives.

Prescription drugs have long been a vehicle for experimenting with value-based insurance designs, with many plans encouraging the use of generic drugs and certain brand drugs considered to be very cost effective (Shrank, Choudhry, et al. 2011; Hoadley et al. 2012). Recently, many employer health insurance plans have experimented with changes to cost sharing structures in order to discourage the use of brand name drugs that are not considered to be cost effective and promote the use of generics or the plan's preferred brands (Fendrick and Chernew 2009; Choudhry, Rosenthal, and Milstein 2010). The policies are designed to encourage the use of lower cost, yet still effective services. If adherence to prescription drugs drops after the implementation of these types of designs, then the insurer may be concerned about both adverse health impacts on the enrollee and the potentially expensive downstream consequences to the insurer.

The downstream consequences may be of particular concern for insurers and payers for populations with large numbers of high-risk individuals. There is little in the literature to guide policymakers on the impact of value-based insurance design on those with multiple chronic conditions. Most of the studies of value-based initiatives have used employer-based populations, with mostly healthy adults or adults suffering from only one chronic condition (e.g.: Gibson, McLaughlin, and Smith 2005). State and federal policy makers, however, have acute interest in the utilization of the new enrollees in the health insurance exchanges. The Affordable Care Act has removed the pre-existing exclusion restriction,

which in the past prevented many chronically ill individuals from accessing insurance on the private, individual market (111th Congress). Existing studies do little to inform us about these potentially high-spending, working-aged adults who will become part of the health exchanges.

While policy makers hope young healthy adults will enter the exchanges to lower the overall risk level, managing the spending of those at the upper risk levels will be key to maintaining affordable premiums. Studies of high-risk pool enrollees may inform us on the portion of exchange enrollees who will be the heaviest users of services. High-risk pools provide coverage for individuals in many states who attempted to purchase coverage on the individual market, but who were denied coverage because of a preexisting condition. Offering coverage since 2002, Maryland has the country's fourth largest high-risk pool (Kaiser State Health Facts 2011). Maryland's high-risk pool implemented a valued-based insurance design initiative in July 2010, where they lowered the copayments on generic drugs and raised them on brand name drugs.

High-risk enrollees will enroll in the exchanges in 2014 and insurers will want to reduce the level of spending for these new enrollees. It is essential to appropriately design health insurance benefits to maximize the health benefit for patients with chronic conditions without unduly burdening them financially, while constraining the level of spending for insurers and the federal government. This study evaluates a change in copayment structure on the demand for drugs, medical services and health spending for both the plan and the patient, focusing on the responses with varying numbers of chronic conditions.

2.3 Data

This paper exploits a change in the copayment structure of Maryland's high-risk pool in July 2010 to evaluate the impact of the change on drug use, medical services and spending. The data consists of medical and pharmacy claims from Maryland's Health Insurance Plan (MHIP). Thirty-five states have high-risk pools outside of the federal program enacted as part of health reform (NASCHIP 2012). Maryland has the country's fourth largest high-risk pool (Kaiser State Health Facts 2011). Starting in 2002, this state-run plan uses funds from a statewide hospital tax to subsidize health insurance premiums for individuals with preexisting conditions. In order to qualify for this insurance, the person must have attempted to purchase coverage on the private individual market and be denied because of pre-existing medical conditions or because the premiums offered are above what MHIP would charge for a similar medical condition.

Premiums for the high-risk pool are generally set at about 125% of the average premium in Maryland's individual market. For the average enrollee in 2012, the premium is about $500 per month. These high-risk pool enrollees do not have the option to enroll in other government programs: they make too much money to qualify for Medicaid, and are younger than the Medicare eligibility age of 65.

Administrative claims data from July 2007-June 2012 were used to analyze the change in utilization of pharmaceuticals, medical services and costs after a copayment change. While all available years of data were used, the population studied was limited to those

continuously enrolled from July 2009 to June 2011, 51 percent of the sample was used. The additional years of data help to establish the underlying trends in utilization for the continuously enrolled group. Claims were excluded if they were beyond June 2012, if the person was under 18 at any time and if there was no enrollment information for the person. Individuals who were enrolled during this time, but who had no claims in a given month, were still eligible and remained in the sample. Possible differences between the sample continuously enrolled and who dropped coverage after the copayment change were assessed. MHIP offers a selected set of plans with added subsidies for low-income individuals. MHIP has two different cost sharing structures for the MHIP+ plans and all other plans (PPO and HMO options) as indicated in Table 2.11.1.

[Table 2.11.1: Drug Tiers, Co-pays and drug examples]

2.4 Variables

2.4.1 Independent

The conceptual model guiding this analysis is shown in Figure 2.12.1, based on Grossman's 1972 work "On the Concept of Health Capital and the Demand for Health." The demand for health care is a function of demographic characteristics, such as age, income and education. Demand for pharmaceuticals, for example, would increase with income since this allows a person to substitute time-consuming health promotion activities, such as going to the gym or eating a better diet, with high blood pressure or high cholesterol medications. Health insurance, though, can increase levels of consumption beyond what would be demanded otherwise, so cost sharing is often instituted as a way to influence utilization in health plans (Pauly 1968). Figure 1 shows

that the demographic characteristics such as education or income can influence health status, and how health status in turn may modify the impact of the copayment change. The main responses for enrollees would be to keep utilization the same, decrease the drugs taken, substitute for cheaper alternatives or stop taking the medications altogether. There could then be down stream health or financial impacts which brings the impact full circle.

Factors such as education, however, are not available in claims data. Ideally, we would like to conduct a randomized experiment so the variety of characteristics could be equal across groups. However, that is not possible in many natural experiments such as MHIP's. As such, this study controls for as many factors as possible in claims data and recognizes that some of the coefficients may suffer from omitted variable bias. Time series analysis methods can control for some of the time invariant unobserved factors, making these designs particularly strong quasi-experimental designs. The main assumption is that in the absence of the policy change, the trend in the pool would continue unaltered. This assumption is violation if there are other, plausible co-occurring policy changes that may affect the outcomes. The main independent variables of interest are those marking the pre/post period and the other time trends (discussed below).

The main covariate variables are age, gender, number of chronic conditions and plan type. Age is measured continuously while gender is coded as binary (1=female). The number of chronic conditions is continuous. International Classification of Disease codes were translated into categories of conditions and chronic diseases using the Clinical

Classifications System (CCS) from the Agency for Healthcare Research and Quality (AHRQ) (Elixhauser, Steiner, and Palmer 2012). For a condition to be counted as chronic, the ICD9 code had to appear in at least two outpatient visits or at least one inpatient visit.

The enrollment files include information on plan type such as Preferred Provider Organization (PPO) or Health Maintenance Organization (HMO), which represent differences across plan benefit structure and to some degree, income. MHIP provides a second set of plans called MHIP+ for the lower income individuals. Across any of the given person-months, approximately 25% are enrolled in MHIP+ in a given month while 40% are enrolled in the PPO plans and 23% are enrolled in a HDHP. The indicator for MHIP+ is a crude measure of income.

2.4.2 Dependent

MHIP covers most prescription drugs, outpatient medical and emergency services, inpatient care, mental health and substance abuse and preventative care. As always with claims data, any amounts spent by the enrollee on services outside what the plan pays for cannot be observed with this data.

Drug use outcomes consist of the number of 30-day fills, the number of generic fills and the number of brand drug fills. As some enrollees are prescribed varying days supplied for drugs, the number of prescription drug fills was normalized to 30-day equivalents (Andrade et al. 2006). For example, one 30-day prescription counts as one fill and one 90-day prescription counts as three 30-day fills. A 7-day prescription for antibiotics

would equal 0.23 (7/30) of one 30-day fill. Since these are drugs for chronic conditions the assumption is made that the drugs need to be taken continuously.

For the generic and brand classifications, drugs were classified as generic or brand name according to MHIP's categorization. For the purpose of counting the number of generic and brand name fills, single and multi-source brands (i.e. have available generic or brand equivalents) were both included in the brand category, if the enrollee filled the brand version.

Health service utilization variables consist of the number of outpatient visits per month, at least one emergency department visit in the month, at least one inpatient visit, at least one ambulatory care sensitive condition (ACSC) admission in the month and at least one 30-day readmission in the month. The readmission variable was equal to 1 if the respondent had at least one admission within 30-days of a discharge. The emergency department, inpatient, ACSC and 30-day readmissions were all coded as binary indicators (0/1). Particular ICD9 codes in AHRQ's Clinical Classifications System were flagged to create indicators for ambulatory care sensitive condition hospitalizations (Elixhauser, Steiner, and Palmer 2012). These codes can be found in AHRQ's Prevention Quality Indicators (AHRQ 2004).

Financial variables are the total drug spending, total medical and total spending. Total drug spending is the sum of the amount paid by the plan, the deductible, copay and dispensing fee paid to the pharmacy and any sales tax. The total medical spending is the

sum of the amount paid by the plan, deductible, copay, coinsurance and non-covered amount. The total spending is the sum of total medical and total drug costs.

2.5 Analysis

An interrupted time series analysis design with individual-level data is used. The key variables of interest are the policy change indicator and the interaction between the number of chronic conditions and the policy change.

$$Y_{it} = f(\beta_0 + \beta_1 time_t + \beta_2 policy_t + \beta_3 posttime_t + \beta_4 chronic_i + \beta_5 chronic*policy_{it} + \beta_6 chronic*posttime_{it} + X_{it}\lambda)$$

$\beta_1 time_t$ is the time trend, measured quarterly since the first quarter in July 2007. MHIP runs on a July-June fiscal year. The policy change is included as a binary indicator equal to zero in the pre-period and one in the post period. The post time variable measures the quarters continuously since the policy change, so it is equal to zero in the pre-period and begins at one in July 2010. $\beta_2 policy_t + \beta_3 posttime_t$ represents the impact of the policy change for the whole sample including both the initial impact and the change in the trend after the intervention. $\beta_4 chronic_i$ details how patients with different numbers of chronic conditions will react. $\beta_5 chronic*policy_{it}$ represents whether individuals with different numbers of chronic conditions act differently and $\beta_6 chronic*posttime_{it}$ represents whether the trend in the post-period changes after the policy change. $X_{it}\lambda$ represents the vector of control covariates: age, gender, plan type and quarter. Dummies for the quarter are included to capture any seasonality, with the first quarter after the policy change acting as the reference quarter.

All outcomes use the same model with different specifications. GEE allows for the specification of the family (i.e. Gaussian) and link function (i.e. identity or log) for the mean. BoxCox tests were used to test for the appropriate link and the modified Park test was used to test for the appropriate family (Cameron and Trivedi 2005). There is also no theoretical reason to anticipate a quadratic relationship, though it is possible that the time trend could be non-linear. The time trend variables (the pre and post period trends) were assessed with both a linear specification, as well as a quadratic specification. However, the quadratic specification was not significant for any outcome and was dropped from further consideration in favor of the simpler, linear specification.

The particular outcomes were analyzed in the following ways. Drug outcomes (the number of 30-day fills, number of generic drug fills, number of brand fills) were modeled using negative binomial models to account for the over dispersion in these outcomes, where the variance is greater than the mean. Health service utilization outcomes were modeled in two ways. The number of outpatient visits was modeled using a negative binomial similar to the drug use outcomes. The binary outcomes (probability of an emergency department, inpatient, ACSCs or 30-day readmission in the month) were modeled using logit models. The financial variables (drug, medical and total spending) were modeled with log links with tests for Gaussian and gamma distribution families.

Sensitivity Analyses

The models are also assessed without the post-time trend. This assumes that in the post period, the policy change did not impact the trend in utilization, though it may have changed the level of utilization. The benefit of this version of the model is that the interpretation of the policy's impact becomes simpler and the coefficient on the policy change is the average impact in the post period.

Prior to the decision to aggregate the data to the quarterly level, several models were tested with the monthly level data. These included regression to compare pooled, fixed effects and random effects to analyze the impact of the policy change. The pooled analysis assumes independence in the observations. However, having a prescription in one month is highly correlated with having a prescription drug in the next month particularly for chronic disease patients, so the fixed and random effects are ways to control for the correlation over time of an individual's observations. These models showed similar results to the GEE models, and are therefore not shown here.

It is possible that these policies may not have an immediate impact because people anticipated the change or took time to learn that the change had actually occurred. To account for these possibilities, a sensitivity analysis was conducted. The three months before and after the policy change were analyzed separately as a falsification test. There could be spikes in utilization in the months prior to the copayment change as people anticipate the change and take action. The spike could make the effect of the policy seem large, when in fact people were just stockpiling drugs. Therefore, to check the robustness

of the results, the models were re-estimated without these six months. This model also showed similar results and results are not shown here.

Analyses were completed using Stata 12.1. The Johns Hopkins Bloomberg School of Public Health's Institutional Review Board approved the study.

2.6 Results

2.6.1 Descriptive Results

There were 44,640 individuals with claims information during the period of July 2007-June 2012. However only 8,893 individuals were continuously enrolled for the year pre- and post the policy change and more were dropped due to the age restriction, leaving the final sample size at 8,865 individuals (Figure 2.12.2). Sensitivity of the results to this choice of sample limitation is discussed below.

[Figure 2.12.2: Dataset Construction]

For those continuously enrolled in the year pre/post the policy change, the average enrollment length was 4.3 years (SD: 0.8). Table 2.11.2 has descriptive statistics for the sample by the number of chronic conditions. As the number of chronic conditions increases, the average age of the individual increases. As we would expect for a high-risk pool, the majority of the pool has some outpatient and prescription drug utilization during the year. These percentages increase as the number of chronic conditions increases.

There are a number of individuals with no chronic conditions, who are likely spouses or dependents on their parent's coverage.

[Table 2.11.2: Descriptive Statistics by number of chronic conditions]

Figures 2.3-2.5 show the average quarterly utilization levels for the sample. Across the time period, aggregate utilization trends remained steady, with slight dips in utilization surrounding the policy change in July 2010. The trend for outpatient, inpatient and emergency department utilization remains relatively stable over time. The medical and drug costs are increasing over time.

[Figure 2.12.3: Drug Use by Quarter, 2007-2012
Figure 2.12.4: Proportion with Any Hospital Visit and Average Number of Outpatient Visits, Quarterly 2007-2012
Figure 2.12.5: Quarterly average spending, 2007-2012.]

In comparing the quarterly means before and after the policy change (Table 2.11.3), the average drug copayment increases slightly. The general trend is for increasing usage of drugs over time (Figure 2.12.3), so the means in the post period all increase despite the change in copayments. Brand drugs have a slight decrease after the copayment change suggesting a continued substitution towards the generic versions of drugs.

[Table 2.11.3: Quarterly service use means before and after the policy change in July 2010]

Generics account for 50% drugs filled in 2007 and this increased to over 70% by 2012 (Figure 2.12.6). This may explain why the average copayments do not shift markedly in the post policy change period as shown in Table 2.11.3 and Figure 2.12.6.

[Figure 2.12.6: Generics as a percent of all drugs filled, monthly average, 2007-2012]

Lastly, Figure 2.12.7 shows the average number of prescriptions filled per quarter by category of chronic conditions. Examining the outcomes, in this case the number of 30-day fills shown as an example, allows us to see descriptively whether there might be a change in the outcome that differs by the number of chronic conditions and whether this trend may change in the post period. This graph shows that the trends seem fairly constant in the post period, except for a small increase in the number of prescriptions filled for those with more than ten chronic conditions.

2.6.2 Multivariate Results

The descriptive graphs of the average utilization per month over time show the copayment change policy has a very small impact. The regression results confirm this finding (Table 2.11.4-Table 2.11.6). The policy level change (β_2) and the trend change in the post-period (β_3) combined show small but statistically significant impact for most outcomes in the regression models. For most of the outcomes, the coefficient on the change in the post-period trend is significant as well as the policy change itself. For the drug outcomes, the coefficient on the policy change indicator is positive ($p<0.01$) while the coefficient on the post-time trend is negative ($p<0.01$). The coefficient on the policy

change for inpatient visits and 30-day readmissions is not significant, while the post time trend for both of these outcomes is significant at the $p<0.01$ level. Drug spending is not significantly impacted. Total spending has a positive coefficient on the policy change ($p<0.01$) but negative coefficients on the post-time trend ($p<0.01$), making the impact unclear.

[Table 2.11.4: Results, Drug and outpatient outcomes, quarterly.
Table 2.11.5: Results, Emergency department and inpatient outcomes, quarterly.
Table 2.11.6: Results, Spending outcomes, quarterly.]

For all outcomes, the number of chronic conditions is significantly associated with increases in utilization and spending, across all outcomes ($p<0.01$). For some outcomes, and not others, the interaction of the policy change and the number of chronic conditions is significant. This interaction shows whether the policy change impacted the level of utilization for a given service. The coefficient is very small but positive for the number of 30-day fills (0.003, $p<0.1$) and the number of brand fills (0.009, $p<0.01$), but not for the number of generic fills (-0.004, $p<0.05$). This indicates that those with increasing numbers of chronic conditions may be less likely to fill generic prescriptions after the policy change. For nearly all outcomes, the interaction between the number of chronic conditions and the post-time trend is not significant, indicating that the trend in the post period is not different across the numbers of chronic conditions.

Given the difficulty in directly interpreting the coefficients on models of non-linear outcomes, marginal effects are presented (Table 2.11.7-Table 2.11.8, and Figure 2.12.8-Figure 2.12.9). These effects are shown over a variety of numbers of chronic conditions, to show how the outcomes change as the number of chronic conditions increase.

[Table 2.11.7: Marginal effects for drug and outpatient, by number of chronic conditions
Table 2.11.8: Marginal effects for inpatient utilization and spending, by number of chronic conditions.
Table 2.11.9: Marginal effects for spending, by number of chronic conditions.]

Overall drug use, calculated as the number of 30-day fills, in the pre-period is shown in the first row of Table 2.11.7. The marginal effects tables show the difference in the immediate post quarter (quarter 13) and the fourth quarter (quarter 16) after the policy change. Examining both time points allows delineation between immediate and longer-term effects. Those with no chronic conditions are predicted to fill just over five prescriptions in a quarter, while those with 14 chronic conditions fill nearly 13. The number of 30-day fills increases in the post period across all numbers of chronic conditions. For those with eight or fewer chronic conditions, the impact is less than one prescription per quarter. The impact is higher in those with more conditions, with one and half more prescriptions filled per quarter in the post period for those with 14 chronic conditions.

The increase in number of prescriptions stems from the increase in generic usage in the post period, while brand usage decreases by less than a prescription per quarter. In the fourth quarter, generic usage still increases compare with the pre-period, but by fewer fills. The effect on brand name fills is stronger in the fourth quarter. For example, those with 14 chronic conditions filled -0.01 prescriptions in the first post-quarter and filled -0.56 fewer brand prescriptions in the fourth quarter ($p<0.05$).

Outpatient visits rose in the immediate post period, however these increases were wiped out by drop in visits in the fourth quarter. Inpatient and ambulatory care sensitive admissions fell after the policy change with the greatest change occurring in the fourth quarter is in those with 10 or more conditions. The overall drug spending changes little following the policy change. Monthly drug spending does not change for those with 14 chronic conditions, from an average pre-period spending of just over $1400 (Table 2.11.9). Medical and total spending are unchanged. Copayments increased over $100 dollars for those with four or more conditions, and more over $150 for those with more than ten chronic conditions.

The finding regarding a drop in inpatient visits is unexpected, given the literature on possible offsets from changes in drug use (Chandra, Gruber, and McKnight 2010). Hospitalizations for MHIP have been decreasing over time in absence of the policy change. Figure 2.12.10 shows the proportion of enrollees with at least one inpatient visit per month over the two-year study period. The linear fit of the proportion with at least one hospital visit on month shows the general decrease over time. It is also clear from the graph that there is an increase in inpatient visits just before the policy change, which may bias upward the impact of the policy change, even though the regressions control for time trend. The overall probability of a hospitalization was low.

Figure 2.12.10: Average monthly probability of at least one inpatient visit with linear fitted values, FY '09 & '10

Age and gender are included in the models and are generally significant predictors of utilization. The low-income plan coefficient is generally not significant, indicating the

behavior of those in this plan is not different from those in the next most generous plan, the $500 deductible plan. The HMO plan has an uncertain impact for many of the outcomes as this coefficient changes sign and significance, depending on the outcome. As expected, the high deductible plan coefficient is consistently negative and significant for all outcomes, which suggests that high deductible plans, with their higher out-of-pocket spending may depress utilization.

2.7 Sensitivity Analyses

The models were also assessed removing the post-time trend variable. The assumption of this model is that there is no difference in the utilization trend after the policy change, but there may be a shift in the level of utilization.

Table 2.11.9: Marginal effects for spending, by number of chronic conditions.

	Rx spending			Medical spending		
Number of chronic conditions	Q12 (Pre)	Q13 (difference)	Q16 (difference)	Q12 (Pre)	Q13 (difference)	Q16 (difference)
0	769.52***	-10.43	-10.69	536.82***	-77.38	-87.37
	[37.014]	[22.787]	[23.494]	[43.247]	[56.173]	[68.578]
2	843.58***	-6.17	-6.29	841.43***	-58.81	-64.89
	[32.313]	[19.524]	[19.966]	[54.245]	[70.598]	[81.153]
4	924.76***	-0.97	-0.98	1,318.88***	12.14	13.09
	[27.520]	[16.714]	[16.960]	[66.950]	[89.876]	[96.396]
6	1,013.76***	5.31	5.36	2,067.26***	193.3	203.71
	[24.179]	[16.108]	[16.222]	[86.543]	[129.724]	[131.299]
8	1,111.33***	12.82	12.87	3,240.28***	594.25**	612.03***
	[25.267]	[19.752]	[19.723]	[132.940]	[232.677]	[230.778]
10	1,218.29***	21.75	21.73	5,078.92***	1,418.53***	1,427.79***
	[32.912]	[27.777]	[27.483]	[247.192]	[471.197]	[461.466]
12	1,335.53***	32.31	32.11	7,960.84***	3,038.33***	2,988.72***
	[46.410]	[39.336]	[38.570]	[491.338]	[964.800]	[924.532]
14	1,464.07***	44.72	44.22	12,478.06***	6,126.28***	5,889.37***
	[64.654]	[54.034]	[52.516]	[966.923]	[1,929.301]	[1,798.997]
	Total spending			**Copayment**		
Number of chronic conditions	Q12 (Pre)	Q13 (difference)	Q16 (difference)	Q12 (Pre)	Q13 (difference)	Q16 (difference)
0	1,043.00***	-161.53**	-177.77**	104.61***	80.84***	63.41***
	[54.137]	[73.637]	[88.355]	[2.951]	[3.607]	[2.155]
2	1,515.06***	-135.72	-146.94	117.54***	90.16***	69.98***
	[62.382]	[85.435]	[97.646]	[2.584]	[3.228]	[1.954]
4	2,200.77***	-44.6	-47.5	132.06***	100.54***	77.23***
	[72.397]	[101.168]	[109.086]	[2.191]	[2.870]	[1.790]
6	3,196.82***	170.56	178.71	148.38***	112.12***	85.22***
	[93.450]	[138.359]	[141.538]	[1.943]	[2.735]	[1.769]
8	4,643.68***	610.96***	629.77***	166.71***	125.03***	94.05***
	[147.753]	[235.644]	[235.500]	[2.186]	[3.129]	[2.025]
10	6,745.38***	1,448.21***	1,468.57***	187.32***	139.43***	103.78***
	[266.063]	[445.705]	[439.041]	[3.115]	[4.214]	[2.622]
12	9,798.31***	2,969.61***	2,962.48***	210.46***	155.49***	114.53***
	[488.419]	[844.709]	[816.140]	[4.637]	[5.945]	[3.544]
14	14,232.96***	5,651.33***	5,546.22***	236.47***	173.39***	126.38***
	[877.291]	[1,559.594]	[1,472.606]	[6.682]	[8.272]	[4.771]

*** p<0.01, ** p<0.05, * p<0.1. Standard error in brackets.

Table 2.11.10 - Table 2.11.13 present the results of this sensitivity analysis.

[

Table 2.11.9: Marginal effects for spending, by number of chronic conditions.

	Rx spending			Medical spending		
Number of chronic conditions	Q12 (Pre)	Q13 (difference)	Q16 (difference)	Q12 (Pre)	Q13 (difference)	Q16 (difference)
0	769.52***	-10.43	-10.69	536.82***	-77.38	-87.37
	[37.014]	[22.787]	[23.494]	[43.247]	[56.173]	[68.578]
2	843.58***	-6.17	-6.29	841.43***	-58.81	-64.89
	[32.313]	[19.524]	[19.966]	[54.245]	[70.598]	[81.153]
4	924.76***	-0.97	-0.98	1,318.88***	12.14	13.09
	[27.520]	[16.714]	[16.960]	[66.950]	[89.876]	[96.396]
6	1,013.76***	5.31	5.36	2,067.26***	193.3	203.71
	[24.179]	[16.108]	[16.222]	[86.543]	[129.724]	[131.299]
8	1,111.33***	12.82	12.87	3,240.28***	594.25**	612.03***
	[25.267]	[19.752]	[19.723]	[132.940]	[232.677]	[230.778]
10	1,218.29***	21.75	21.73	5,078.92***	1,418.53***	1,427.79***
	[32.912]	[27.777]	[27.483]	[247.192]	[471.197]	[461.466]
12	1,335.53***	32.31	32.11	7,960.84***	3,038.33***	2,988.72***
	[46.410]	[39.336]	[38.570]	[491.338]	[964.800]	[924.532]
14	1,464.07***	44.72	44.22	12,478.06***	6,126.28***	5,889.37***
	[64.654]	[54.034]	[52.516]	[966.923]	[1,929.301]	[1,798.997]
	Total spending			**Copayment**		
Number of chronic conditions	Q12 (Pre)	Q13 (difference)	Q16 (difference)	Q12 (Pre)	Q13 (difference)	Q16 (difference)
0	1,043.00***	-161.53**	-177.77**	104.61***	80.84***	63.41***
	[54.137]	[73.637]	[88.355]	[2.951]	[3.607]	[2.155]
2	1,515.06***	-135.72	-146.94	117.54***	90.16***	69.98***
	[62.382]	[85.435]	[97.646]	[2.584]	[3.228]	[1.954]
4	2,200.77***	-44.6	-47.5	132.06***	100.54***	77.23***
	[72.397]	[101.168]	[109.086]	[2.191]	[2.870]	[1.790]
6	3,196.82***	170.56	178.71	148.38***	112.12***	85.22***
	[93.450]	[138.359]	[141.538]	[1.943]	[2.735]	[1.769]
8	4,643.68***	610.96***	629.77***	166.71***	125.03***	94.05***
	[147.753]	[235.644]	[235.500]	[2.186]	[3.129]	[2.025]
10	6,745.38***	1,448.21***	1,468.57***	187.32***	139.43***	103.78***
	[266.063]	[445.705]	[439.041]	[3.115]	[4.214]	[2.622]
12	9,798.31***	2,969.61***	2,962.48***	210.46***	155.49***	114.53***
	[488.419]	[844.709]	[816.140]	[4.637]	[5.945]	[3.544]
14	14,232.96***	5,651.33***	5,546.22***	236.47***	173.39***	126.38***
	[877.291]	[1,559.594]	[1,472.606]	[6.682]	[8.272]	[4.771]

*** p<0.01, ** p<0.05, * p<0.1. Standard error in brackets.

Table 2.11.10: Sensitivity analysis, removing the post-time trend, drug and outpatient outcomes, coefficients and 95% confidence intervals.
Table 2.11.14: Sensitivity analysis, removing the post-time trend, emergency department and inpatient outcomes, coefficients and 95% confidence intervals.
Table 2.11.13 Sensitivity analysis, removing the post-time trend, spending outcomes, coefficients and 95% confidence intervals.]

The policy change coefficient is significant for all the overall number of drug fills ($p<0.01$), but not for the generic or brand fills. The coefficient for outpatient visits is negative and significant ($p<0.01$). The coefficient on the interaction between the policy change and the number of chronic conditions varies in significance, while the number of chronic conditions is positively associated with increases in service utilization for all outcomes.

The marginal effects for this model give the average difference across the post period (Table 2.11.17). Drug use change by less than one fill per quarter, though generic drugs do increase while brand drugs decrease. The probability of inpatient visits drops less than 10% for nearly all chronic condition levels. There are no significant changes in spending, though out of pocket costs do increase. Copayments increase $50 per quarter for those with 14 chronic conditions.

Table 2.11.17: Sensitivity analysis, marginal effects, difference in outcomes attributable to the policy change, by number of chronic conditions.

It is possible that the small effects seen for this population could result from the majority of the people being over their out-of-pocket maximums and facing no cost sharing

beyond a certain point in the year. This would be more likely to happen for those with the highest numbers of chronic conditions, since they are generally using more services. Therefore, an additional analysis was conducted where the sample was limited to those who were at or below $100 from reaching their out-of-pocket maximums in the year after the policy change. The $100 cutoff was used in the RAND health insurance experiment to examine this same issue (Manning et al. 1987). For example, the standard PPO plans had drug deductibles of $2,000 in fiscal year 2010. To remain in the sample, the enrollee had to have $1,900 or less in combined drug deductible and copayments. The distribution, of those under/over the out-of-pocket maximums, is shown in Table 2.11.18.

Table 2.11.18: Distribution of insurance plan types, FY 10

The majority of respondents (90%) are under their OOP max for the post policy change year. Selected marginal effects are presented in Table 2.11.20. Drug spending is significantly reduced, primarily driven by a greater reduction in the use of brand name drugs in the first quarter after the policy change than the full sample. Once a person is over their out-of-pocket maximum, the expectation is that they are no longer price sensitive since the insurer is now paying the full cost of the drug. Examples from the Medicare Part D program have shown that consumers will take into account their probability of hitting the coverage gap, or out-of-pocket maximum and this will change their effective prices (Jung, Feldman, and McBean 2014).

Table 2.11.20: Marginal effects for the policy change for those under the out-of-pocket maximum.

2.8 Discussion

While the copayment policy change results in significant changes in service utilization, the magnitudes are generally small for this population. This study does show that as the number of chronic conditions increases, service utilization increases across all types of services. Drug fills increased by less than one in the immediate post period, driven by an increase in generic usage.

The individuals studied for this analysis are an important group of high-risk, working-aged adults, many of whom will enroll in the health insurance exchanges in 2014. The significant, though tiny magnitude of the effects may be due to a relatively sicker population than that of the employer-sponsored health care pools used in many of the other studies in this literature. If this study had shown more variation in the impact on those with greater numbers of chronic conditions, then this would more directly confirm the theory and findings of Remler and Atherly (2003), whose model predicts that those who are sicker are more inelastic in their demand for healthcare utilization.

The probability of an inpatient admission declined after the drug copayment change. This finding is contrary to the results of Chandra, Gruber and McKnight (2010) who found an increase of $2 in hospital spending for every $1 saved in drug costs in a pool of California retirees. While it could be that the difference seen here is due to a working-aged adult rather than an elderly population, Liu et al. (2011) find no offset effects in the elderly (Liu et al. 2011). Inpatient visits for this pool had been undergoing a general

downward trend, and the drop may be the result of a slight uptick in the months right before the drug copayments switched. Indeed, when examining the inpatient model without the six months surrounding the policy change, the coefficient is 22% smaller. The lower inpatient visits could plausibly be tied to an increase in generic drug usage, however, given this type of study design with no control group, it is possible the drop in inpatient could be related to something besides the plan's copayment change.

An additional finding of this paper is that while utilization and health outcomes were not dramatically impacted, the plan saw no significant changes in spending. This finding should be interpreted with caution, as other studies in the field do not find similar savings. Lee et al (2013) in a review of studies in this area find mixed results on cost savings for insurers or employers, leading the authors to conclude that there is no consensus on whether value-based designs save money (Lee et al. 2013). Several studies have found reduced drug spending with no changes in adherence (Motheral and Fairman 2001). However, others have found increased adherence with no impacts on spending (Choudhry, Avorn, et al. 2011). More research in the area of whether these designs reduce insurer spending is needed.

The one significant policy finding of this paper is that out-of-pocket costs rose significantly, particularly for those with the most chronic conditions. Copayments increased $55 per quarter for those with 14 chronic conditions. While the overall household financial impacts cannot be studied with this dataset, the literature on cost burdens in medical care suggests possible consequences. For example, studies describe

the most common strategies are to cut back on other necessities, go into credit card debt or borrow money from family members (Heisler, Wagner, and Piette 2005; Zivin et al. 2010; K. R. Martin et al. 2012). Piette et al. in the development of their conceptual model on adherence to medications acknowledge that there are a variety of other factors in addition to spending, such as patient educational levels or the complexity of medication regimens (Piette et al. 2006). Heisler et al. 2004, using the Health and Retirement Survey, found that those reporting cost-related non-adherence problems were more likely to report significant declines in health status (Heisler et al. 2004). While these impacts of copayment changes cannot be studied here, they pose a complication for insurers or policymakers who might want to continue to increase cost sharing in prescription drug plans.

2.9 Limitations

There are several limitations to this study. The first is limiting the sample to those continuously enrolled from July 2009 to June 2011. In limiting the sample to those continuously enrolled for the one before and after the policy change, there may be differences in characteristics between the those who were continuously enrolled and those who were not. The concern is that those who left the plan may be the most price-sensitive. Their leaving, therefore, would have amplified any drops in utilization after the policy change if they dropped out.

In order to assess the extent to which enrollees may have dropped coverage due to the policy change, survival models were used to examine the probability of dropping

coverage. Everyone enrolled three months prior to the coverage change was analyzed, leading to a sample size of 17,644. As Table 2.11.21 shows, those continuously enrolled in the high-risk pool are older, had more chronic conditions and used more services.

[Table 2.11.21: Descriptive characteristics continuously enrolled vs those who are not, after dropping those enrolled completely outside study period.]

Younger or healthier people were more likely to drop coverage after the initiation of the copayment change. Dropping coverage throughout the year may be a usual state of affairs for a state-run pool where premiums are higher than the market average. When examining the survival curves for the hazard of dropping coverage during the year prior to the copayment change, a similar pattern is found (Figure 2.12.11). This suggests that the attrition observed during the year after the policy change is likely not due to the policy change itself, but is the natural attrition pattern for the pool.

[Figure 2.12.11: Kaplan-Meier survival curves for the probability of dropping coverage, FY '09 vs FY '10]

The second limitation is that the impact of the policy change could be due to some form of stockpiling medications in the pre period, causing a drop in the immediate post period. As a sensitivity analysis, the three months before and after the policy change were dropped, and the GEE models were re-run to test the coefficients. In these models, the coefficients either lose their statistical significance or they are similar in magnitude (not shown). This indicates there was not substantial stockpiling of medications in the pre-period.

Plan switching could also potentially affect the results if individuals switch to a plan with a different copayment structure that would allow them to maintain their current utilization. However, the number of individuals who switched at the time of the policy change (July 2010) is small. 959 (10%) of individuals switch plan types in this month, however, 494 (52%) are switching from a low-income MHIP+ plan into the PPO $500 deductible plan. This indicates they are moving to plans where they would face more cost sharing. For comparison, about 9% of the enrollees shifted plans in the year prior, but the distribution of plan types individuals shifted between was spread more evenly across the plan types.

Given the results show decreases in inpatient and medical costs, there could be some other change happening at the same time within Maryland's health care system, such as improved care coordination or higher quality hospital care. Unfortunately, there was no ready control group for this population, given the nature of the high-risk pool. Controlling for the trend over time should account for this variation, but there may some additional unobserved threat.

One last limitation in this analysis is that only fills of drugs and days supplied were analyzed. A more nuanced view of particular drug classes could better inform whether patients were trading off between classes while maintaining an overall stable level of medication use.

2.10 Policy Implications

The results of this paper show the burden of copayment changes has the greatest financial impact on those people with multiple chronic conditions. Therefore, future policy development in the value-based insurance design field should take into account the differences in health status when assessing the impact of the programs. The results from Maryland high-risk pool show that copayments can be raised on brand name drugs quite substantially without adverse impacts. However, this may force those with multiple chronic conditions to cut back financially in other areas in order to maintain medical utilization. Studies examining self-reported burden have found many strategies patients with multiple chronic diseases use to cope with medical costs and passing higher costs on to consumers will likely only increase out of pocket burden (Piette et al. 2006; Mojtabai and Olfson 2003). Other strategies such as case management or medical homes may be needed to manage the utilization in these high-cost patients.

2.11 Tables

Table 2.11.1: Drug Tiers, Co-pays and drug examples

Drug Tiers, Co-pays and drug examples				
	Tier 1	Tier 2	Tier 3	Specialty Tier
	Generic	Preferred Brand	Non-preferred Brand	Select classes
2010 Co-pay, MHIP+	10	25	50	75
Change from 2009	**-5**	**5**	**15**	**25**
90-day supply	20	50	100	150
Change from 2009	**-10**	**10**	**30**	**50**
2010 Co-pay, All other plans	15	35	75	125
Change from 2009	**-5**	**8**	**28**	**50**
90-day supply	30	70	150	250
Change from 2009	**-10**	**16**	**56**	**100**
Examples of Drugs in Different Tiers				
Diabetes, antidiabetics	acarbos	Actos	Amayrl	
Hypertension, ACE inhibitors	coptopril	Multa Q	Accupril	
Depression, antidepressants	citalopram	Effexor XR	Prozac	
Arthritis	hydroxychloroquine	Enebrel	Arava	
High cholesterol, statins	lovastatin	Lipitor	Vytorin	
COPD	cromolyn sodium	Advair	Intal	
Pain management, NSAIDs	ibuprofen	-	Celebrex	
HIV/AIDS, antivirals				Reyataz
Notes: The change in price for the specialty tier assumes the drug was Tier 3 in 2009.				
The main indications in the specialty tiers are genetic disorders, antivirals, cancer, some thyroid medications and antibacterials.				

Table 2.11.2: Descriptive Statistics by number of chronic conditions

Descriptive Statistics by number of chronic conditions (column percents).

	Zero	One-Two	Three-Five	Six-Nine	Ten+	Total
Total, n	625	1,442	2,508	2,513	1,777	8,865
%	7	16	28	28	20	100
Age, %						
18-39	35	35	20	12	8	19
40-54	33	34	32	29	22	29
55+	33	31	48	59	70	52
Gender, %						
Male	50	49	46	44	39	45
Female	50	51	54	56	61	55
Percent with any utilization						
Outpatient	27	53	71	88	98	75
Inpatient	81	99	100	100	100	98
ED	21	39	46	60	79	53
Rx	65	91	98	99	100	95

Table 2.11.3: Quarterly service use means before and after the policy change in July 2010

Pre-Post means, n=8,865

	Pre: July 2007-June 2010	SD Pre	Post: July 2010 - June 2012	SD Post	Significant difference
#30-day fills	7.33	8.14	8.57	9.27	
# Generic fills	3.24	4.29	4.06	5.17	***
# Brand fills	2.41	3.44	2.08	3.18	***
Outpatient visits	2.75	3.94	2.83	4.14	***
ED visits	0.06	0.24	0.08	0.27	***
Inpatient visits	0.19	0.39	0.14	0.34	***
ACSC admissions	0.06	0.23	0.04	0.20	***
30-day visits	0.05	0.23	0.03	0.18	***
Rx spending	967	1825	1108	2287	***
Medical spending	3047	28352	4262	28230	***
Total spending	169	229	192	276	***
Plan spending	3502	28239	4688	28034	***

*** p<0.01, ** p<0.05, * p<0.1

Table 2.11.4: Results, Drug and outpatient outcomes, quarterly.

Variable	# 30-day fills	Generic	Brand	Outpatient
Time trend	0.031***	-0.001	0.024***	0.032***
	[0.028 - 0.034]	[-0.005 - 0.002]	[0.021 - 0.028]	[0.023 - 0.042]
Policy change	**0.107*** **	**0.091*** **	**0.025**	**0.325*** **
	[0.080 - 0.135]	[0.060 - 0.122]	[-0.018 - 0.067]	[0.202 - 0.449]
Post-time trend	**-0.042*** **	**-0.047*** **	**-0.064*** **	**-0.038*** **
	[-0.048 - -0.036]	[-0.054 - -0.040]	[-0.072 - -0.055]	[-0.061 - -0.015]
Quarter 2	0.034***	0.036***	0.033***	-0.007
	[0.025 - 0.043]	[0.027 - 0.045]	[0.019 - 0.048]	[-0.061 - 0.047]
Quarter 3	0.033***	0.020***	0.041***	0.015
	[0.023 - 0.043]	[0.010 - 0.030]	[0.025 - 0.057]	[-0.042 - 0.071]
Quarter 4	0.044***	0.045***	0.062***	-0.001
	[0.034 - 0.054]	[0.034 - 0.055]	[0.046 - 0.079]	[-0.060 - 0.058]
Age	0.007***	0.005***	-0.002***	-0.032***
	[0.005 - 0.009]	[0.003 - 0.007]	[-0.004 - -0.001]	[-0.035 - -0.029]
Gender	0.115***	-0.111***	0.252***	0.064**
	[0.074 - 0.156]	[-0.160 - -0.063]	[0.219 - 0.285]	[0.002 - 0.126]
Plan type (PPO $500, reference)				
MHIP+	0.021	0.031	0.017	0.047
	[-0.015 - 0.057]	[-0.008 - 0.070]	[-0.021 - 0.055]	[-0.029 - 0.123]
PPO $1000	-0.051**	-0.094***	-0.116***	-0.117***
	[-0.092 - -0.011]	[-0.145 - -0.043]	[-0.158 - -0.073]	[-0.205 - -0.029]
HDHP	-0.190***	-0.253***	-0.165***	-0.231***
	[-0.238 - -0.141]	[-0.312 - -0.194]	[-0.208 - -0.121]	[-0.321 - -0.141]
HMO	0.038	0.401***	-0.061**	0.285***
	[-0.044 - 0.119]	[0.304 - 0.498]	[-0.117 - -0.005]	[0.174 - 0.396]
Number of chronic conditions, continuous	0.111***	0.099***	0.119***	0.146***
	[0.107 - 0.115]	[0.094 - 0.103]	[0.115 - 0.122]	[0.138 - 0.154]
CC * Policy change	**0.003***	**-0.004** **	**0.009*** **	**-0.004**
	[-0.000 - 0.006]	[-0.007 - -0.001]	[0.005 - 0.013]	[-0.015 - 0.008]
CC * Post time trend	**0**	**0**	**0**	**-0.001**
	[-0.000 - 0.001]	[-0.000 - 0.001]	[-0.000 - 0.001]	[-0.003 - 0.001]
Constant	-0.310***	-0.066	-0.069*	-2.535***
	[-0.413 - -0.208]	[-0.176 - 0.044]	[-0.152 - 0.013]	[-2.687 - -2.383]
Observations	151,284	151,284	151,284	151,284
Number of subid	8,865	8,865	8,865	8,865

ci in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 2.11.5: Results, Emergency department and inpatient outcomes, quarterly.

Variable	Emergency department	Inpatient	ACSC Admission	30-day readmission
Time trend	0.066***	0.065***	0.069***	0.042***
	[0.059 - 0.073]	[0.054 - 0.077]	[0.057 - 0.080]	[0.037 - 0.048]
Policy change	**-0.134*** **	**-0.001**	**-0.367*** **	**0.026**
	[-0.230 - -0.038]	[-0.156 - 0.154]	[-0.549 - -0.185]	[-0.031 - 0.084]
Post-time trend	**-0.229*** **	**-0.206*** **	**-0.207*** **	**-0.040*** **
	[-0.248 - -0.209]	[-0.236 - -0.175]	[-0.244 - -0.170]	[-0.055 - -0.024]
Quarter 2	0.062***	0.037	-0.060*	0.027***
	[0.026 - 0.099]	[-0.025 - 0.100]	[-0.122 - 0.002]	[0.011 - 0.043]
Quarter 3	-0.042**	-0.075**	-0.055	0.040***
	[-0.082 - -0.003]	[-0.143 - -0.007]	[-0.124 - 0.014]	[0.021 - 0.058]
Quarter 4	0.078***	-0.035	0.011	0.071***
	[0.038 - 0.119]	[-0.107 - 0.036]	[-0.059 - 0.080]	[0.052 - 0.090]
Age	-0.011***	-0.006***	-0.024***	-0.004
	[-0.013 - -0.009]	[-0.010 - -0.002]	[-0.028 - -0.020]	[-0.008 - 0.001]
Gender	0.135***	-0.126***	0.028	-0.361***
	[0.083 - 0.186]	[-0.209 - -0.043]	[-0.065 - 0.121]	[-0.481 - -0.241]
Plan type (PPO $500, reference)				
MHIP+	0.006	0.182***	0.011	0.054*
	[-0.058 - 0.070]	[0.081 - 0.282]	[-0.100 - 0.122]	[-0.005 - 0.114]
PPO $1000	-0.087**	0.055	-0.114*	-0.129***
	[-0.159 - -0.015]	[-0.060 - 0.171]	[-0.244 - 0.017]	[-0.199 - -0.059]
HDHP	-0.132***	-0.182***	-0.155**	-0.292***
	[-0.206 - -0.059]	[-0.301 - -0.063]	[-0.288 - -0.021]	[-0.381 - -0.204]
HMO	0.175***	0.255***	0.131	0.766***
	[0.082 - 0.268]	[0.110 - 0.400]	[-0.035 - 0.297]	[0.657 - 0.876]
Number of chronic conditions, continuous	0.153***	0.175***	0.185***	0.047***
	[0.147 - 0.159]	[0.165 - 0.184]	[0.175 - 0.194]	[0.036 - 0.058]
CC * Policy change	**0.035*** **	**0.005**	**0.028*** **	**0.003**
	[0.024 - 0.046]	[-0.008 - 0.019]	[0.013 - 0.043]	[-0.005 - 0.011]
CC * Post time trend	**-0.005*** **	**0**	**-0.003***	**-0.001**
	[-0.007 - -0.003]	[-0.002 - 0.003]	[-0.006 - 0.000]	[-0.003 - 0.001]
Constant	-2.567***	-4.438***	-3.676***	6.402***
	[-2.700 - -2.434]	[-4.671 - -4.205]	[-3.905 - -3.447]	[6.170 - 6.634]
Observations	151,284	151,284	151,284	151,284
Number of subid	8,865	8,865	8,865	8,865

ci in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 2.11.6: Results, Spending outcomes, quarterly.

Variable	Rx Spending	Medical spending	Total spending	Out-of-pocket spending
Time trend	0.049***	0.043***	0.018***	0.025***
	[0.025 - 0.073]	[0.026 - 0.059]	[0.013 - 0.023]	[0.022 - 0.027]
Policy change	**-0.212**	**-0.199***	**0.328*****	**0.095*****
	[-0.519 - 0.094]	[-0.414 - 0.016]	[0.279 - 0.377]	[0.072 - 0.119]
Post-time trend	**0**	**-0.005**	**-0.042*****	**-0.037*****
	[-0.081 - 0.082]	[-0.063 - 0.052]	[-0.057 - -0.027]	[-0.047 - -0.027]
Quarter 2	-0.071	-0.05	-0.394***	0.026***
	[-0.375 - 0.233]	[-0.265 - 0.166]	[-0.419 - -0.368]	[0.017 - 0.034]
Quarter 3	-0.107	-0.075	-0.648***	0.015***
	[-0.373 - 0.159]	[-0.265 - 0.115]	[-0.680 - -0.615]	[0.007 - 0.023]
Quarter 4	-0.128	-0.073	-0.772***	0.056***
	[-0.399 - 0.142]	[-0.266 - 0.120]	[-0.808 - -0.736]	[0.046 - 0.065]
Age	-0.021***	-0.016***	0	0.018***
	[-0.031 - -0.010]	[-0.024 - -0.009]	[-0.003 - 0.003]	[0.015 - 0.020]
Gender	0.081	-0.012	-0.151***	-0.054**
	[-0.084 - 0.246]	[-0.130 - 0.106]	[-0.222 - -0.080]	[-0.106 - -0.003]
Plan type (PPO $500, reference)				
MHIP+	0.127	0.051	-0.333***	0.063***
	[-0.137 - 0.391]	[-0.138 - 0.241]	[-0.389 - -0.278]	[0.028 - 0.099]
PPO $1000	-0.043	-0.118**	0.174***	-0.006
	[-0.170 - 0.083]	[-0.212 - -0.025]	[0.120 - 0.229]	[-0.046 - 0.034]
HDHP	-0.034	-0.266***	0.509***	-0.126***
	[-0.233 - 0.164]	[-0.411 - -0.121]	[0.427 - 0.592]	[-0.180 - -0.072]
HMO	0.059	0.783***	0.994***	0.074**
	[-0.143 - 0.260]	[0.685 - 0.880]	[0.913 - 1.075]	[0.000 - 0.149]
Number of chronic conditions, continuous	0.225***	0.187***	0.065***	0.062***
	[0.207 - 0.243]	[0.174 - 0.200]	[0.057 - 0.072]	[0.056 - 0.067]
CC * Policy change	**0.039*****	**0.035*****	**-0.005**	**0.003****
	[0.012 - 0.066]	[0.016 - 0.055]	[-0.012 - 0.002]	[0.000 - 0.006]
CC * Post time trend	**-0.004**	**-0.003**	**-0.001**	**-0.001**
	[-0.010 - 0.002]	[-0.007 - 0.002]	[-0.003 - 0.000]	[-0.002 - 0.000]
Constant	6.716***	7.228***	4.528***	0.497***
	[5.800 - 7.631]	[6.575 - 7.881]	[4.357 - 4.700]	[0.363 - 0.631]
Observations	151,284	151,284	151,284	151,284
Number of subid	8,865	8,865	8,865	8,865

ci in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 2.11.7: Marginal effects for drug and outpatient, by number of chronic conditions.

	30-day fills			Generic fills		
Number of chronic conditions	Q12 (Pre)	Q13 (difference from pre)	Q16 (difference from pre)	Q12 (Pre)	Q13 (difference)	Q16 (difference)
0	5.41***	0.38***	0.37***	1.63***	0.15***	0.14***
	[0.125]	[0.065]	[0.061]	[0.032]	[0.023]	[0.022]
2	6.12***	0.47***	0.46***	2.03***	0.20***	0.19***
	[0.114]	[0.061]	[0.057]	[0.034]	[0.025]	[0.024]
4	6.92***	0.58***	0.56***	2.54***	0.26***	0.25***
	[0.101]	[0.058]	[0.054]	[0.036]	[0.027]	[0.025]
6	7.82***	0.70***	0.68***	3.17***	0.34***	0.34***
	[0.090]	[0.058]	[0.054]	[0.040]	[0.030]	[0.028]
8	8.85***	0.85***	0.81***	3.95***	0.45***	0.45***
	[0.092]	[0.063]	[0.059]	[0.048]	[0.037]	[0.035]
10	10.00***	1.03***	0.98***	4.93***	0.60***	0.59***
	[0.118]	[0.078]	[0.072]	[0.066]	[0.050]	[0.048]
12	11.31***	1.23***	1.17***	6.16***	0.78***	0.77***
	[0.169]	[0.104]	[0.094]	[0.095]	[0.072]	[0.069]
14	12.79***	1.48***	1.39***	7.68***	1.02***	1.02***
	[0.244]	[0.141]	[0.126]	[0.140]	[0.107]	[0.103]
	Brand fills			**Outpatient visits**		
Number of chronic conditions	Q12 (Pre)	Q13 (difference)	Q16 (difference)	Q12 (Pre)	Q13 (difference)	Q16 (difference)
0	1.13***	0.08***	0.07***	1.26***	-0.01	-0.01
	[0.025]	[0.017]	[0.015]	[0.022]	[0.025]	[0.023]
2	1.37***	0.09***	0.08***	1.60***	0.02	0.02
	[0.027]	[0.018]	[0.015]	[0.024]	[0.028]	[0.025]
4	1.67***	0.10***	0.08***	2.03***	0.06*	0.05*
	[0.028]	[0.019]	[0.016]	[0.026]	[0.031]	[0.028]
6	2.04***	0.10***	0.09***	2.58***	0.12***	0.11***
	[0.030]	[0.020]	[0.018]	[0.031]	[0.036]	[0.032]
8	2.48***	0.10***	0.09***	3.26***	0.21***	0.19***
	[0.035]	[0.024]	[0.021]	[0.039]	[0.043]	[0.039]
10	3.02***	0.11***	0.09***	4.14***	0.34***	0.31***
	[0.046]	[0.032]	[0.028]	[0.053]	[0.057]	[0.051]
12	3.69***	0.10**	0.09**	5.25***	0.53***	0.48***
	[0.063]	[0.044]	[0.039]	[0.076]	[0.082]	[0.072]
14	4.49***	0.09	0.08	6.65***	0.79***	0.73***
	[0.090]	[0.063]	[0.056]	[0.111]	[0.121]	[0.107]

*** p<0.01, ** p<0.05, * p<0.1. Standard error in brackets.

Table 2.11.8: Marginal effects for inpatient utilization and spending, by number of chronic conditions.

	ED visit (probability of)			Inpatient Visit (probability)		
Number of chronic conditions	Q12 (Pre)	Q13 (difference)	Q16 (difference)	Q12 (Pre)	Q13 (difference)	Q16 (difference)
0	0.03***	0.01***	0.01***	0.10***	-0.01***	-0.01***
	[0.001]	[0.002]	[0.002]	[0.003]	[0.003]	[0.002]
2	0.03***	0.01***	0.01***	0.13***	-0.01**	-0.01**
	[0.001]	[0.002]	[0.002]	[0.003]	[0.004]	[0.002]
4	0.05***	0.01***	0.01***	0.16***	0	0
	[0.001]	[0.002]	[0.002]	[0.003]	[0.004]	[0.003]
6	0.06***	0.02***	0.02***	0.21***	0.01**	0.01**
	[0.002]	[0.003]	[0.002]	[0.003]	[0.004]	[0.003]
8	0.08***	0.02***	0.02***	0.27***	0.02***	0.02***
	[0.002]	[0.003]	[0.003]	[0.004]	[0.005]	[0.003]
10	0.10***	0.03***	0.03***	0.33***	0.04***	0.03***
	[0.003]	[0.004]	[0.004]	[0.005]	[0.007]	[0.005]
12	0.13***	0.03***	0.03***	0.40***	0.06***	0.05***
	[0.004]	[0.005]	[0.005]	[0.006]	[0.009]	[0.007]
14	0.17***	0.04***	0.04***	0.47***	0.08***	0.07***
	[0.005]	[0.008]	[0.007]	[0.007]	[0.011]	[0.009]
	ACSC Visits (probability)			**30-day readmissions (probability)**		
Number of chronic conditions	Q12 (Pre)	Q13 (difference)	Q16 (difference)	Q12 (Pre)	Q13 (difference)	Q16 (difference)
0	0.02***	0	0	0.02***	-0.00***	-0.00***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
2	0.03***	0	0	0.02***	-0.01***	-0.00***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
4	0.04***	0	0	0.04***	-0.01***	-0.00***
	[0.001]	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]
6	0.05***	0	0	0.05***	-0.01***	-0.01***
	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]	[0.002]
8	0.07***	0.00*	0.00*	0.07***	-0.01***	-0.01***
	[0.002]	[0.003]	[0.002]	[0.002]	[0.003]	[0.002]
10	0.10***	0.01*	0.00**	0.10***	-0.01*	-0.00*
	[0.003]	[0.004]	[0.002]	[0.003]	[0.004]	[0.003]
12	0.13***	0.01*	0.01**	0.14***	0	0
	[0.004]	[0.005]	[0.004]	[0.005]	[0.005]	[0.004]
14	0.18***	0.01*	0.01*	0.19***	0	0
	[0.006]	[0.008]	[0.006]	[0.007]	[0.008]	[0.006]

*** p<0.01, ** p<0.05, * p<0.1. Standard error in brackets.

Table 2.11.9: Marginal effects for spending, by number of chronic conditions.

	Rx spending			Medical spending		
Number of chronic conditions	Q12 (Pre)	Q13 (difference)	Q16 (difference)	Q12 (Pre)	Q13 (difference)	Q16 (difference)
0	769.52***	-10.43	-10.69	536.82***	-77.38	-87.37
	[37.014]	[22.787]	[23.494]	[43.247]	[56.173]	[68.578]
2	843.58***	-6.17	-6.29	841.43***	-58.81	-64.89
	[32.313]	[19.524]	[19.966]	[54.245]	[70.598]	[81.153]
4	924.76***	-0.97	-0.98	1,318.88***	12.14	13.09
	[27.520]	[16.714]	[16.960]	[66.950]	[89.876]	[96.396]
6	1,013.76***	5.31	5.36	2,067.26***	193.3	203.71
	[24.179]	[16.108]	[16.222]	[86.543]	[129.724]	[131.299]
8	1,111.33***	12.82	12.87	3,240.28***	594.25**	612.03***
	[25.267]	[19.752]	[19.723]	[132.940]	[232.677]	[230.778]
10	1,218.29***	21.75	21.73	5,078.92***	1,418.53***	1,427.79***
	[32.912]	[27.777]	[27.483]	[247.192]	[471.197]	[461.466]
12	1,335.53***	32.31	32.11	7,960.84***	3,038.33***	2,988.72***
	[46.410]	[39.336]	[38.570]	[491.338]	[964.800]	[924.532]
14	1,464.07***	44.72	44.22	12,478.06***	6,126.28***	5,889.37***
	[64.654]	[54.034]	[52.516]	[966.923]	[1,929.301]	[1,798.997]
	Total spending			**Copayment**		
Number of chronic conditions	Q12 (Pre)	Q13 (difference)	Q16 (difference)	Q12 (Pre)	Q13 (difference)	Q16 (difference)
0	1,043.00***	-161.53**	-177.77**	104.61***	80.84***	63.41***
	[54.137]	[73.637]	[88.355]	[2.951]	[3.607]	[2.155]
2	1,515.06***	-135.72	-146.94	117.54***	90.16***	69.98***
	[62.382]	[85.435]	[97.646]	[2.584]	[3.228]	[1.954]
4	2,200.77***	-44.6	-47.5	132.06***	100.54***	77.23***
	[72.397]	[101.168]	[109.086]	[2.191]	[2.870]	[1.790]
6	3,196.82***	170.56	178.71	148.38***	112.12***	85.22***
	[93.450]	[138.359]	[141.538]	[1.943]	[2.735]	[1.769]
8	4,643.68***	610.96***	629.77***	166.71***	125.03***	94.05***
	[147.753]	[235.644]	[235.500]	[2.186]	[3.129]	[2.025]
10	6,745.38***	1,448.21***	1,468.57***	187.32***	139.43***	103.78***
	[266.063]	[445.705]	[439.041]	[3.115]	[4.214]	[2.622]
12	9,798.31***	2,969.61***	2,962.48***	210.46***	155.49***	114.53***
	[488.419]	[844.709]	[816.140]	[4.637]	[5.945]	[3.544]
14	14,232.96***	5,651.33***	5,546.22***	236.47***	173.39***	126.38***
	[877.291]	[1,559.594]	[1,472.606]	[6.682]	[8.272]	[4.771]

*** p<0.01, ** p<0.05, * p<0.1. Standard error in brackets.

Table 2.11.10: Sensitivity analysis, removing the post-time trend, drug and outpatient outcomes, coefficients and 95% confidence intervals.

Variable	# 30-day fills	Generic	Brand	Outpatient
Time trend	0.009***	0.020***	-0.013***	0.008***
	[0.006 - 0.011]	[0.018 - 0.022]	[-0.015 - -0.010]	[0.005 - 0.010]
Number of chronic conditions, continuous	0.060***	0.110***	0.098***	0.118***
	[0.054 - 0.066]	[0.106 - 0.114]	[0.094 - 0.103]	[0.115 - 0.122]
Policy change	0.054***	0.016	-0.015	-0.112***
	[0.015 - 0.094]	[-0.010 - 0.041]	[-0.044 - 0.014]	[-0.148 - -0.076]
CC * Policy change	0	0.005***	-0.002	0.011***
	[-0.003 - 0.004]	[0.003 - 0.008]	[-0.004 - 0.001]	[0.008 - 0.014]
Quarter 2	0.015***	0.025***	0.025***	0.019**
	[0.006 - 0.024]	[0.016 - 0.034]	[0.016 - 0.034]	[0.004 - 0.033]
Quarter 3	-0.008*	0.016***	0.001	0.013
	[-0.016 - 0.001]	[0.006 - 0.026]	[-0.009 - 0.011]	[-0.003 - 0.029]
Quarter 4	0.024***	0.020***	0.019***	0.029***
	[0.014 - 0.033]	[0.010 - 0.030]	[0.008 - 0.030]	[0.012 - 0.045]
Age	0.019***	0.008***	0.005***	-0.002***
	[0.016 - 0.022]	[0.006 - 0.010]	[0.003 - 0.007]	[-0.004 - -0.001]
Gender	-0.059**	0.115***	-0.109***	0.252***
	[-0.113 - -0.005]	[0.074 - 0.156]	[-0.157 - -0.061]	[0.220 - 0.285]
Plan type (PPO $500, reference)				
MHIP+	0.074***	0.026	0.037*	0.025
	[0.038 - 0.110]	[-0.009 - 0.061]	[-0.001 - 0.076]	[-0.012 - 0.063]
PPO $1000	0.007	-0.045**	-0.086***	-0.108***
	[-0.033 - 0.048]	[-0.085 - -0.006]	[-0.136 - -0.036]	[-0.150 - -0.066]
HDHP	-0.110***	-0.187***	-0.249***	-0.159***
	[-0.167 - -0.054]	[-0.235 - -0.140]	[-0.307 - -0.191]	[-0.202 - -0.115]
HMO	0.075**	0.038	0.402***	-0.058**
	[0.000 - 0.149]	[-0.042 - 0.118]	[0.305 - 0.498]	[-0.114 - -0.002]
Constant	0.583***	-0.222***	0.041	0.077*
	[0.445 - 0.721]	[-0.324 - -0.121]	[-0.067 - 0.149]	[-0.003 - 0.158]
Observations	151,284	151,284	151,284	151,284
Number of subid	8,865	8,865	8,865	8,865

ci in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 2.11.14: Sensitivity analysis, removing the post-time trend, emergency department and inpatient outcomes, coefficients and 95% confidence intervals.

Variable	Emergency department	Inpatient	ACSC Admission	30-day readmission
Time trend	0.017***	0.008***	0.020***	0.024***
	[0.009 - 0.025]	[0.003 - 0.013]	[0.010 - 0.029]	[0.014 - 0.034]
Number of chronic conditions, continuous	0.145***	0.149***	0.172***	0.181***
	[0.138 - 0.153]	[0.143 - 0.155]	[0.163 - 0.181]	[0.172 - 0.191]
Policy change	0.288***	-0.586***	-0.475***	-0.852***
	[0.185 - 0.390]	[-0.667 - -0.506]	[-0.606 - -0.344]	[-1.005 - -0.700]
CC * Policy change	-0.009**	0.016***	0.007	0.018***
	[-0.017 - -0.001]	[0.009 - 0.022]	[-0.003 - 0.016]	[0.008 - 0.029]
Quarter 2	-0.019	-0.001	-0.013	-0.114***
	[-0.073 - 0.035]	[-0.037 - 0.034]	[-0.074 - 0.049]	[-0.175 - -0.053]
Quarter 3	-0.009	-0.156***	-0.164***	-0.150***
	[-0.064 - 0.047]	[-0.194 - -0.117]	[-0.230 - -0.098]	[-0.217 - -0.084]
Quarter 4	-0.034	-0.071***	-0.151***	-0.112***
	[-0.092 - 0.024]	[-0.110 - -0.032]	[-0.219 - -0.083]	[-0.178 - -0.046]
Age	-0.032***	-0.011***	-0.006***	-0.024***
	[-0.035 - -0.029]	[-0.013 - -0.009]	[-0.010 - -0.001]	[-0.028 - -0.019]
Gender	0.065**	0.132***	-0.121***	0.031
	[0.003 - 0.127]	[0.082 - 0.183]	[-0.204 - -0.039]	[-0.061 - 0.123]
Plan type (PPO $500, reference)				
MHIP+	0.051	0.034	0.202***	0.033
	[-0.025 - 0.128]	[-0.030 - 0.099]	[0.102 - 0.301]	[-0.078 - 0.143]
PPO $1000	-0.114**	-0.067*	0.063	-0.1
	[-0.202 - -0.026]	[-0.138 - 0.004]	[-0.051 - 0.178]	[-0.228 - 0.029]
HDHP	-0.227***	-0.111***	-0.169***	-0.155**
	[-0.317 - -0.138]	[-0.183 - -0.039]	[-0.286 - -0.051]	[-0.286 - -0.024]
HMO	0.286***	0.190***	0.271***	0.136
	[0.176 - 0.397]	[0.100 - 0.281]	[0.127 - 0.416]	[-0.028 - 0.299]
Constant	-2.399***	-2.033***	-4.018***	-3.249***
	[-2.544 - -2.253]	[-2.159 - -1.908]	[-4.241 - -3.795]	[-3.464 - -3.033]
Observations	151,284	151,284	151,284	151,284
Number of subid	8,865	8,865	8,865	8,865

ci in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 2.11.13 Sensitivity analysis, removing the post-time trend, spending outcomes, coefficients and 95% confidence intervals.

Variable	Rx Spending	Medical spending	Total spending	Out-of-pocket spending
Time trend	0.024***	0.043***	0.037***	-0.002
	[0.020 - 0.029]	[0.025 - 0.061]	[0.024 - 0.050]	[-0.006 - 0.002]
Number of chronic conditions, continuous	0.046***	0.225***	0.187***	0.065***
	[0.036 - 0.057]	[0.207 - 0.243]	[0.174 - 0.200]	[0.058 - 0.072]
Policy change	-0.018	-0.157	-0.171**	0.352***
	[-0.077 - 0.040]	[-0.373 - 0.059]	[-0.323 - -0.019]	[0.311 - 0.392]
CC * Policy change	0	0.022	0.023**	-0.009***
	[-0.006 - 0.006]	[-0.007 - 0.052]	[0.002 - 0.044]	[-0.012 - -0.005]
Quarter 2	0.017**	-0.077	-0.055	-0.419***
	[0.002 - 0.032]	[-0.373 - 0.219]	[-0.265 - 0.155]	[-0.445 - -0.392]
Quarter 3	0.019**	-0.115	-0.083	-0.699***
	[0.002 - 0.036]	[-0.358 - 0.129]	[-0.256 - 0.090]	[-0.733 - -0.664]
Quarter 4	0.041***	-0.137	-0.083	-0.850***
	[0.022 - 0.060]	[-0.377 - 0.102]	[-0.253 - 0.088]	[-0.890 - -0.811]
Age	-0.003	-0.021***	-0.016***	0
	[-0.007 - 0.002]	[-0.031 - -0.010]	[-0.023 - -0.009]	[-0.003 - 0.003]
Gender	-0.367***	0.079	-0.013	-0.153***
	[-0.488 - -0.245]	[-0.084 - 0.242]	[-0.130 - 0.103]	[-0.227 - -0.080]
Plan type (PPO $500, reference)				
MHIP+	0.052*	0.128	0.052	-0.340***
	[-0.006 - 0.110]	[-0.129 - 0.385]	[-0.132 - 0.237]	[-0.398 - -0.282]
PPO $1000	-0.111***	-0.044	-0.119**	0.193***
	[-0.180 - -0.042]	[-0.170 - 0.081]	[-0.212 - -0.025]	[0.137 - 0.250]
HDHP	-0.263***	-0.035	-0.267***	0.551***
	[-0.349 - -0.177]	[-0.231 - 0.161]	[-0.410 - -0.124]	[0.466 - 0.637]
HMO	0.728***	0.059	0.783***	1.015***
	[0.616 - 0.840]	[-0.142 - 0.260]	[0.685 - 0.880]	[0.933 - 1.097]
Constant	6.554***	6.762***	7.274***	4.632***
	[6.321 - 6.787]	[5.935 - 7.590]	[6.685 - 7.864]	[4.463 - 4.801]
Observations	151,284	151,284	151,284	151,284
Number of subid	8,865	8,865	8,865	8,865

ci in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 2.11.17: Sensitivity analysis, marginal effects, difference in outcomes attributable to the policy change, by number of chronic conditions.

	Number of chronic conditions							
Outcome	**0**	**2**	**4**	**6**	**8**	**10**	**12**	**14**
30-day fills, difference post vs. pre	0.29	0.33	0.37	0.43	0.49	0.56	0.64	0.73
Significance of difference	***	***	***	***	***	***	***	***
Generic fills	0.02	0.05 **	0.09 ***	0.14 ***	0.22 ***	0.33 ***	0.47 ***	0.67 ***
Brand fills	-0.02	-0.02	-0.03 *	-0.05 **	-0.07 ***	-0.09 ***	-0.12 ***	-0.16 ***
Outpatient visits	-0.12 ***	-0.13 ***	-0.12 ***	-0.11 ***	-0.07	0.00	0.10	0.27 ***
ED visit (probability of)	0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.02 ***	0.02 ***	0.02 ***	0.02 ***
Inpatient Visit (probability)	-0.03 ***	-0.04 ***	-0.05 ***	-0.06 ***	-0.07 ***	-0.08 ***	-0.08 ***	-0.08 ***
ACSC Visits (probability)	-0.01 ***	-0.01 ***	-0.01 ***	-0.01 ***	-0.02 ***	-0.03 ***	-0.03 ***	-0.04 ***
30-day readmissions (probability)	-0.01 ***	-0.01 ***	-0.02 ***	-0.02 ***	-0.03 ***	-0.04 ***	-0.05 ***	-0.06 ***
Rx spending	-13	-15	-17	-19	-21	-23	-26	-29
Medical spending	-77	-88	-85	-46	72	350	936	2105
Total spending	-161	-174	-161	-95	75	432	1121	2379
Copay	33 ***	36 ***	38 ***	40 ***	43 ***	46 ***	48 ***	50 ***

*** p<0.01, ** p<0.05, * p<0.10

Table 2.11.18: Distribution of insurance plan types, FY 10

Distribution of Plan Types, FY10

		Under OOP Max	Over OOP Max	Total
MHIP+	N	1,245	156	1,401
	%	16	18	16
PPO $500	N	1,985	105	2,090
	%	24	12	24
PPO $1000	N	1,932	33	1,965
	%	24	4	22
HDHP	N	2,370	52	2,422
	%	30	6	27
HMO	N	469	518	987
	%	5.86	59.95	11
Total	N	8,001	864	8,865
	%	100	100	100

Note: The OOP max in FY2010 for MHIP+=$1500, HDHP=4600 (combined medical and drug), all others = $2000.

Table 2.11.20: Marginal effects for the policy change for those under the out-of-pocket maximum.

Change in outcome, post period vs. pre period.

	Number of chronic conditions							
Outcome	0	2	4	6	8	10	12	14
30-day fills	0.22	0.24 *	0.26 **	0.27 ***	0.29 ***	0.31 ***	0.33 ***	0.35 **
Generic fills	0.02	0.04 *	0.08 ***	0.12 ***	0.19 ***	0.27 ***	0.39 ***	0.55 ***
Brand fills	-0.10 ***	-0.11 ***	-0.13 ***	-0.15 ***	-0.17 ***	-0.20 ***	-0.22 ***	-0.25 ***
Outpatient visits	-0.12 ***	-0.13 ***	-0.13 ***	-0.12 ***	-0.09 **	-0.03	0.06	0.20 **
ED visit (probability of)	0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.02 ***	0.02 ***	0.02 ***	0.02 ***
Inpatient Visit (probability)	-0.03 ***	-0.04 ***	-0.05 ***	-0.06 ***	-0.07 ***	-0.08 ***	-0.09 ***	-0.09 ***
ACSC Visits (probability)	-0.01 ***	-0.01 ***	-0.01 ***	-0.01 ***	-0.02 ***	-0.03 ***	-0.04 ***	-0.05 ***
30-day readmissions (probability)	-0.01 ***	-0.01 ***	-0.02 ***	-0.02 ***	-0.03 ***	-0.04 ***	-0.05 ***	-0.07 ***
Rx spending	-150 ***	-155 ***	-161 ***	-166 ***	-170 ***	-174 ***	-177 ***	-180 ***
Medical spending	-73	-85	-83	-48	61	322	881	2004
Total spending	-215 ***	-244 ***	-247 **	-192	-20	374	1172	2679
Copay	14 ***	15 ***	16 ***	17 ***	17 ***	18 ***	18 ***	19 ***

*** p<0.01, ** p<0.05, * p<0.10

Table 2.11.21: Descriptive characteristics continuously enrolled vs those who are not, after dropping those enrolled completely outside study period.

Sample characteristics, continuously enrolled vs not, after dropping those enrolled completely outside study period, N= 17,664 (column percents)[a]

	Enrolled	Not Enrolled
Total	8,983	8,681
	51	49
Age[b]		
18-39, N	1,670	2,440
%	19	28
40-54	2,609	2,387
%	29	28
55+	4,704	3,854
%	52	44
Chronic Conditions		
0	599	1,295
	7	15
1-2	1,450	2,284
	16	27
3-5	2,532	2,591
	28	30
6-9	2,540	1,596
	28	19
10+	1,834	780
	20	9
Gender		
Male	4,025	3,694
%	45	43
Female	4,958	4,946
%	55	57
Percent with any utilization		
Outpatient	8,848	8,363
%	99	96
Inpatient	6,760	4,977
%	75	57
ED	4,823	3,223
%	54	37
Rx	8,548	7,891
%	95	91

[a.] All comparisons have chi-squared significance levels of <0.01.

[b.] Includes those enrolled for at least the three months prior to the coverage change and who may have dropped coverage at anytime in the following year.

2.12 FIGURES

Figure 2.12.1: Conceptual Model

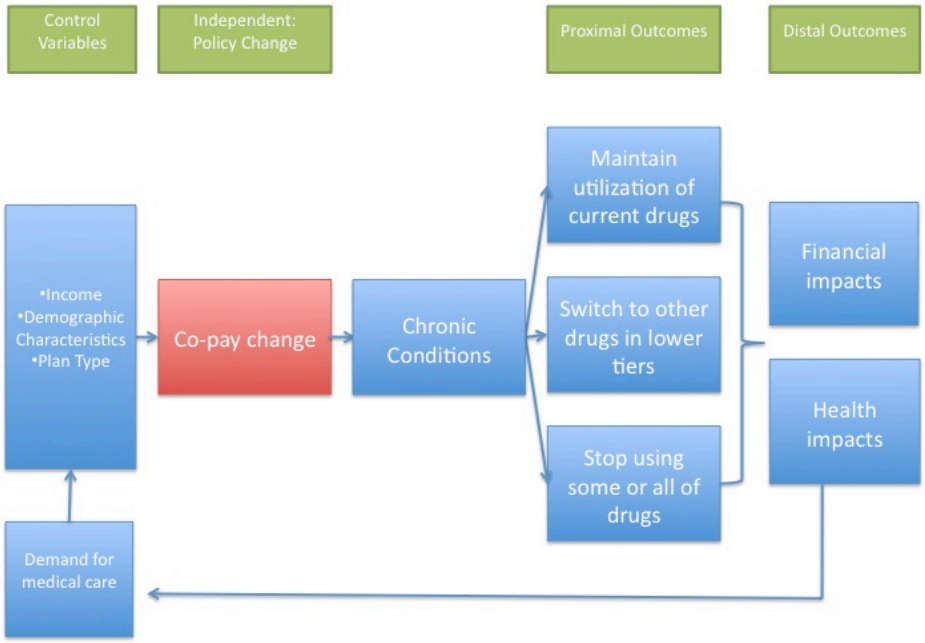


Figure 2.12.2: Dataset Construction

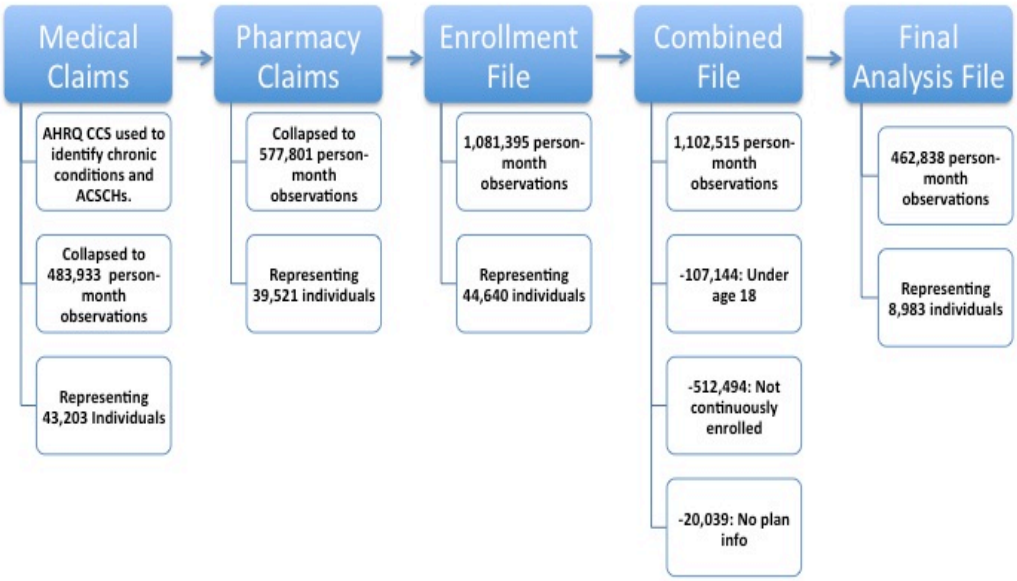


Figure 2.12.3: Drug Use by Quarter, 2007-2012

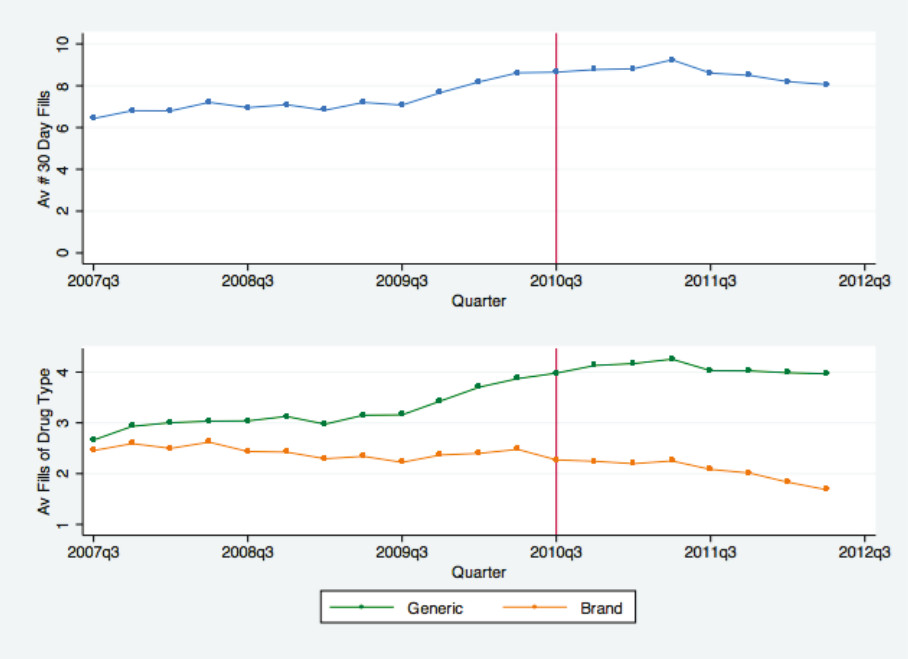


Figure 2.12.4: Proportion with Any Hospital Visit and Average Number of Outpatient Visits, Quarterly 2007-2012

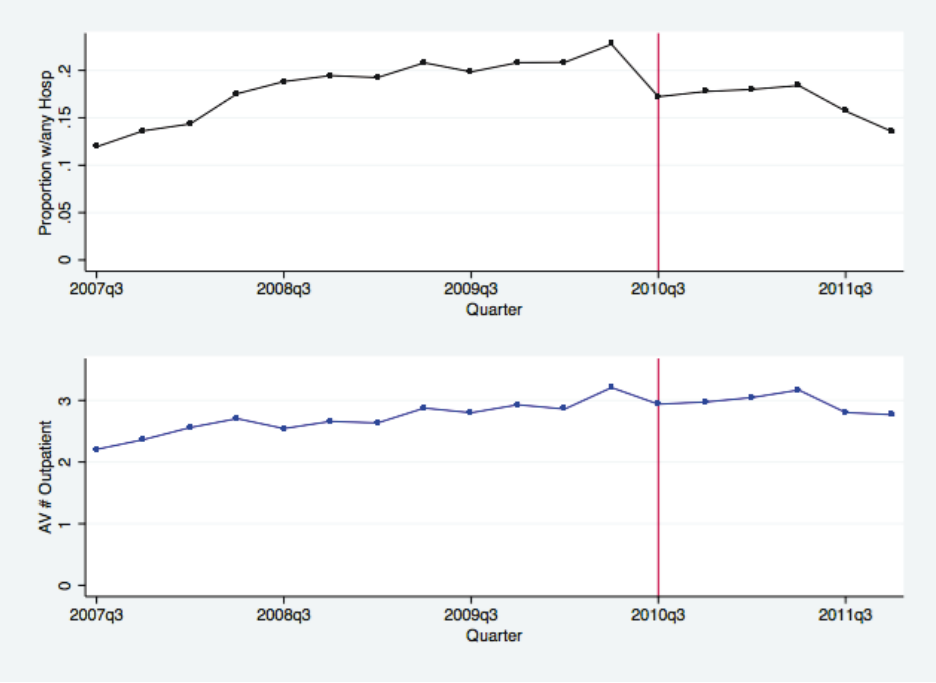


Figure 2.12.5: Quarterly average spending, 2007-2012.

Figure 2.12.6: Generics as a percent of all drugs filled, monthly average, 2007-2012

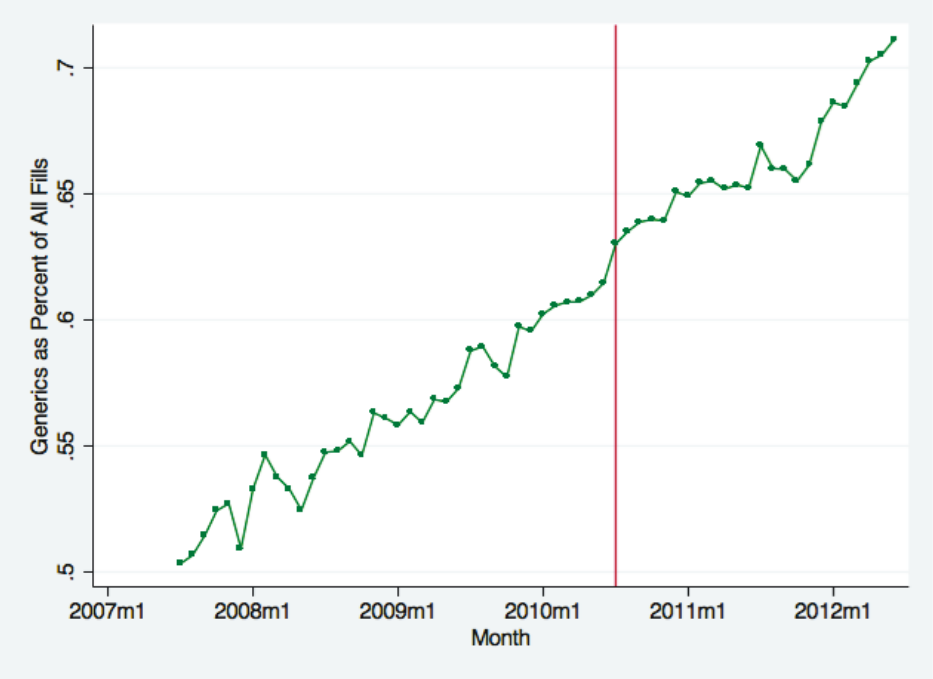


Figure 2.12.7: Number of 30-day fills by the number of chronic conditions, quarterly.

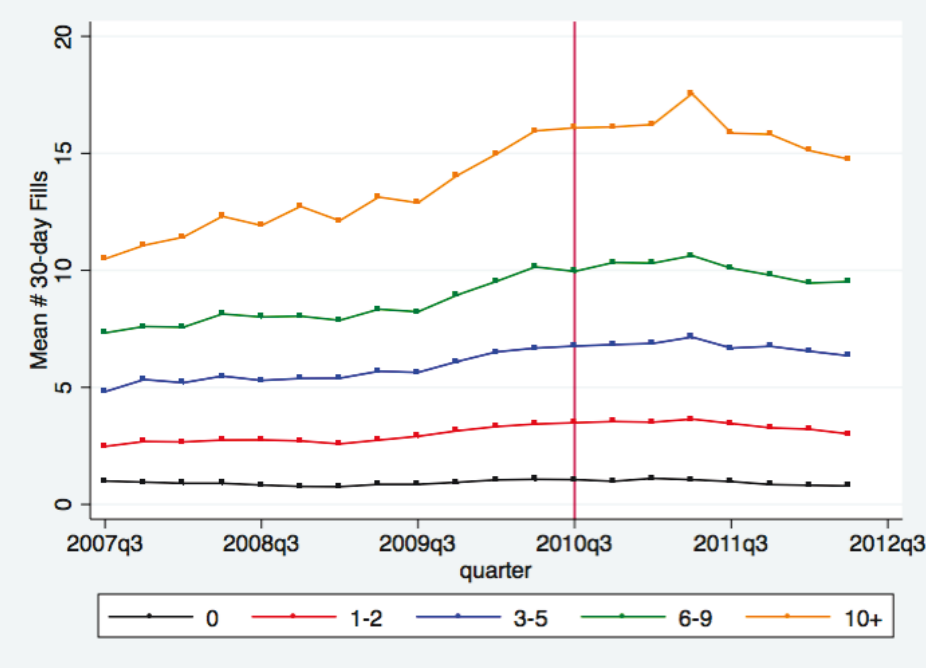


Figure 2.12.8: Marginal effects, number of 30-day fills, by number of chronic conditions.

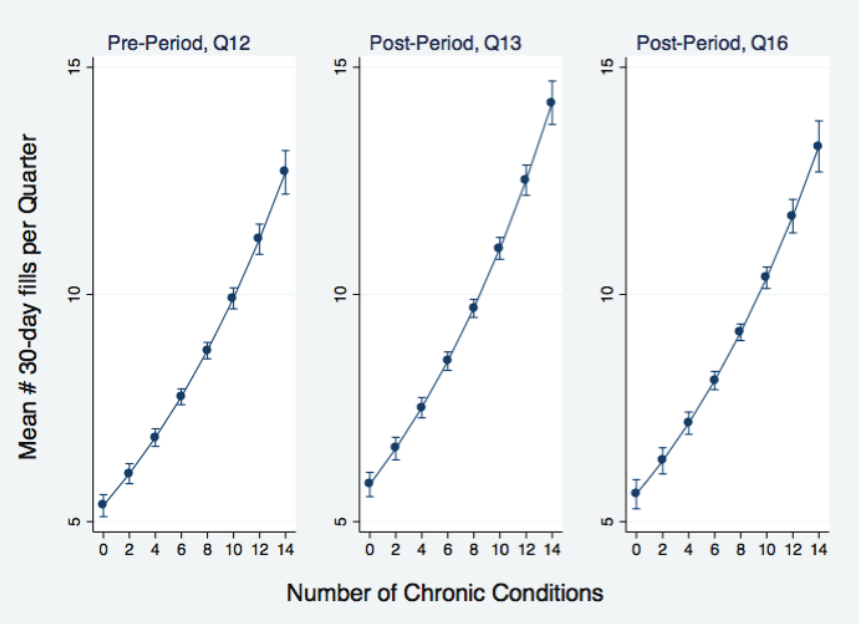


Figure 2.12.9: Marginal effects, total spending, by number of chronic conditions.

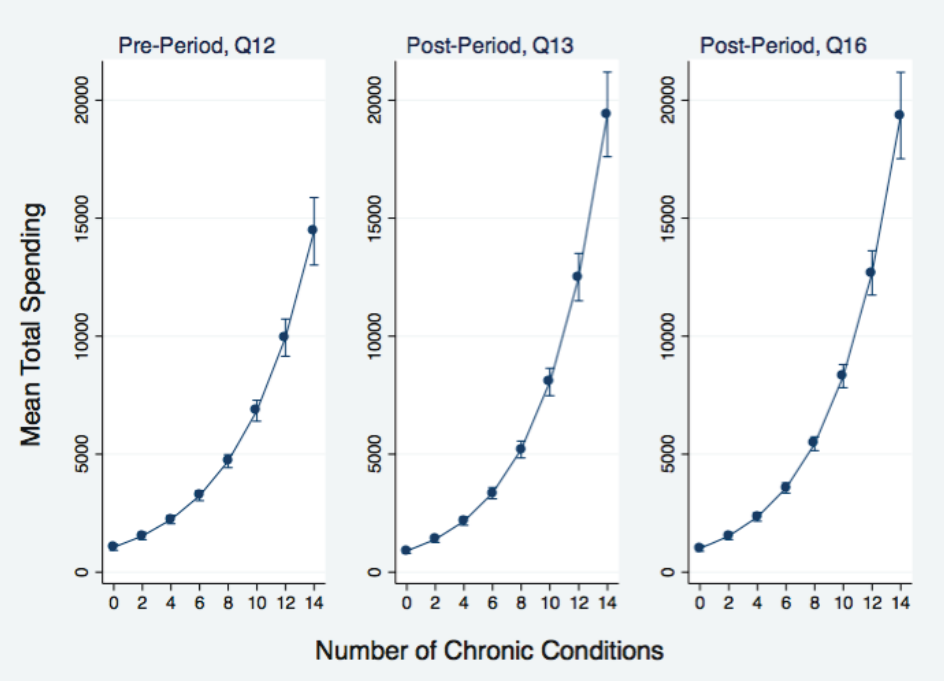


Figure 2.12.10: Average monthly probability of at least one inpatient visit with linear fitted values, FY '09 & '10

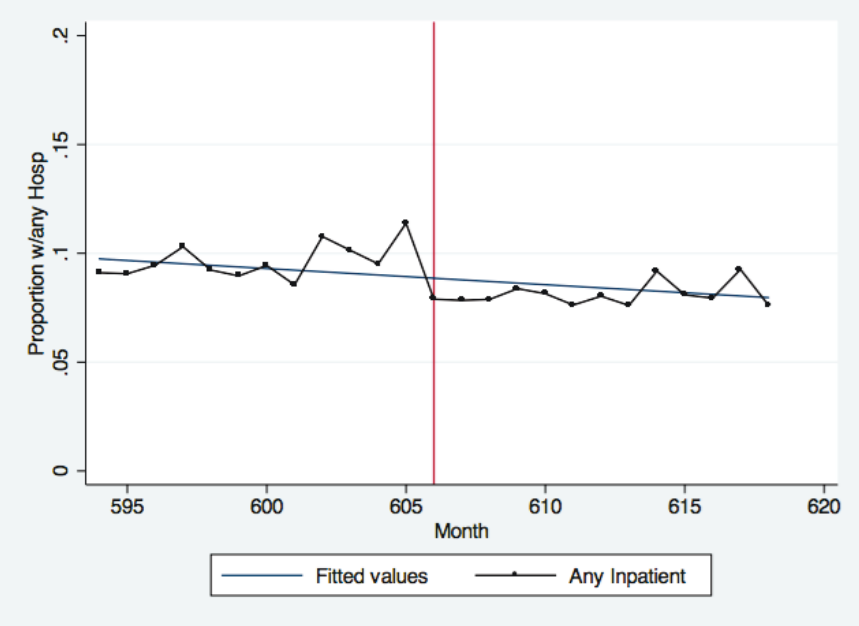
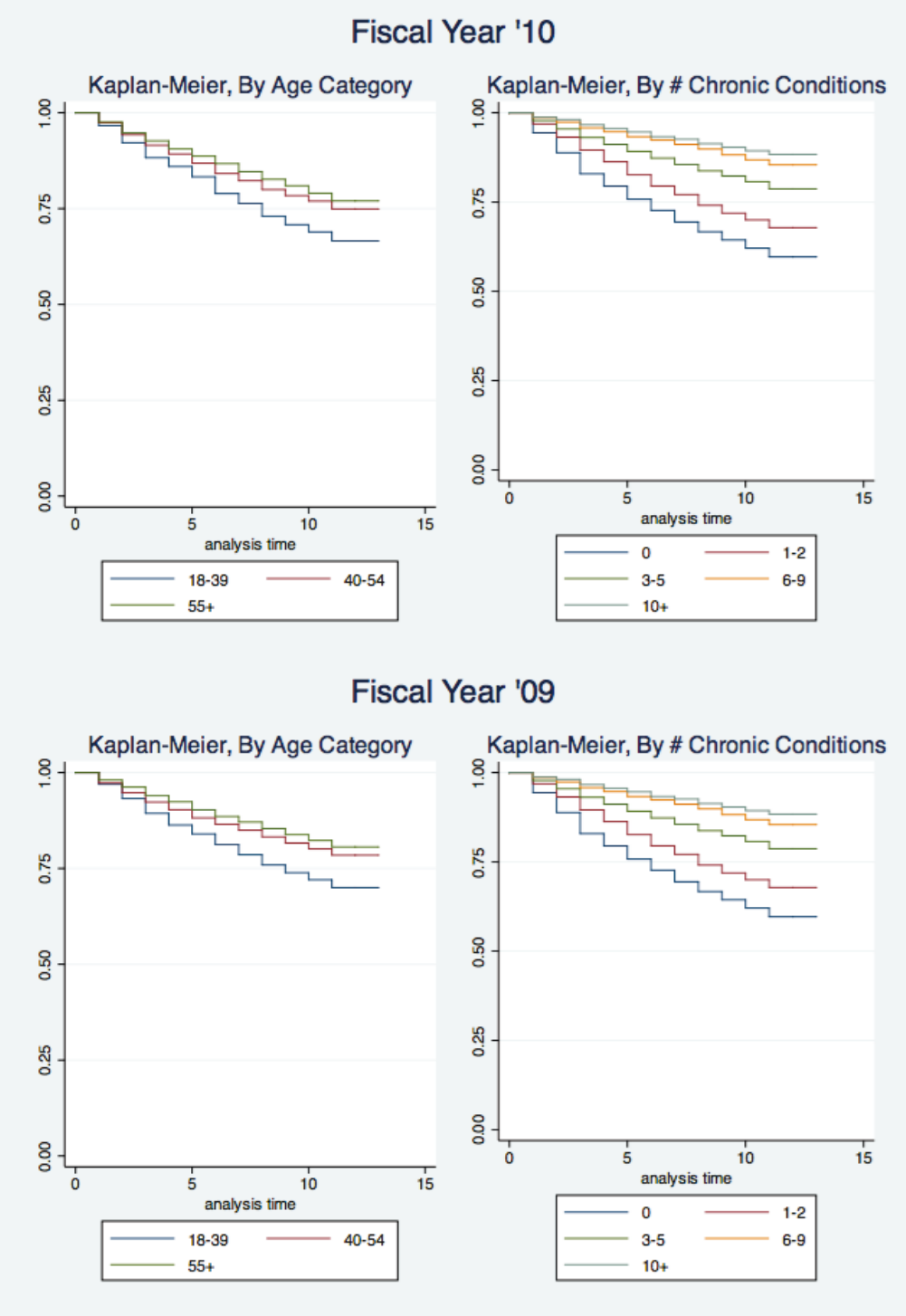


Figure 2.12.11: Kaplan-Meier survival curves for the probability of dropping coverage, FY ’09 vs FY ‘10



2.13 Appendix

Table 2.13.1: Categorization of Health Plans

MHIP Plan Type	Plan Categorization
BluePreferred PPO MD MHIP $200 DED	MHIP+
MHIP+ BC HMO Option 1	MHIP+
MHIP+ BC HMO Option 1 6 Month WP	MHIP+
MHIP+ BC HMO Option 1 w/Pre-Ex Surcharge	MHIP+
MHIP+ BC HMO Option 2	MHIP+
MHIP+ BC HMO Option 2 6 Month WP	MHIP+
MHIP+ BC HMO Option 2 w/Pre-Ex Surcharge	MHIP+
MHIP+ Blue Preferred PPO $200 Ded Level	MHIP+
MHIP+ Blue Preferred PPO $500 Ded Level	MHIP+
BluePreferred PPO MD MHIP $500 DED	PP0 $500 deductible
MHIP Standard Blue Preferred PPO $500	PP0 $500 deductible
BluePreferred PPO MD MHIP $1000 DED	PPO $1000 deductible
MHIP Standard Blue Preferred PPO $1000	PPO $1000 deductible
MHIP BluePreferred PPO HD CDH $2600	HDHP
MHIP PPO HD CDH $2600 Integrated Ded Plan	HDHP
MHIP Standard High Ded PPO Plan $2600	HDHP
MHIP BlueChoice HMO Plan	HMO
MHIP BlueChoice HMO Plan w/ Waiting Period	HMO
MHIP Standard BC HMO Option 1	HMO
MHIP Standard BC HMO Option 1 6 Month Waiting period	HMO
MHIP Standard BC HMO Option 1 w/Pre-Ex	HMO
MHIP HealthyBlue Triple Option HD MD IN	HealthyBlue

Notes: MHIP+ refers to low-income plans. PPO=preferred provider organization, HDHP=high deductible health plan, HMO=health maintenance organization.

Table 2.13.2: Categorization of service types

Place of Service Codes	Collapsed Place of Service
AMBULANCE - AIR OR WATER	ed
AMBULANCE - LAND	ed
EMERGENCY ROOM HOSPITAL	ed
Urgent Care Facility	ed
AMBULATORY SURGICAL CENTER	inpatient
BIRTHING CENTER	inpatient
COMPREHENSIVE INPATIENT TREATMENT FACILITY	inpatient
INPATIENT HOSPITAL	inpatient
INDEPENDENT LABORATORY	lab
Homeless Shelter	other
OTHER (UNDEFINED SOURCE DATA)	other
PHARMACY	other
Pharmacy Professional	other
PRISON-CORRECTIONAL FACILITY	other
SOURCE SYSTEM UNIQUE VALUE	other
TEST	other
UNKNOWN (NO SOURCE DATA AVAILABLE)	other
COMPREHENSIVE OUTPATIENT TREATMENT FACILITY	outpatient
END STAGE RENAL DISEASE TREATMENT FACILITY	outpatient
FEDERALLY QUALIFIED HEALTH CENTER	outpatient
HOME	outpatient
Independent Clinic	outpatient
Indian Health Service Free-Standing Facility	outpatient
Indian Health Service Provider-Based Facility	outpatient
Mass Immunization Center	outpatient
MILITARY TREATMENT FACILITY	outpatient
Mobile unit	outpatient
OFFICE	outpatient
OUTPATIENT HOSPITAL	outpatient
RURAL HEALTH CLINIC	outpatient
School	outpatient
STATE OR LOCAL PUBLIC HEALTH CLINIC	outpatient
Tribal 638 Free-Standing Facility	outpatient
Tribal 638 Provider-Based Facility	outpatient
INPATIENT PSYCHIATRIC FACILITY	psych inpatient
PSYCHIATRIC FACILITY PARTIAL HOSPITALIZATION	psych inpatient
COMMUNITY MENTAL HEALTH CENTER	psych outpatient
INTERMEDIATE CARE FACILITY / MENTALLY RETARDED	psych outpatient

NON-RESIDENTIAL SUBSTANCE ABUSE TREATMENT FACILITY	psych outpatient
PSYCHIATRIC RESIDENTAIL TREATMENT CENTER	psych outpatient
RESIDENTIAL SUBSTANCE ABUSE TREATMENT FACILITY	psych outpatient
ADULT LIVING CARE FACILITIES	skilled nursing
Assisted Living Facility	skilled nursing
CUSTODIAL CARE FACILITY	skilled nursing
Group Home	skilled nursing
HOSPICE	skilled nursing
NURSING FACILITY	skilled nursing
SKILLED NURSING FACILITY	skilled nursing

Note: In analyses, the psych inpatient/outpatient were collapsed into the respective inpatient and outpatient categories.

3 Generic drug use under a value-based insurance design initiative: implications for those with multiple chronic conditions.

3.1 Abstract

Background: Value-based insurance design creates incentives for patients to use lower priced services with equal or greater clinical effectiveness, such as generic drugs. The impact of these designs, and whether they increase the use of generic drugs, has been relatively untested in working-aged populations with multiple chronic conditions.

Objective: To analyze whether greater generic substitution occurs in certain classes of drugs following a change in value based insurance design initiative.

Data: High-risk pools insure a population of working-aged adults with multiple chronic conditions, who tried to get coverage on the private, individual market, but who were denied coverage because of pre-existing conditions. Pharmacy and medical claims data from Maryland's high-risk pool are used, covering two plan years from July 2009-July 2011.

Study Design: Interrupted time series design exploits a natural experiment in plan drug benefit redesign. The benefit redesign occurred in July 2010. The pool lowered copayments on generic drugs and raised them on preferred and non-preferred brands.

Methods: Generalized estimating equations were used to analyze the impact of the policy change on the percentage of generics utilized in the most common chronic disease medication classes. The outcome for each class is the average percentage of generics filled in the class.

Results: The largest change was a nine percent increase in the generic utilization for antidepressants. The rate remained unchanged for most other classes in the quarter immediately following the policy change. As the number of chronic conditions increased, the GUR tended to decrease.

Conclusions: While the policy change did increase the generic utilization rate in antidepressants, the copayment change in MHIP did little to increase the GUR in other classes. As the number of chronic conditions increases, the generic utilization rate decreases. Understanding why the GUR decreases with more chromic conditions may involve surveys, as there is little in the literature to explain this finding.

3.2 Introduction

Insurers have been encouraging the use of lower cost generics to stem rising health care spending. Generic use has grown substantially in the US over the last three decades and now account for 86% of all prescriptions filled (IMS Institute for Healthcare Informatics 2014).

The savings to health insurers and patients can be substantial from increased generic substitution. One study estimated the savings on just three drugs could be 100 million dollars for state Medicaid programs (Shrank et al. 2010). Another study estimated the savings to Medicare's Part D program could be a billion dollars for every ten percent increase in the use of generics (Hoadley et al. 2012). Using employer data, Liberman and Roebuck found that a one-percent increase in the use of generics could lower plan expenditures for pharmaceuticals by 2.5 percent (Liberman and Roebuck 2010).

While the overall use of generics has increased, the generic use rate across particular drug classes varies. The Office of the Inspector General used the Medicare Part D program to examine the generic substitution rate (number of generic fills/total number of generic plus multisource brand fills) across several drug classes in Part D plans (Office of Inspector General 2007). The authors examined a wide range of Part D plans with different formularies and cost sharing arrangements and found that generic usage also variedly widely. Generics account for between 75-98 percent of diuretic prescriptions, but only 33-77 percent of diabetic therapies when the generics were available. The report hypothesized that some plans have more single-source brand name drugs filled which lowers the opportunity for generic drugs to be used instead.

The major tool used to increase generic usage has been to lower copayments on generic drugs, raise them on brand name drugs, or some combination of the two. Even though consumers have been shown to be somewhat responsive to the copayments they face when filling prescriptions, other factors may prevent them from switching to generics (Goldman, Joyce, and Zheng 2007b). While the Food and Drug Administration requires that all generic drugs have the same active molecule, in practice, there are disputes as to whether the generic versions are exactly bioequivalent. Some drugs may have different inert ingredients to which some individuals may be allergic. Studies such as have confirmed that there is no evidence indicating that generic versions of drugs operate differently than their brand name counterpart, but this perception may impact prescriber behavior (Kesselheim et al. 2008).

Some patients may be established on their current regimens, and may be reluctant to switch, fearing the generic versions could act differently or there could be switching costs, such as going to the doctor to get a different prescription. West et al. (2012) found that the Medicare Part D benefit designs could limit patients' access to particular drugs within the mental health classes. The authors found that 68% of dual eligibles who were forced to switch medications experienced adverse events versus 40% in the control group (West et al. 2012). This could be due to clinical problems with the different medications or the time spent switching to new medications.

Mental health medications may pose their own challenge where older generation medications have lost their patents and have generic versions, but may be perceived as less effective than newer generations of drugs. Some older mental health medications are thought to have particularly bad side effects such as weight gain, tardive dyskenesia (involuntary movement) and metabolic problems (NIMH 2014). As such, the National Institutes of Health sponsored a trial to determine whether the second-generation mental health medications were better particularly for schizophrenia. The CATIE trial determined that patients were more likely to keep taking one of the second generation (newer) antipsychotics (onlanzapine) than the other second or first generation drugs, meaning patients perceived the drugs to have fewer side effects or were perceived as more effective (Lieberman et al. 2005).

Finally, patient perceptions of generic drugs also play a role. Shrank and colleagues conducted a patient survey on attitudes towards generic usage. The authors found that while 70 percent of respondents said the generics were a better value, only 38 percent agreed that they would rather take generics (Shrank et al. 2009). Physicians may also impact generic usage if they do not realize the variation in out-of-pocket costs each patient faces for various medications (Shrank, Liberman, et al. 2011).

Among multi-morbid populations where respondents may be taking many different drugs across multiple classes simultaneously, little is known regarding the effect of copay increases on generic substitution. A review of the literature on generic substitution found there was mixed evidence of shifts towards generic drugs in large employer-based

populations when brand-name copayments were increased, but these results were not broken down by number of chronic conditions (Gibson, Ozminkowski, and Goetzel 2005). A follow-up empirical study from the same lead author examined the generic substitution among those with diabetes and found that increased cost sharing did lead to more generic substitution in classes related to diabetes, however, the authors did not examine the generic substitution for other classes (Gibson, McLaughlin, and Smith 2010). Working-aged adults may have different needs than elderly with Medicare or low-income Americans with Medicaid that may present challenges with generic substitution. Working-aged adults with multiple chronic conditions may be less responsive to shifts in cost sharing, which will increase their out-of-pocket costs, sometimes substantially (Remler and Atherly 2003).

In July 2010, Maryland's high-risk pool reduced copayments on generic drugs and raised them on preferred and non-preferred brand name drugs. This was designed to create incentives for patients to substitute generics. The objective of this paper is to examine whether the percentage of generic fills increased within particular drug classes for chronic diseases. High risk pool enrollees will enter the health insurance exchanges in 2014, and understanding how to control spending while maintaining health will be key issues for insurers and policy makers in designing future iterations of the health insurance exchanges.

3.3 High Risk Pools

Thirty-five states have high-risk pools outside of the federal program enacted as part of health reform (NASCHIP 2012). Maryland has the country's fourth largest high-risk

pool (Kaiser State Health Facts 2011). Starting in 2002, this state-run plan uses funds from a statewide hospital tax to subsidize health insurance premiums for individuals with preexisting conditions. In order to qualify for this insurance, the person must have attempted to purchase coverage on the private individual market and be denied because of pre-existing medical conditions.

Premiums for the high-risk pool are generally set at about 125% of the average premium in Maryland's individual market. For the average individual in 2012, the premium is about $500 per month. These high-risk pool enrollees do not have the option to enroll in other government programs: either because they make too much money to qualify for Medicaid, or are younger than the Medicare eligibility age of 65.

3.4 Policy change

In July 2010, MHIP restructured its pharmacy benefit program. The pool lowered copayments on generic drugs and raised them on preferred and non-preferred brands. In this year, the pool also created a specialty or fourth tier. MHIP offers a selected set of plans with added subsidies for low-income individuals. MHIP has two different cost sharing structures for the MHIP+ plans and all other plans (PPO and HMO options) as indicated in Table 2.11.1.

[Table 2.11.1: Drug Tiers, Co-pays and drug examples]

3.5 Data

The data consists of medical and pharmacy claims from Maryland's Health Insurance Plan (MHIP). Administrative claims data from July 2009-June 2011 were used to

analyze the change in the generic utilization rate for selected classes. The shorter time frame was used to ensure that individuals were taking the drug in the year before the policy change. The sample consisted of those continuously enrolled for the two-year analysis period, those who were 18-64 and those who had at least one fill in the selected classes in the year before the policy change.

Drugs were assigned to classes using Multum's Lexicon database, which groups National Drug Codes into therapeutic classes. 17 classes were selected for initial analysis: antihyperlipidemic agents, antidiabetic agents, beta-adrenergic blocking agents, ACE inhibitors, antihypertensive combinations, sex hormones, thyroid hormones, bronchodilators, diuretics, calcium channel blockers, angiotensin II inhibitors, leukotriene modifiers, antidepressants, anxiolytics, sedatives, and hypnotics, anticonvulsants, antipsychotics and CNS stimulants.

The particular classes used in this analysis are used to treat chronic conditions and therefore should be taken regularly. The particular chronic condition classes selected were the most filled by volume in the data set. Two exclusions of note: Analgesics were the top class by volume and have been removed because of their use in acute pain management. Antiviral medications are also one of the top classes of medications in the pool that have also been excluded. HIV/AIDS patients are eligible in Maryland for a separate drug assistance program that will fund the copayments for these drugs, thus insulating these individuals from the price increases.

3.6 Variables

3.6.1 Independent Variables

Conceptual models governing the selection of generics are not currently available in the literature. There are economic models such as the Grossman model, which would say that the amount of money spent on manufacturing health is dependent on income, but that other factors, such as education can make the person a more efficient producers of health (Grossman 1972). As we age we are in need of more health care and are therefore more likely to consume medical care. We would anticipate higher education, more income or older ages more likely to be more efficient producers of medical care and therefore, more likely to select generic drugs (Figure 2.12.1). However, many of these variables are not available in claims data which could lead to omitted variable bias in some of the coefficients

The main covariate variables available in the MHIP claims are age, gender, number of chronic conditions and plan type. These variables capture some of the factors in the above model in the financial pressures and patient characteristics sections. Age is measured continuously and gender is binary (1=female). The number of chronic conditions is continuous. International Classification of Disease codes were translated into categories of conditions and chronic diseases using the Clinical Classifications System from the Agency for Healthcare Research and Quality (AHRQ) (Elixhauser, Steiner, and Palmer 2012). For a condition to be counted as chronic, the ICD9 code had to appear in at least two outpatient visits or at least one inpatient visit.

The enrollment files include information on plan type such as Preferred Provider Organization (PPO) or Health Maintenance Organization (HMO), which represent differences across plan benefit structure. Plan type also reflects differences in income since MHIP provides a second set of plans called MHIP+ for lower income individuals. The data do not have income explicitly contained, but to qualify for MHIP+, the person must have an annual income below 200% of the Federal Poverty Level. In 2010, this was $21,660. Across any of the given person-quarters, approximately 28% are enrolled in MHIP+ in a given month while 21% are enrolled in the PPO plans and 21% are enrolled in a HDHP. The rest of the enrollees are in the HMO plans. Since the cost sharing structure is slightly different for the MHIP+ versus all the other plans, the plan type has been included as a series of dummy variables to capture any differences in drug utilization by plan type and to control for income.

3.6.2 Dependent Variable

The main outcome is the percentage generic of all drugs filled in a particular class. The OIG report for Medicare showed great variation in generic drug use across classes (Office of Inspector General 2007). This could reflect availability of generics, preferences for certain brand name drugs, patient and physician characteristics or the formulary design of the health plan.

The generic utilization rate is calculated as the number of generic fills in the class divided by the total number of fills in the class. Other work in this area also calculates the generic substitution rate, which is the number of generics in the class divided by the total

number of generics and multisource brands in a class. This particular dataset did not have enough multi-source brand fills to create a meaningful measure.

3.7 Analysis

An interrupted time series design using individual-level data is used. The key variable of interest is the policy change indicator, where the null hypothesis is that an absence of the policy change, the trend of generic utilization would have remained constant.

$$Y_{it} = f(\beta_0 + \beta_1 time_t + \beta_2 policy_t + \beta_3 posttime_t + \beta_4 chronic_i + \beta_5 chronic*policy_{it} + \beta_6 chronic*posttime_{it} + X_{it}\lambda)$$

$\beta_1 time_t$ is the time trend, measured quarterly since July 2009. The policy change is included as a binary indicator equal to zero in the pre-period and one in the post period. The post time variable measures the quarters continuously since the policy change, so it is equal to zero in the pre-period and begins at one in July 2010. $\beta_2 policy_t + \beta_3 posttime_t$ represents the impact of the policy change for the whole sample including both the initial impact and the change in the trend after the intervention. $\beta_4 chronic_i$ details how patients with different numbers of chronic conditions will react. $\beta_5 chronic*policy_{it}$ represents how the policy impact changes across groupings of numbers of chronic conditions and $\beta_6 chronic*posttime_{it}$ represents whether the trend in the post-period is different for different numbers of chronic conditions after the policy change. $X_{it}\lambda$ represents the vector of control covariates: age, gender and plan type.

All outcomes are analyzed using generalized estimating equations (GEE) specifications to analyze the impact of the policy change because having a prescription in one month is highly correlated with having a prescription drug in the next month, particularly for chronic disease patients. GEE allows for the specification of the family (i.e. Gaussian) and link function (i.e. identity or log) for the mean, making this a very flexible regression model. The correlation structure was assessed through examining the correlation between the outcome overtime. BoxCox tests were used to test for the appropriate link and the modified Park test was used to test for the appropriate family (Cameron and Trivedi 2005).

3.8 Results

The final sample consisted of 6,125 individuals who were age 18-64, were continually enrolled across the two-year study period and who filled at least one prescription in the selected classes in the pre-year. As the number of chronic conditions increases, the number of different drug classes the person used also increases. Those with six or more chronic conditions used more than 10 different classes of medications each quarter.

[Table 3.12.1: Sample Characteristics by Number of Chronic Conditions]

The included drug classes, based on those with the highest volume, include medications for depression and other mental health conditions, diabetes, cardiovascular and heart diseases, asthma and thyroid problems. Based on exploratory descriptive analyses, the quarterly generic utilization rate (generic fills divided by the total number of fills) increases for 12 of the 16 classes in the post-period, but many by not more then one or

two percentage points (Table 3.12.2). Generic utilization in two classes, bronchodilators and antipsychotics, decreases one percentage point. Diuretics and ACE inhibitors stay the same, but these classes already have 100 and 99% (respectively) generic utilization in both time periods. Anxiolytics/sedatives, antidepressants, antihypertensives and sex hormones are classes that do large increase in generic percentage in the post period. The generic utilization rate for antidepressants increases from 62% to 71% in the post period. The use of antihypertensives increases from 56 to 64% in the post period.

[Table 3.12.2: Average percent generic in selected classes]

Times series trends of the quarterly generic utilization rate show that for most classes, the GUR remained stable over the two-year period. For these charts, the following figures have been grouped into mental health medications, cardiovascular-related medications and others. They are grouped the same way for the regression result tables as well. Figure 3.13.1 shows the time trends in the average GUR for mental health classes of medications. The GUR for antidepressants and anxiolytics/sedatives steadily increases over the two-year period. The GUR for antihypertensives shows a continual increase over the two-year period, as do antihyperlipidemics (Figure 3.13.2). Asthma drugs and thyroid medications remained stable, but the GUR for sex hormones (birth control, testosterone) increased (Figure 3.13.3).

[Figure 3.13.2: Average quarterly generic proportion, cardiovascular medication classes
Figure 3.13.2: Average quarterly generic proportion, cardiovascular medication classes

Figure 3.13.3: Average quarterly generic proportion, other medication classes]

It might also be the case that those with multiple chronic conditions may have a different trend in the post time period, as well as a change in the level of utilization. Figure 3.13.4 shows the quarterly trend in generic usage separated by the number of chronic conditions. This figure shows that once a person has a chronic condition, they are less likely to be using generic drugs. The graph shows that the usage of generic drugs is increasing steadily over time across all chronic conditions. There does not appear to be a marked shift in the trend or the level of generic usage at the policy change time point.

[Figure 3.13.4: Quarterly generic usage separated by the number of chronic conditions.]

3.9 Regression Results

Due to the high proportion of generics already being utilized in this sample for diuretics, calcium channel blockers, ACE-inhibitors and beta-blockers in the pre-period, these classes are been removed from consideration for further analysis. For these drugs there is clear provider and patient preference for them, and little room left for increasing the generic utilization rate. Leukotriene modifiers are also being removed from further analysis because of the absence of generic alternatives.

Across all drug classes, the interaction of the number of chronic conditions and the policy change is not significant, nor is the incident rate ratio on the interaction of the number of

chronic conditions and the post-time trend. This indicates that the policy does not have a differential impact on those with different numbers of chronic conditions.

For the classes of mental health medications, antidepressants are the only class with a statistically significant increase in the generic utilization rate (IRR: 1.09, $p<0.01$) (Table 3.12.3). Plan type (HMO, PPO, etc) is not a significant driver for any of the mental health classes except for antipsychotics. The $500 PPO group was held as reference group to examine the impact on the low-income plans in MHIP+. For antipsychotics, the GUR rate is 13% higher in MHIP+ than the $500 PPO rate. For the rest of the mental health classes, the low-income plans, MHIP+, are not significant in the regression models, indicating that this is not a factor influencing generic usage. For cardiovascular-related medications, antihypertensives and thyroid hormones have a positive and significant trend towards an increasing generic utilization rate. However, only the antihyperlipidemics are significantly different at the policy change, in a negative direction, meaning the use of generics dropped (Table 3.12.4).

[Table 3.12.3: Regression results, mental health medication classes, incidence rate ratios and 95% confidence intervals.
Table 3.12.4: Regression results, cardiovascular medication classes, incidence rate ratios and 95% confidence intervals.]

Across almost all classes, the percentage of generic drugs used is lower as the number of chronic conditions increases. For example, the predicted use of generic antidepressants is 61% for those with 14 chronic conditions compared with 68% for those with no chronic conditions Table 3.12.5 and Table 3.12.6. The explanations for why those with more

conditions are taking fewer generics are unclear. It could be that they are sicker and are taking more medications where more careful drug selection may be important to avoid drug interactions. While polypharmacy, the notion of taking many drugs at once, has become a topic of interest for the elderly in recent years (e.g.: (Ballentine 2008), there is little similar literature in the working aged-adult population. Working aged adults could have the same constellations of chronic conditions as the elderly, but may be better functioning at younger ages (i.e. less frailty or cognitive decline). As such, once stabilized on a complex regimen of drugs, patients may be less willing to switch drugs.

[Table 3.12.5: Predicted percent generic (marginal effects), immediate post quarter (5) and fourth post quarter (8)
Table 3.12.6: Predicted percent generic (marginal effects), immediate post quarter (5) and fourth post quarter (8)]

Another possible explanation for the decreasing use of generics among those with the higher numbers of chronic conditions could be that they may be in more generous health plans and are therefore more protected from the impact of cost sharing. The distribution of chronic conditions across plan types is relatively similar in the pre-period, with less generous plans, HDHP and HMO attracting a slightly lower percentages of those with ten ore more chronic conditions (18% and 17%, respectively) than the MHIP+, $500 PPO and $1000 PP0 (26, 25, 24%, respectively) (Figure 3.13.5). However, the models already control for plan type, and are not significant except for antipsychotics.

[Figure 3.13.5: Distribution of chronic conditions across plan types, pre-period, FY ’09.]

The generic utilization rate is the number of generics prescribed divided by the number of total prescriptions. It is possible that the generic percentage filled may appear to increase because the number of brand name medications drops while the number of generic filled stayed unchanged. If brand name drug use drops while generic utilization stays unchanged, then this suggests some enrollees stop taking those brand name medications, and are not substituting any generic drugs. In the case of bronchodilators for asthma, where the majority drug was still under patent until 2012 (Advair), we see a small dip in the number of brand name medications filled while the generic fills do not change (Figure 3.13.6). This suggests there may be a decrease in adherence. For antidepressants, there does appear to be a corresponding increase in generics as brand name drug fills decrease, indicating a substitution effect.

[Figure 3.13.6: Quarterly average utilization rates for bronchodilators and antidepressants]

3.10 Discussion

Over the two-year study period, generic utilization increases steadily in most classes for Maryland's high risk pool, a continuing trend across the US (IMS Institute for Health Informatics 2012). The copayment policy change does not impact the use of generics for most classes studied. The policy change was associated with an increase in the generic utilization rate for antidepressants and lowered it for antidiabetic combinations.

In almost all classes, except bronchodilators and anxiolytics, the effect of the person having more chronic conditions is to decrease the percentage generic used. It is unclear why this might be happening, since sensitivity analyses show the trend is unchanged, even after removing those who were over the out-of-pocket maximum in the second year. Plan types were also not significant in the regression models, except for antipsychotics, and the percentage of individuals with each grouping of chronic conditions was relatively evenly distributed across plans.

There appears to be little literature to explain why those with multiple chronic conditions would be especially reluctant or unable to use generic medications. Shrank et al. (2009) in a survey of adult prescription drug users found that those in excellent health were more than two times as likely to say that brand name drugs are more effective than generics. Those with better health were also less likely to switch to generic drugs. This may indicate that those with less serious conditions feel safer in switching to generics.

3.10.1 Limitations

With this type of analysis, using the percent generic filled per quarter in the class, there is a concern that simultaneous patent expiries could be causing the shift in utilization, rather than the copayment change. This may not be an issue for this analysis, however, given most of the recent blockbuster drugs went off patent in 2011 and 2012, after the policy change of interest. Lipitor (high cholesterol), Concerta (ADHD) and Zyprexa (antipsychotic) all went off patent in 2011, which would have been towards the end of the MHIP fiscal year, therefore not simultaneously impacting usage at the time of the policy

change. Effexor (venlafaxine, an antidepressant) did go off patent in 2010, but its use was a small fraction of all the antidepressants.

This analysis is also limited in the causal implications because there is no control group to rule out any further co-occurring changes that may impact generic drug utilization. With claims data, there are substantial limitations in identifying other unmeasured factors that may also influence utilization.

The sample was limited to one year continuously enrolled in the pre and post period surrounding the policy change. Those who dropped coverage during the year tended to be healthier and younger. However, this pattern is not markedly different in the post period versus the pre-period. Finally, this analysis only examines the high-risk pool in one state, Maryland, so this may further limit the generalizability of the findings.

3.11 Conclusions

The copayment increase for this pool did increase the generic usage of antidepressants, but did little to increase the trend towards generic usage for almost all other classes studied. There were several classes already at their maximum generic usage, particularly the cardiovascular-related medications. Therefore, this policy did little to encourage those with multiple chronic conditions to switch to generics. Value-based insurance design may be of limited use in these populations of those with multiple chronic conditions because there are factors impacting drug usage, other than price alone (Piette et al. 2006).

3.12 Tables

Table 3.12.1: Sample Characteristics by Number of Chronic Conditions

Number of chronic conditions	Age, mean (sd)	Gender (% female)	Total number of different drug classes	N
Zero	41	55	4	121
SD	15		3	2
One-Two	44	56	6	668
SD	14		3	11
Three-Five	50	56	7	1,764
SD	12		4	28
Six-Nine	53	57	10	2,053
SD	11		4	33
Ten+	56	62	14	1,609
SD	10		5	26
Total	51	58	10	6,215
	12		5	100

Table 3.12.2: Average percent generic in selected classes

Drug Class	Condition	Examples	Average % Generic in Pre-Year	Average % Generic in Post-Year	
Antidepressants	depression	Escitalopram (Lexapro), Duloxetine (Cymbalta)	62	71	*
Anxiolytics/sedatives	anxiety	Diazepam (Valium), Alprazolam (Xanax), Zolpidem tartrate (Ambien)	85	91	*
Anticonvulsants	bipolar disorder, epilepsy	Gabapentin (Neurontin), Lamictal (Lamotrigine), Ativan (Lorazepam)	84	86	
Antipsychotics	bipolar disorder, schizophrenia	Lithium carbonate, Quetiapine (Seroquel), Aripiprazole (Abilify), Risperidone (Risperdal)	38	37	
CNS Stimulants	attention deficit disorder	Methylphenidate (Concerta, Ritalin), Amphetamine salts	52	56	*
Antihypertensive combinations	hypertension	Hydrochlorothiazide/Lisinopril, Triamterene/Hydrochlorothiazide, Valsartan (Diovan)	56	64	*
Antihyperlipidemics	high cholesterol	Simvastatin (Zocor), Atorvastatin (Lipitor)	41	45	*
Antidiabetics	diabetes	Metformin, Sitagliptin (Januvia), Insulin glargine (Lantus)	53	54	
Beta Blockers	hypertension, heart failure	Metoprolol (Lopressor), Atenolol (Tenormin)	91	92	*
ACE Inhibitors	hypertension, heart failure	Lisinopril (Zestril), Ramipril (Altace)	99	99	
CCBs	high blood pressure	Amlodipine Besylate (Norvasc), Nifedipine (Procardia)	97	99	*
Diuretics	high blood pressure	Furosemide (Lasix), Hydrochlorothiazide, Spironolactone (Aldactone)	100	100	
Sex hormones	birth control, low testosterone, menopause	Ethinyl estradiol/Norethindrone (LoEstrin), Testosterone (Androgel), Estradiol (Vagifem)	41	47	*
Thyroid hormones	hypothyroidism	Levothyroxine (Synthroid)	63	66	*
Bronchodilators	asthma, COPD	Albuterol (Proventil, Ventolin), LABA (Advair)	8	7	
Leukotrine modifiers	asthma, allergy	Montelukast (Singulair)	0	1	

Notes: Brand names are in parentheses. CNS = Central Nervous System, ACE = angiotensin-converting enzyme , CCB = calcium channel blocker,COPD = chronic obstructive pulmonary disease, LABA = long-acting beta agonist. * = Significant Difference ($p<0.05$)

Table 3.12.3: Regression results, mental health medication classes, incidence rate ratios and 95% confidence intervals.

Variable	Antidepressants	Anxiolytics	Anticonvulsants	Antipsychotics	CNS Stimulants
Quarter	1	1	1.01***	0.98	1
95% CI	[0.993 - 1.007]	[0.996 - 1.007]	[1.004 - 1.016]	[0.963 - 1.003]	[0.983 - 1.022]
Chronic category, continuous	0.99***	1	0.99***	0.96***	0.98**
	[0.986 - 0.998]	[0.996 - 1.003]	[0.990 - 0.998]	[0.945 - 0.984]	[0.967 - 0.998]
Post quarters	**1.01***	**1.03*****	**0.99****	**1.01**	**1**
	[0.999 - 1.023]	**[1.013 - 1.042]**	**[0.978 - 0.998]**	**[0.980 - 1.047]**	**[0.962 - 1.035]**
Chronic*Post quarters	1	1	1	1	1
	[0.999 - 1.001]	[0.999 - 1.002]	[1.000 - 1.002]	[0.999 - 1.005]	[0.996 - 1.005]
Policy change	**1.09*****	**0.99**	**1.01**	**1.05**	**1.02**
	[1.048 - 1.135]	**[0.959 - 1.014]**	**[0.981 - 1.034]**	**[0.967 - 1.133]**	**[0.937 - 1.113]**
CC*Policy Change	1	1	1	0.99	1
	[0.996 - 1.005]	[0.997 - 1.003]	[0.995 - 1.001]	[0.985 - 1.003]	[0.992 - 1.014]
Age	1.00***	1.00*	1.00***	1.01***	1
	[1.001 - 1.005]	[0.998 - 1.000]	[0.997 - 0.999]	[1.005 - 1.019]	[0.998 - 1.006]
Gender	0.98	1.02	1.01	0.88	1.14**
	[0.930 - 1.024]	[0.989 - 1.042]	[0.968 - 1.046]	[0.745 - 1.040]	[1.007 - 1.283]
Plan type ($500 PPO, reference)					
MHIP+	0.99	1	1	1.13*	0.92
	[0.935 - 1.042]	[0.965 - 1.031]	[0.982 - 1.023]	[0.998 - 1.279]	[0.809 - 1.037]
$1000 PPO	0.96	1.01	0.99	1.18*	0.97
	[0.889 - 1.036]	[0.974 - 1.043]	[0.953 - 1.032]	[0.985 - 1.407]	[0.869 - 1.081]
HDHP	1.03	1.03	1.02	1.23	0.95
	[0.963 - 1.091]	[0.974 - 1.090]	[0.980 - 1.069]	[0.939 - 1.618]	[0.830 - 1.093]
HMO	0.95	1.04	1.01	1.15	0.97
	[0.854 - 1.049]	[0.982 - 1.108]	[0.943 - 1.079]	[0.917 - 1.448]	[0.776 - 1.222]
Constant	0.60***	0.88***	0.94*	0.30***	0.56***
	[0.539 - 0.668]	[0.834 - 0.939]	[0.880 - 1.011]	[0.223 - 0.417]	[0.450 - 0.691]
Observations	14,854	9391	7702	3505	3249
Number of individuals	2,729	2253	1725	723	629

Robust confidence interval in brackets. PPO= preferred provider organization. MHIP+ = Maryland Health Insurance Plan low income plans. HDHP= high deductible health plans. HMO= health maintenance organization, CC=chronic condition. GEE use negative binomial family and log links.

*** p<0.01, **
p<0.05, * p<0.1

Table 3.12.4: Regression results, cardiovascular medication classes, incidence rate ratios and 95% confidence intervals.

Variable	Antihypertensives	Antihyperlipidemics	Antidiabetics	Sex hormones	Thyroid hormones	Bronchodilators
Quarter	1.04***	1	0.99***	1.03***	1.02***	0.94
95% CI	[1.024 - 1.047]	[0.994 - 1.012]	[0.980 - 0.996]	[1.012 - 1.054]	[1.006 - 1.030]	[0.815 - 1.081]
Chronic conditions	0.98***	0.99*	0.98***	1	1	1.06***
	[0.971 - 0.993]	[0.983 - 1.001]	[0.974 - 0.990]	[0.979 - 1.015]	[0.991 - 1.010]	[1.027 - 1.090]
Post quarters	**0.99**	**1.01***	**1**	**0.96****	**0.98****	**1.1**
	[0.966 - 1.010]	**[0.997 - 1.033]**	**[0.977 - 1.017]**	**[0.929 - 0.997]**	**[0.954 - 0.999]**	**[0.824 - 1.474]**
Chronic*Post quarters	1	1	1	1.01***	1	1
	[0.998 - 1.002]	[0.998 - 1.002]	[0.998 - 1.002]	[1.002 - 1.010]	[0.999 - 1.003]	[0.988 - 1.013]
Policy change	**0.94****	**1**	**1.02**	**1.06**	**1.08****	**0.87**
	[0.889 - 0.995]	**[0.958 - 1.051]**	**[0.966 - 1.071]**	**[0.969 - 1.165]**	**[1.006 - 1.168]**	**[0.499 - 1.534]**
CC*Policy Change	1.01***	1	1	0.99	0.99	1.01
	[1.004 - 1.017]	[0.995 - 1.006]	[0.994 - 1.005]	[0.978 - 1.003]	[0.986 - 1.002]	[0.981 - 1.040]
Age	0.99**	0.99**	1.01***	0.97***	1	1
	[0.989 - 1.000]	[0.989 - 0.999]	[1.010 - 1.020]	[0.969 - 0.978]	[0.998 - 1.007]	[0.979 - 1.017]
Gender	1.12**	1.14***	1.11**	5.30***	0.87***	0.87
	[1.028 - 1.224]	[1.048 - 1.229]	[1.023 - 1.196]	[3.092 - 9.079]	[0.788 - 0.950]	[0.574 - 1.327]
Plan type ($500 PPO, reference)						
MHIP+	0.98	1.02	0.97	1.02	1.08**	0.99
	[0.883 - 1.092]	[0.964 - 1.085]	[0.910 - 1.032]	[0.895 - 1.155]	[1.003 - 1.161]	[0.584 - 1.692]
$1000 PPO	0.95	0.99	0.93	0.90*	0.98	0.97
	[0.824 - 1.096]	[0.909 - 1.080]	[0.849 - 1.018]	[0.803 - 1.018]	[0.887 - 1.089]	[0.540 - 1.750]
HDHP	1.04	1.15***	1.08*	0.9	1	0.83
	[0.888 - 1.213]	[1.042 - 1.260]	[0.997 - 1.169]	[0.728 - 1.121]	[0.902 - 1.115]	[0.420 - 1.632]
HMO	1.20**	0.88*	1.02	1.28**	1.19**	0.79
	[1.019 - 1.414]	[0.753 - 1.023]	[0.928 - 1.125]	[1.040 - 1.573]	[1.039 - 1.356]	[0.379 - 1.660]
Constant	0.79	0.55***	0.31***	0.22***	0.57***	0.04***
	[0.590 - 1.054]	[0.421 - 0.723]	[0.238 - 0.411]	[0.122 - 0.394]	[0.453 - 0.728]	[0.013 - 0.118]
Observations	6474	16977	8264	5547	6168	3841
Number of individuals	1127	2916	1330	1227	999	1274

Robust confidence interval in brackets. PPO= preferred provider organization. MHIP+ = Maryland Health Insurance Plan low income plans. HDHP= high deductible health plans. HMO= health maintenance organization, CC=chronic condition. GEE use negative binomial family and log links.

*** p<0.01, ** p<0.05, * p<0.1

Table 3.12.5: Predicted percent generic (marginal effects), immediate post quarter (5) and fourth post quarter (8), mental health classes.

Number of chronic conditions	**Antidepressants, Q4 (pre)**	Difference (Q5 vs. Q4)	Difference (Q8 vs Q4)	**Anxiolytics**	Difference (Q5 vs. Q4)	Difference (Q8 vs Q4)
0	**0.68**	0.06***	0.06***	**0.86**	-0.01	-0.01
		[0.015]	[0.015]		[0.012]	[0.014]
2	**0.67**	0.06***	0.06***	**0.86**	-0.01	-0.01
		[0.012]	[0.012]		[0.010]	[0.011]
4	**0.66**	0.06***	0.06***	**0.86**	-0.01*	-0.01
		[0.009]	[0.009]		[0.008]	[0.009]
6	**0.65**	0.06***	0.06***	**0.86**	-0.01**	-0.02**
		[0.008]	[0.008]		[0.007]	[0.008]
8	**0.64**	0.06***	0.06***	**0.86**	-0.01**	-0.02**
		[0.007]	[0.007]		[0.006]	[0.007]
10	**0.63**	0.06***	0.06***	**0.86**	-0.02**	-0.02**
		[0.008]	[0.008]		[0.007]	[0.007]
12	**0.62**	0.06***	0.06***	**0.86**	-0.02**	-0.02**
		[0.009]	[0.009]		[0.008]	[0.009]
14	**0.61**	0.06***	0.06***	**0.86**	-0.02*	-0.02
		[0.011]	[0.011]		[0.010]	[0.011]
Number of chronic conditions	**Anticonvulsants**	Difference (Q5 vs. Q4)	Difference (Q8 vs Q4)	**Antipsychotics**	Difference (Q5 vs. Q4)	Difference (Q8 vs Q4)
0	**0.90**	0.01	0.01	**0.51**	0.02	0.02
		[0.012]	[0.012]		[0.021]	[0.020]
2	**0.89**	0	0	**0.47**	0.02	0.02
		[0.010]	[0.010]		[0.017]	[0.016]
4	**0.88**	0	0	**0.44**	0.01	0.01
		[0.007]	[0.007]		[0.013]	[0.013]
6	**0.87**	-0.01	-0.01	**0.41**	0	0
		[0.006]	[0.006]		[0.012]	[0.012]
8	**0.86**	-0.01*	-0.01*	**0.38**	0	0
		[0.005]	[0.005]		[0.011]	[0.012]
10	**0.85**	-0.01**	-0.01**	**0.35**	0	0
		[0.006]	[0.006]		[0.012]	[0.012]
12	**0.84**	-0.02**	-0.02**	**0.33**	-0.01	-0.01
		[0.007]	[0.008]		[0.013]	[0.014]
14	**0.83**	-0.02**	-0.02**	**0.30**	-0.01	-0.01
		[0.009]	[0.010]		[0.014]	[0.015]

*** p<0.01, ** p<0.05, * p<0.1. Standard error in brackets.

Table 3.12.6: Predicted percent generic (marginal effects), immediate post quarter (5) and fourth post quarter (8).

Number of chronic conditions	CNS Stimulants	Difference (Q5 vs. Q4)	Difference (Q8 vs Q4)	Antihypertensives	Difference (Q5 vs. Q4)	Difference (Q8 vs Q4)
0	**0.63**	0.01	0.01	**0.71**	-0.04**	-0.05**
		[0.028]	[0.028]		[0.020]	[0.022]
2	**0.61**	0.02	0.02	**0.69**	-0.03*	-0.03*
		[0.022]	[0.022]		[0.016]	[0.017]
4	**0.59**	0.02	0.02	**0.66**	-0.01	-0.01
		[0.018]	[0.018]		[0.011]	[0.012]
6	**0.57**	0.02	0.02	**0.64**	0	0
		[0.016]	[0.016]		[0.008]	[0.009]
8	**0.55**	0.03	0.02	**0.62**	0.01*	0.01*
		[0.016]	[0.017]		[0.007]	[0.008]
10	**0.53**	0.03	0.03	**0.59**	0.03***	0.03***
		[0.019]	[0.019]		[0.009]	[0.009]
12	**0.51**	0.03	0.03	**0.57**	0.04***	0.04***
		[0.023]	[0.023]		[0.012]	[0.012]
14	**0.50**	0.03	0.03	**0.55**	0.05***	0.05***
		[0.027]	[0.027]		[0.015]	[0.015]
Number of chronic conditions	Antihyperlipidemics	Difference (Q5 vs. Q4)	Difference (Q8 vs Q4)	Antidiabetics	Difference (Q5 vs. Q4)	Difference (Q8 vs Q4)
0	**0.44**	0	0	**0.69**	0.01	0.01
		[0.011]	[0.011]		[0.018]	[0.017]
2	**0.44**	0	0	**0.66**	0.01	0.01
		[0.008]	[0.009]		[0.014]	[0.013]
4	**0.43**	0	0	**0.64**	0.01	0.01
		[0.006]	[0.006]		[0.011]	[0.011]
6	**0.42**	0	0	**0.61**	0.01	0.01
		[0.004]	[0.005]		[0.009]	[0.008]
8	**0.41**	0	0	**0.59**	0.01	0.01
		[0.004]	[0.004]		[0.007]	[0.007]
10	**0.41**	0	0	**0.57**	0.01	0.01
		[0.005]	[0.006]		[0.007]	[0.007]
12	**0.40**	0	0	**0.55**	0	0
		[0.007]	[0.007]		[0.008]	[0.008]
14	**0.39**	0	0	**0.53**	0	0
		[0.009]	[0.009]		[0.010]	[0.010]

*** p<0.01, ** p<0.05, * p<0.1. Standard error in brackets.

Table 3.12.7: Predicted percent generic (marginal effects), immediate post quarter (5) and fourth post quarter (8).

Number of chronic conditions	**Thyroid**	Difference (Q5 vs. Q4)	Difference (Q8 vs Q4)	**Bronchodilators**	Difference (Q5 vs. Q4)	Difference (Q8 vs Q4)
0	**0.64**	0.05**	0.05**	**0.02**	0	0
		[0.025]	[0.023]		[0.006]	[0.008]
2	**0.64**	0.05**	0.04**	**0.03**	0	0
		[0.020]	[0.019]		[0.007]	[0.008]
4	**0.64**	0.04**	0.04**	**0.03**	0	0
		[0.015]	[0.014]		[0.007]	[0.008]
6	**0.64**	0.03***	0.03***	**0.03**	0	0
		[0.011]	[0.011]		[0.007]	[0.009]
8	**0.64**	0.02**	0.02**	**0.04**	0	0
		[0.009]	[0.009]		[0.008]	[0.009]
10	**0.64**	0.01	0.01	**0.04**	0	0
		[0.010]	[0.010]		[0.008]	[0.010]
12	**0.64**	0.01	0.01	**0.05**	0	0
		[0.014]	[0.014]		[0.009]	[0.010]
14	**0.64**	0	0	**0.05**	0	0
		[0.018]	[0.019]		[0.010]	[0.011]

*** p<0.01, ** p<0.05, * p<0.1. Standard error in brackets.

3.13 Figures

Figure 3.13.1: Average quarterly generic proportion, mental health medication classes

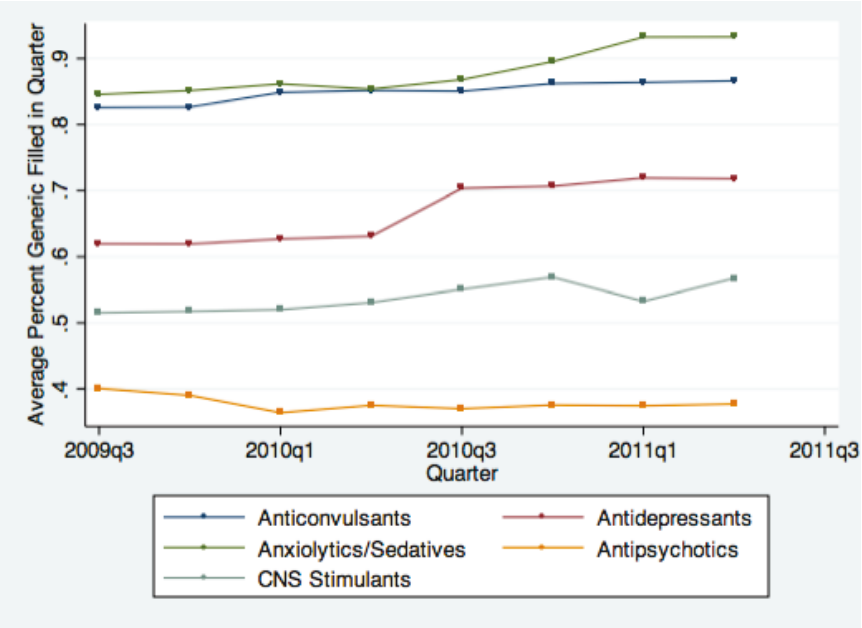


Figure 3.13.2: Average quarterly generic proportion, cardiovascular medication classes

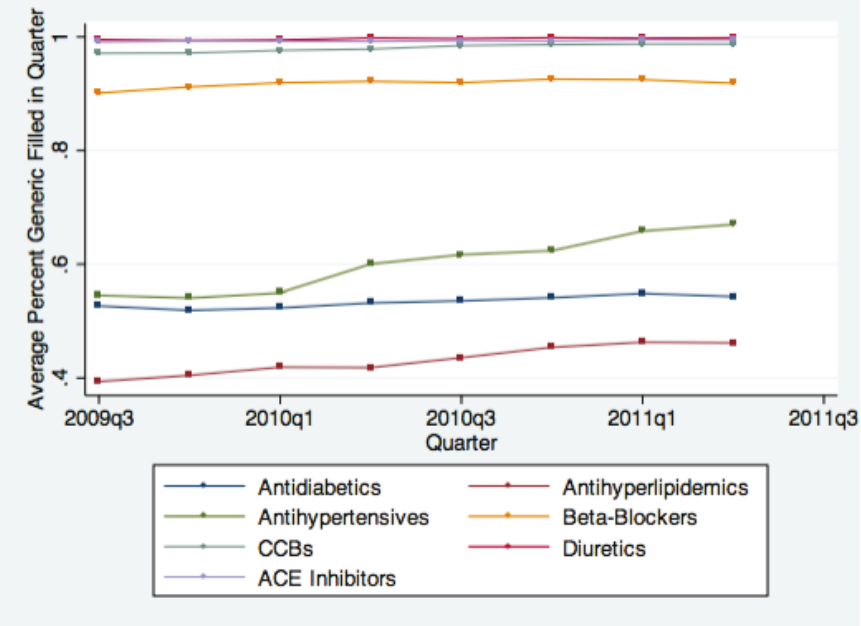


Figure 3.13.3: Average quarterly generic proportion, other medication classes

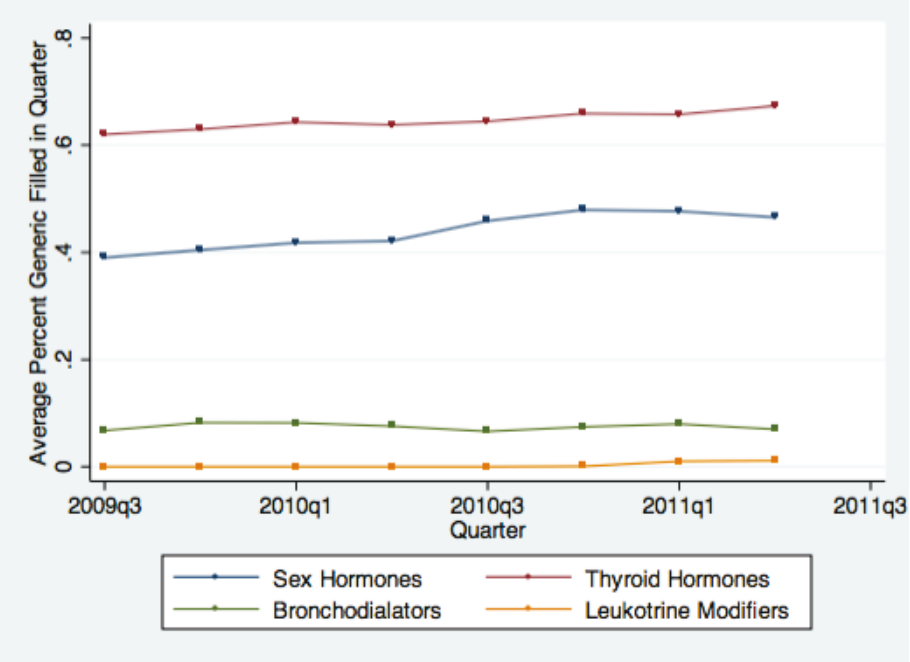


Figure 3.13.4: Quarterly generic usage separated by the number of chronic conditions.

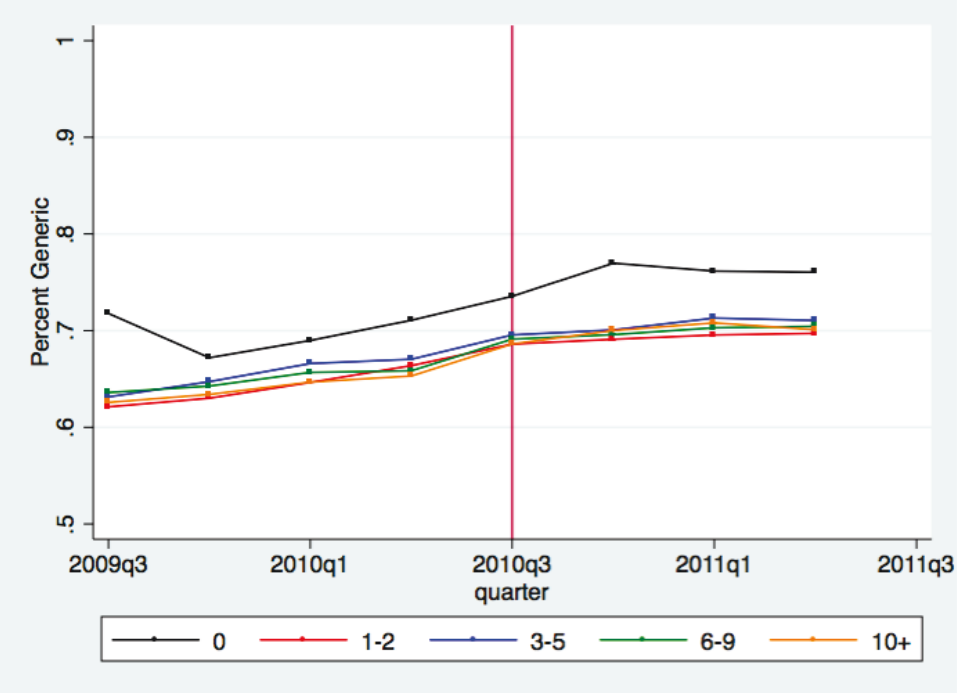


Figure 3.13.5: Distribution of chronic conditions across plan types, pre-period, FY '09.

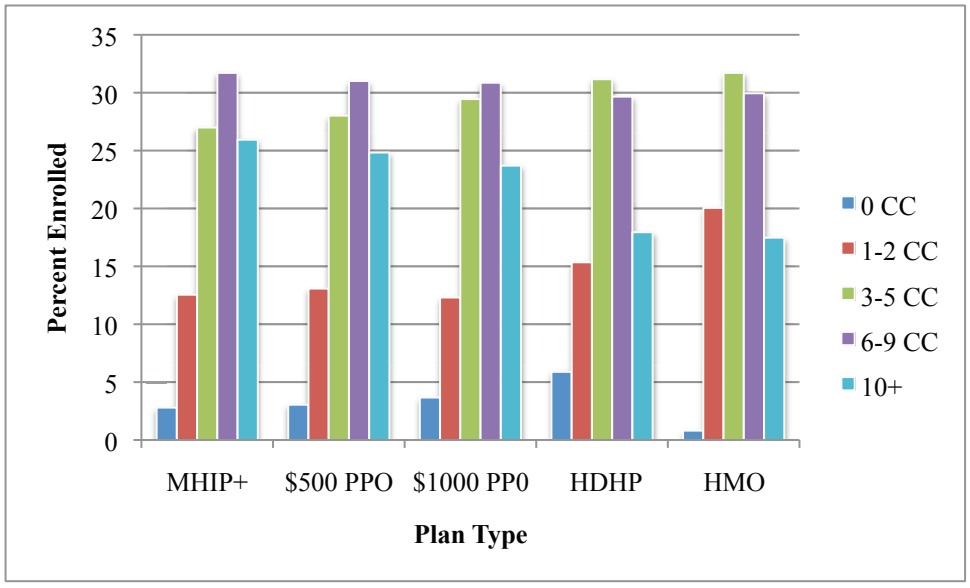
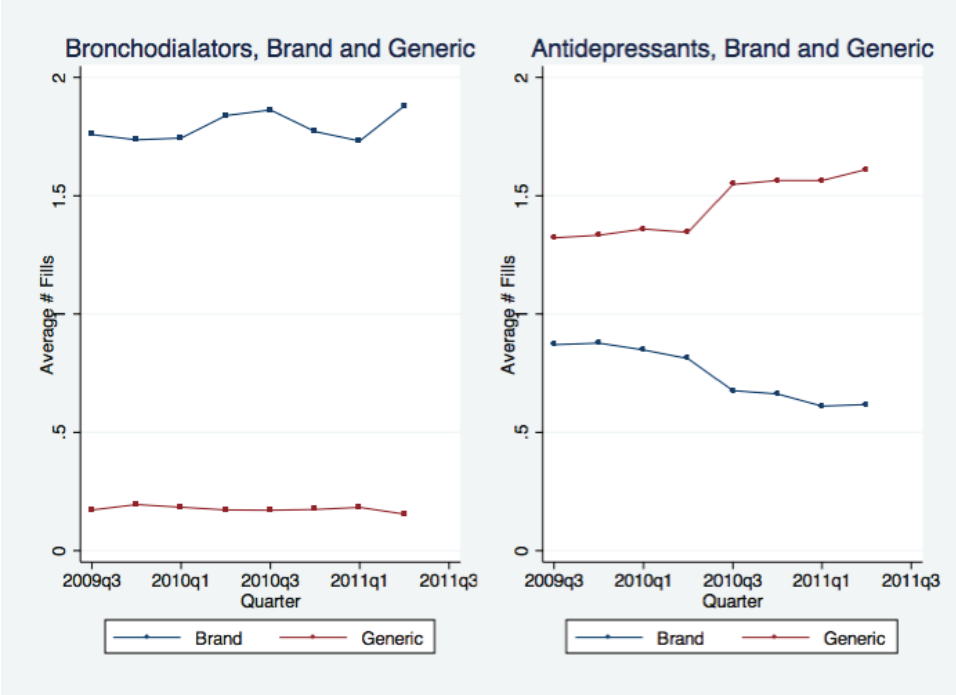


Figure 3.13.6: Quarterly average utilization rates for bronchodilators and antidepressants



4 The impact of copayment changes on adherence to prescription drugs for patients with comorbid physical and mental health conditions.

4.1 Abstract

Background: Trends in insurance benefit design are moving towards lower copayments for generic drugs while raising copayments on more expensive brand-name drugs in the hopes of reducing overall health care spending. High-risk patients, including those with both mental health and physical comorbidities, may face problems in maintaining both mental health and chronic condition medications regimens when cost sharing changes.

Objective: The objective of this paper is to assess whether adherence to medications changes in those with mental health and chronic physical conditions following a change in copayment structure.

Data: This study uses claims data from Maryland's high-risk pool, an insurance plan for individuals who were denied coverage on the individual insurance market because of pre-existing conditions. In July 2010, the high-risk pool lowered copayments on generics and raised them on non-preferred and preferred brand drugs.

Sample: The sample is limited to adults living in Maryland aged 18-64 filling at least two prescriptions in the year prior to the copayment change: one in the mental health classes of antidepressants, antipsychotics, mood stabilizers, stimulants and anti-anxiety

medications and at least one drug in one of the chronic medical disease categories including anti-diabetics, cardiovascular medications and respiratory agents. Since many drugs can be used for purposes other than the main indication, sensitivity analyses were conducted for the sample inclusion method, using diagnosed condition as well as a combination of condition and drug use.

Methods: An interrupted time-series design with individual-level data was used to exploit both the patient-level data and the natural experiment of a change in insurance benefit design. Given the longitudinal nature of the data, generalized estimating equations are used to control for correlations within an individual over time. The main outcome, adherence within class, was calculated as the proportion of days where a drug was available from the time of the first prescription through the end of the calendar quarter.

Results: 2,846 individuals that were enrolled across the study period had fills in at least one chronic medical and one mental health medication. Adherence declines over time in all classes, regardless of the policy change. The odds ratio for the policy change was significant for only one class, however, many of the changes in predicted probability were significant, though small in magnitude, particularly for those with multiple chronic conditions.

Conclusions: This insurance benefit design change did not significantly impact patient adherence to medications, among those with both mental and physical health comorbidities. Factors other than copayments may be influencing patient adherence.

4.2 Introduction

Only about 50% of patients living high-income countries take medications as prescribed (World Health Organization 2003; Osterberg and Blaschke 2005). Many factors can affect whether patients adhere to recommended medication regimens including the cost to the patient (copay or coinsurance), perceived and real side effects, personal characteristics or prescriber behavior (Piette, Heisler, and Wagner 2004; Piette et al. 2006). Lower adherence is often associated with higher mortality and increased incidence of further health complications in chronic diseases (Horwitz et al. 1990; Sokol et al. 2005; Ho, Bryson, and Rumsfeld 2009). Increased adherence has also been associated with lower medical spending (Stuart et al. 2011).

Adherence to medications for chronic diseases varies widely by condition in the United States. Hypertension medications have shown to have quite high adherence, with over 70% of individuals having the medication on hand at least 80% of the time, a commonly used measure of adherence (Briesacher et al. 2008; Cramer et al. 2008). Adherence to type II diabetes medications has been found to be 62-64% (Cramer 2004), while adherence to asthma medications is well below 50%, even as low as 10% in the elderly (Gillissen 2007; Bozek and Jarzab 2010).

Medication adherence to mental health medications among those with mental illnesses in the US varies widely with estimates ranging from 20 to 90% depending on the population and condition (Cramer and Rosenheck 1998). Pompili et al. (2013) in a systematic review found that those with mood disorders were at high risk for non-adherence to mental health medications for a variety of reasons including co-occurring substance abuse, perceived side effects of the medications and patient/provider characteristics (Pompili et al. 2013). There are several studies showing the importance of factors such as side effects for medication adherence in serious and persistent mental illnesses such as schizophrenia or bi-polar disorder (e.g. Dolder et al. 2003).

While 29% of those with medical illnesses also have a mental health condition, 68% of those with mental disorders also have chronic physical comorbidities (Druss and Walker 2011). Those with co-occurring depression have been shown to be much more likely to use a variety of emergency services than those without co-occurring depression, suggesting the diagnosis of depression is a mediating factor in health care usage (Himelhoch et al. 2004). For those with co-occurring physical comorbidities, the mental illness may impact the adherence for both medical and physical medications. For example, depression makes people less likely to take medication for cardiovascular conditions and diabetes (Gehi et al. 2005; Kronish et al. 2006; W. Katon et al. 2009). Grendard et al. in a systematic review, determined that depressed patients were 76% more likely to be non-adherent for physical illness medications than non-depressed patients (Grenard et al. 2011).

There are a multitude of proposed interventions to improve adherence for those with mental health issues (Dolder et al. 2003; Viswanathan et al. 2012). However, few studies have examined the impact of cost sharing changes on adherence to either mental health classes or chronic medical medications, even though those with mental health conditions have high comorbidity rates. This is despite the fact that evidence suggests that mental health services are more responsive to cost sharing than other health services (Manning et al. 1986). Soumerai and colleagues found that when New Hampshire Medicaid implemented a cap on prescription drugs, those with schizophrenia increased their clinic visits and had more emergency hospitalizations (Soumerai et al. 1994). Goldman et al. (2004) examined a large, multi-employer database and found that among those with chronic illnesses and mental health conditions had lower rates of responsiveness to increases in cost sharing. For example, Goldman found that the number of days supplied for antidepressants decreased 8% for those with depression, while the use of antidepressants decreased 25% for the rest of the population (Goldman et al. 2004).

Recent experiments have tried to remove copayments in order to increase adherence for chronic physical ailments (Choudhry, Avorn, et al. 2011; Maciejewski et al. 2010). Choudhry and colleagues found that giving patients with recent heart attacks drugs without any cost sharing increased adherence by 4-6 percentage points, but did not reduce the incidence of subsequent health events. However, the time when an adverse event occurred was shortened. This change in cost sharing also did not significantly impact health care spending. Maciejewski et al. (2010) evaluated a policy to lower copayments

for patients with diabetes, hypertension, hyperlipidemia and congestive heart failure and found that adherence increased 1.5 to 3.8 percentage points more than in the control group.

The objective of this paper is to assess how adherence to medications among those with both mental health and chronic physical conditions changes with alterations to copayment structures. In this case, a value-based insurance design initiative, which lowered the copayments for generic drugs while increasing them for brand name drugs. Given the concerns regarding adherence among those with mental illnesses, it is not known how changes in cost sharing would work in a population with both mental illnesses and comorbid physical illnesses. As such, the direction of the expected effect is unclear.

4.3 Data

Data for this analysis consist of pharmacy and medical claims from Maryland's Health Insurance Plan, the state's high-risk pool, from 2009-2011. High-risk pools insure those who tried to get coverage on the private market and who were denied because of preexisting conditions. Thirty-five states have high-risk pools outside of the federal program enacted as part of health reform (NASCHIP 2012). Maryland has the country's fourth largest high-risk pool (Kaiser State Health Facts 2011). These high-risk pool enrollees do not have the option to enroll in other government programs: they make too much money to qualify for Medicaid and are younger than the Medicare eligibility age of 65. Ultimately these pools will be incorporated into the health exchanges. For health

plans as well as the state and federal governments, finding ways to control spending in the high-risk populations in the exchanges will be key in keeping premiums low.

Starting in 2002, this state-run plan uses funds from a statewide hospital tax to subsidize health insurance premiums for individuals with preexisting conditions. In order to qualify for this insurance, the person must have attempted to purchase coverage on the private individual market and be denied because of pre-existing medical conditions, or because the premiums offered are more expensive than what MHIP would charge for a similar medical condition. Premiums for the high-risk pool are generally set at about 125% of the average premium in Maryland's individual market. For the average enrollee in 2012, the premium is about $500 per month.

This analysis exploits a change in the pharmacy benefit structure in July 2010. The pool lowered the copayments on generic drugs and raised them on all other tiers. Additionally, the pool created a specialty tier (fourth tier) for very expensive drugs, such as many of the drugs to treat HIV/AIDS and rheumatoid arthritis.

MHIP offers a selected set of plans with added subsidies for low-income individuals. MHIP has two different cost sharing structures for the MHIP+ plans and all other plans (PPO and HMO options). As such, plan type is included as a covariate in the regression models. Table 2.11.1 shows an example of given tiers and copayments as they changed across the two fiscal years of interest.

[Table 2.11.1: Drug Tiers, Co-pays and drug examples]

4.4 Sample

For inclusion in the sample, enrollees had to be continuously enrolled for one year before and after the policy change and be aged 18-64. The primary method for identifying who was in the sample was whether they also had to have at least one fill of a prescription for a drug in the mental health medications classes and at least one fill of a chronic medical condition medication class in the pre-period. The included classes are:

1. Physical health
    a. antihyperlipidemic agents
    b. antidiabetic agents
    c. beta-adrenergic blocking agents (Beta Blockers)
    d. angiotensin converting enzyme inhibitors (ACE inhibitors)
    e. antihypertensive combinations
    f. sex hormones
    g. thyroid hormones
    h. bronchodilators
    i. diuretics
    j. calcium channel blocking agents (CCBs)
    k. leukotriene modifiers
2. Mental health
    a. antidepressants
    b. anxiolytics, sedatives, and hypnotics
    c. anticonvulsants
    d. antipsychotics
    e. central nervous system (CNS) stimulants

The primary approach of using drug usage in the pre-period only, may introduce some bias since some of these drugs can be used for other purposes. As a sensitivity analysis, the sample has also been constructed using International Classification of Disease – 9 (ICD9) codes for a specified group of chronic conditions. This means the person had to have visited a health care provider and have been diagnosed with both a mental health condition such as depression and a physical comorbidity such as hypertension.

Another approach was also taken. The most restrictive way to define the sample is to identify those with at least one mental health and physical comorbidity AND at least one drug in both categories. In total, three different ways to determine if the person had both a chronic condition and a mental illness were conducted.

The chronic conditions selected are those that are most likely to use the medication classes selected above, using the Agency for Healthcare Research and Quality's Clinical Classifications Software (AHRQ CCS) (Elixhauser, Steiner, and Palmer 2012). Sample conditions include mood and anxiety disorders, hypertension, diabetes, arthritis, cardiovascular and other heart problems, asthma and chronic obstructive pulmonary disorders (Table 4.9.1).

[Table 4.9.1: Included Conditions in Mental Health/Physical Comorbidity Groupings]

4.5 Variables

4.5.1 Independent Variables

Adherence to medication can be conceptualized with Figure 4.10.1, adapted from two sources, Piette et al. 2005 and Osterberg and Blaschke 2005. Both sets of authors conceptualized adherence being not only the result of patient-level factors, but also the patient's interaction with physicians, the health system and the drugs themselves. The blue boxes represent the patient-level factors associated with adherence. Health status, such as the number of chronic conditions, or the presence of a mental health condition

could lower adherence. The policy change of altering the copayment structure, could also affect adherence. The green boxes represent other factors outside the patient's control such as the regimen complexity of a particular drug or whether the pharmacy has the drug in stock.

[Figure 4.10.1: Barriers to adherence.]

There are many patient, physician and systems-level characteristics that could affect a patient's adherence. These are all factors that would ideally be measured in analyses looking at the impact of copayment changes, however, factors such as education or health literacy are not available in claims data. These omitted variables could bias coefficients if the omitted variables are correlated with the included variables. Ideally, we would like to conduct a randomized experiment so the variety of characteristics could be equal across groups. However, that is not possible in many natural experiments such as MHIP's. As such, this study controls for as many factors as possible in claims data. Time series analysis methods can control for some of the time invariant unobserved factors, making these designs particularly strong quasi-experimental designs.

The main covariate variables are age, gender, number of chronic conditions and plan type. Age is measured continuously and gender is measured as binary (1=female). The number of chronic conditions is measured continuously, using AHRQ's Clincial Classifications Software (Elixhauser, Steiner, and Palmer 2012). For a condition to be counted as chronic, the ICD9 code had to appear in at least two outpatient visits or at least one

inpatient visit, in order to be sure this was for a diagnosed condition, rather than a code used for a diagnostic visit to "rule out" if someone had a particular condition.

The enrollment file includes information on plan type such as Preferred Provider Organization (PPO) or Health Maintenance Organization (HMO), which represent differences across plan benefit structure and income. MHIP provides a second set of plans called MHIP+ for the lower income individuals, for those making less than 250% of the federal poverty level, which was about $27,000 annually for an individual in 2009. Across any of the given person-months, approximately 25% are enrolled in MHIP+ in a given month while 40% are enrolled in the PPO plans and 23% are enrolled in a HDHP. This is a crude proxy for income.

Plan types are included as separate dummy variables, because the cost sharing structures across the different plans may also affect adherence, in addition to the copayment shift. The $500 PPO deductible plan is used as a reference group to allow for an examination of whether the low-income individuals in MHIP+ are behaving differently after the copayment shift than those in the regular MHIP plans.

4.5.2 Dependent Variable: Measuring Adherence

The main outcome for this analysis is the adherence to medication within a drug class, like antidepressants or antipsychotics. Adherence is a previously validated, commonly used metric for assessing how well patients are taking drugs they are prescribed. The

metric is used in the HEDIS health plan quality measures and the measurement of adherence has been standardized by the International Society of Pharmacoeconomics and Outcomes Research (B. C. Martin et al. 2009; Cramer et al. 2008).

Adherence can be measured in a variety of ways, including direct methods, such as observing patients taking medications and indirectly using claims data algorithms (Osterberg and Blaschke 2005). While directly observing someone taking their medication would be the most accurate way to ensure valid measurement of adherence, this is time consuming and expensive. Claims data measures do make the assumption that if a person has filled the medication, they are taking it for the indicated days supplied (Osterberg and Blaschke 2005).

This analysis uses pharmacy claims data measures. Since individuals with chronic medical conditions could require several medications within a class, adherence is measured following a procedure developed by Choudhry et al. (2009). This measure calculates the proportion of days covered by a medication in a class, regardless of how many medications are available on a given day. Table 4.9.2 shows an example of how this measure is calculated. An interval measure takes the proportion of days where at least one drug was supplied divided by the number days from the start of the first medication to the end of the interval, in this case, the calendar quarter (Choudhry et al. 2009). The first example in table shows someone with a 28-day antipsychotic prescription for the 90-day quarter, resulting in 0.31 proportion of days covered. The second example shows someone with several antidepressant prescriptions. The first and

second fills of the medication overlap, and this method of calculation counts the overlap (bright green) as extra days of medication.

[Table 4.9.2: Example adherence calculation]

4.5.3 Analysis

An interrupted time series design using individual-level data is used. The key variable of interest is the policy change indicator, where the null hypothesis is that an absence of the policy change, the trend of generic utilization would have remained constant.

$$Y_{it} = f(\beta_0 + \beta_1 time_t + \beta_2 policy_t + \beta_3 posttime_t + \beta_4 chronic_i + \beta_5 chronic*policy_{it} + \beta_6 chronic*posttime_{it} + X_{it}\lambda)$$

$\beta_1 time_t$ is the time trend, measured quarterly since July 2009. The policy change is included as a binary indicator equal to zero in the pre-period and one in the post period. The post time variable measures the quarters continuously since the policy change, so it is equal to zero in the pre-period and begins at one in July 2010. $\beta_2 policy_t + \beta_3 posttime_t$ represents the impact of the policy change for the whole sample including both the initial impact and the change in the trend after the intervention. $\beta_4 chronic_i$ details how patients with different numbers of chronic conditions will react. $\beta_5 chronic*policy_{it}$ represents how the policy impact changes across groupings of numbers of chronic conditions and $\beta_6 chronic*posttime_{it}$ represents whether the trend in the post-period is different for

different numbers of chronic conditions after the policy change. $X_{it}\lambda$ represents the vector of control covariates: age, gender and plan type.

All outcomes are analyzed using generalized estimating equations (GEE) specifications to analyze the impact of the policy change because having a prescription in one month is highly correlated with having a prescription drug in the next month, particularly for chronic disease patients. GEE allows for the specification of the family (i.e. Gaussian) and link function (i.e. identity or log) for the mean, making this a very flexible regression model. The correlation structure was assessed through examining the correlation between the outcome over time (Cameron and Trivedi 2005). Due to the binary nature of the outcome, models used the logit link with binomial family.

4.6 Results

4.6.1 Descriptive Results

The final sample size using the primary sample inclusion definition resulted in 2,846 individuals taking both a mental health medication and a physical health medication. Table 4.9.3 shows the changes in sample size between the methods, from the least to most restrictive. For the main analysis, the sample taking both a mental health medication and a physical health medication is analyzed. Given the uncertainty in claims data for identifying the sample based off of pharmacy records alone, the sensitivity of the results to this choice is also analyzed, using two other methods: identifying from diagnosed conditions as well as those with both drug use and diagnosed conditions.

[Table 4.9.3: Sample Sizes According to Inclusion Method]

The most common chronic conditions are lipid disorders (high cholesterol), hypertension, and mood disorders, though individual constellations vary widely. Table 4.9.4 shows a few example individuals from the sample and their conditions. For example, person one has high cholesterol, nervous system disorders, cardiac dysrhythmias, heart valve problems and mood disorders (depression). Person two has two mental health conditions (mood and adjustment disorders) as well as upper respiratory problems, high cholesterol and an endocrine disorder.

[Table 4.9.4: Example Individuals' Chronic Conditions]

Across drug classes, adherence varies. **Error! Reference source not found.** displays the average proportion of days covered within each class, across the three sample size groups in the year before and after the policy change. From this figure, it is clear that the proportion of days covered is similar across sample inclusion methods, therefore the main results presented are those with the largest sample size: those using drugs in at least one mental health and at least one physical health condition. Average proportion of days covered is highest for thyroid medications at nearly 90% in the pre-period and about 85% in the post period. Antidepressants and several of the cardiovascular medications such as beta-blockers and antihypertensives are above 80% in the pre-period and just above 70% in the post period.

[

Figure 4.10.3: Yearly proportion of days covered across sample definitions.]

Adherence in all classes declines over time. Adherence is lowest in anxiolytics/sedatives (~60% in the pre-period) and bronchodilators (~50% in the pre-period). The lower adherence in the bronchodilator class is being driven primarily by a large number of albuterol medications (50% in the class). While these are the same molecule as more long-acting formulas, then tend to be used more as rescue medications. However, they have been left in the class as the drugs are the same molecules.

For the main sample (drug usage only), Figure 4.10.5 - Figure 4.10.7 show the quarterly average proportion of days covered in each group. For all classes, shown in adherence decreases over time, as is consistent with other studies (e.g. Lieberman et al. 2005; Benner et al. 2002). Over time, the mental health classes have lower adherence than the cardiovascular medications, with the average proportion of days covered in the last quarter ranging from 20-30%, compared with 40-50% of the days covered in the cardiovascular classes.

Figure 4.10.4: Average proportion of days covered per quarter for cardiovascular diseases and diabetes.
Figure 4.10.4: Average proportion of days covered per quarter for cardiovascular diseases and diabetes
Figure 4.10.7: Average proportion of days covered for hormones and lung disease]

4.6.2 Multivariate Results

After adjusting for the adherence trend, gender, plan type and number of chronic conditions, most drug classes did not show significant changes in adherence at the policy

change. The coefficient is significant in a negative direction (less likely to be adherent) for anxiolytics, anticonvulsants and bronchodialators. However the post-period time trend is significant for nearly all drug classes (Table 4.9.6 - Table 4.9.8).

[Table 4.9.6: Regression results, mental health classes, odds ratios with 95% confidence intervals.
Table 4.9.6: Regression results, cardiovascular-related classes, odds ratios with 95% confidence intervals.
Table 4.9.8: Regression results, other classes, odds ratios with 95% confidence intervals]

Examining the marginal effects gives a more comprehensive view of the impact of the policy across selected numbers of chronic conditions. The impact of having multiple morbidities on adherence for those with both mental and physical comorbidities, is generally not significant for most drug classes

Plan type has the potential to change utilization of medical services because plans have different deductible and cost-sharing structures. Consumers in MHIP's high deductible plan, for example, have to spend $4600 before the drug cost sharing begins. However, across all regular MHIP plans, the cost sharing structure is the same. For some drug classes, the plan type did impact utilization. The MHIP+ plans are for those with incomes below 250% of the federal poverty level, $25,000 annually for an individual. The MHIP+ plans have lower copayments than the regular MHIP plans, but the copayment structure is the same for all MHIP+ plans (Table 2.11.1). As such, the MHIP+ plan allows some control for income, but only whether a person is above or below 250% of the Federal Poverty Level.

Across the different classes, each plan type had an inconsistent relationship. For example, the HDHP plans did not consistently decrease utilization across all classes, but did for some. For those who used antidepressants, the high deductible plan meant 28% less likely to be adherent compared with those in the $500 deductible PPO plan ($p<0.01$). Those in the HDHP were also 25% less likely ($p<0.05$) less likely to be adherent to high cholesterol drugs. Those in MHIP+ plans were 24% more likely ($p<0.1$) to be adherent to anticonvulsants compared with those in the $500 deductible PPO plan. Hypothetically, those in the less generous plans would be expected to be more non-adherence because of spending levels, but this relationship does not hold consistently across classes. It is possible that for some of the classes, the sample sizes get too small to achieve statistical significance.

The impact of age on the odds of adherence was different for each drug class, but very low in magnitude (less than 3% increase/decrease) across all classes. For example, every year increase in age increases the odds of adherence 2% ($p<0.01$) for antidepressants and 4% for antidiabetics ($p<0.01$). Gender had a varying impact depending on class. Women were over two times as likely to be adherent to sex hormones than men, likely because the majority subclass is birth control pills. Women were 21% more likely to be adherent then men to antidepressants, while about 35% less likely to be adherent to antihyperlipidemics or antidiabetics.

4.6.3 Sensitivity Analyses

The primary sensitivity analysis was to test the robustness of the results to the sample inclusion method, since identifying the sample by drug use alone could include those who are taking particular drugs for other reasons than the indicated condition. For those with both a mental health and chronic physical condition, as identified with ICD9 codes, the impact of the policy change is only significant for antidepressants. The likelihood of adherence to antidepressants is 30% less in the post period ($p<0.05$). When the sample is restricted even further to those with both drug use in the given classes and the ICD9 code diagnoses, the policy change is no longer significant for antidepressants. Most of the odds ratios for age, plan type, gender and chronic conditions are no longer significant. This is likely due to the dropping sample sizes when restricting the samples. These tables can be found in the appendix (Table 4.11.1 - Table 4.11.6).

Further sensitivity analysis was done for two of the larger classes (antidepressants and antihyperlipidemics) to assess whether adherence to generic drugs improved in the post period, since the copayment change was dropping the copayments for the generic drugs in all plans (Table 4.9.11). For both classes the likelihood of adherence to generics in these classes increased, with postive odds ratios for the post-time trend, but not the policy change itself. The number of chronic conditions is not a significant predictor of adherence to generics in this sample.

Table 4.9.11: Regression results, generics (tier 1) antidepressants and antihyperlipidemics, odds ratios with 95% confidence intervals

4.7 Discussion

This study finds overall, little impact of a policy change on adherence across a broad range of both mental health, cardiovascular, hormone and lung-disease medications from the change in copayments. Adherence decreases over time across all drug classes. While several classes saw reduced odds of adherence at the point of the policy change, when coupled with the post-time trend, these were not significant. Plan type and the various deductible arrangements can impact the use of some classes, so that those plans requiring the high deductibles or the HMO plans generally lead to lower adherence. However, the plan type was an inconsistent predictor of low adherence. The impact varied by class and was not significant for many. The low-income were not more or less likely to change their adherence pattern following the policy change, as proxied through the indicator for MHIP+.

Few studies have examined how those with multi morbidities react to changes in cost sharing. There are two studies in particular, and both confirm the general direction of results found here, though the populations are different. While this study uses working aged adults with both mental and physical comorbidities, Goldman et al. (2004) used and employer population while Wang et al. (2011) used Veteran's Administration enrollees. Goldman et al. (2004) examined the drug use associated with particular conditions for those who had the condition, and then compared this utilization to others also using these drugs. For example, those with a depression diagnosis reduced antidepressant use 8 percent after an increase, versus 26% for the rest of the study sample (Goldman et al.

2004). Wang et al. (2011) examined how a five-dollar copayment increase impacted adherence in those with high and low comorbidity burdens. They found that despite the increase in copayments for those with higher numbers of chronic conditions, the sicker group did not reduce adherence as much as the lower comorbidity group (V. Wang et al. 2011).

The decreasing adherence rates over time in this study are consistent with other studies in the adherence literature. The Clinical Antipsychotic Trials of Intervention Effectiveness (CATIE) trial, for example, found that 74% of participants discontinued antipsychotic medication within 18 months (Lieberman et al. 2005). Many other studies show decreases in adherence over time, but show increases with lower copayments (Chernew et al. 2008; Maciejewski et al. 2010; Maciejewski et al. 2014) These analyses focus on broader employer groups, which may not be informative for the high-risk individual market group.

For those with 10+ conditions, increase in the odds of being adherent is much smaller than or those with three, four or five conditions. This may be a function of having more medications, adding therapeutic complexity to the calculations of making changes in drug selection. Choudhry et al. (2011) examined several measures of complexity including number of different drugs filled, number of pharmacies used and the number of different physicians prescribing the fills. The authors found that overall, the greater the number of drugs, physicians and pharmacies all lowered adherence for ACE inhibitor users (Choudhry, Fischer, et al. 2011). The authors conclude that taking more medications

makes it more challenging to follow the directions of physicians. However, Grant and colleagues published two studies examining those with diabetes and high cholesterol and found that the number of medications did not impact adherence. The findings of these authors suggest that those with multiple morbidities and medications may be more risk-averse to changing complex medication regimens once they have an established routine (Grant et al. 2003; Grant et al. 2004).

A physician's influence could also matter. Goldman et al. (2004) found that for those diagnosed with a chronic condition and were seeing a physician; the decrease in days supplied of a particular drug was much smaller after a doubling of copayments, compared with those who were not under ongoing care. Unfortunately, this study could not examine the behavior of the physicians.

Other studies examining the impact of mental illness and adherence show that conditions such as depression can decrease adherence to all medications (Chapman, Perry, and Strine 2005). The MHIP study sample used here was restricted to those with both mental health and chronic medical conditions, and shows overall, this group to be fairly unresponsive to the copayment shift. Since no great impacts on adherence were found, it may be that this sample is experiencing low severity mental health conditions. To even buy into the pool, the person must have enough money to pay the premiums, and is therefore evidence that they must have lower severity conditions that allow them to work. The fact that there is increased adherence to antidepressants as the number of chronic conditions increases suggests that those with more chronic conditions may be more

depressed (W. J. Katon 2011). This could be the result of those with more health problems are more likely to also be depressed, but this study is not set up to assess the direction of this causality.

4.7.1 Limitations

Copayments or coinsurance are not the only factor that affect patient adherence. Many others such as side effects, patient characteristics like education, social supports or provider characteristics can impact whether patients continue to take medications as prescribed for chronic ailments. Unfortunately, many of those cannot be examined with claims data. This could have biased the results. However, the interrupted time series design with individual level data is one of the strongest experimental designs in the absence of a control group.

A major limitation for this analysis is that the actual number of individuals in each drug class was quite small for many of the models; particularly as the sample sizes were restricted in the sensitivity analysis. Leukotriene modifiers, used in the treatment of asthma, only had 184 individuals, which limits the generalizability of these results. As a result of the small sample sizes, the coefficients for many of the variables in some of the classes may have reduced or no statistical significance. Studies on larger populations are needed to confirm the impact of copayment increases in individuals with multiple morbidities.

The other major assumption underlying this study is that if a person has filled the medication, they are assumed to be taking it as directed. Unfortunately, the direct methods of observation are expensive, and the claims data measures have been shown to correlate with the reported measures (Cramer et al. 2008). One additional limitation should also be noted, that of restricting the sample to those continuously enrolled for the year before and after the policy change. The likely impact of this analysis choice is to bias results downward, since those who are younger and healthier are more likely to be more price-sensitive and therefore drop coverage.

4.8 Conclusions

This particular value-based insurance design had limited impact on adherence to medications used to treat chronic diseases. Even though generic medication copayments were lowered between 33-50%, and brand name drugs rose 20-40%, adherence was not substantially shifted in either a positive or negative direction. If the objective of value-based insurance design is to change behavior in favor of lower cost, clinically effective services, and if no response was recorded, then this policy is not causing the intended effect. Adherence was not significantly impacted in the post-implementation period, suggesting enrollees were forced to bear increased financial burden.

4.9 Tables

Table 4.9.1: Included Conditions in Mental Health/Physical Comorbidity Groupings

Mental Health/Physical comorbidity Grouping	Condition
MH	Mood disorders
MH	Anxiety disorders
MH	Other nervous system disorders
MH	Screening and history of mental health
MH	Adjustment disorders
MH	Attention-deficit, conduct, and disrupt
MH	Substance-related disorders
MH	Alcohol-related disorders
MH	Schizophrenia and other psychotic disorders
MH	Personality disorders
MH	Impulse control disorders
PC	Essential hypertension
PC	Disorders of lipid metabolism
PC	Diabetes mellitus without complication
PC	Thyroid disorders
PC	Osteoarthritis
PC	Diabetes mellitus with complications
PC	Other upper respiratory disease
PC	Asthma
PC	Coronary atherosclerosis and other hear
PC	Cardiac dysrhythmias
PC	Hypertension with complications
PC	Heart valve disorders
PC	Chronic obstructive pulmonary disease
PC	Other endocrine disorders
PC	Peripheral and visceral atherosclerosis
PC	Other and ill-defined heart disease
PC	Chronic renal failure
PC	Congestive heart failure; nonhypertensive
PC	Peri-; endo-; and myocarditis; cardiomyopathy
PC	Acute cerebrovascular disease
PC	Occlusion or stenosis of precerebral artery
PC	Transient cerebral ischemia
PC	Other circulatory disease
PC	Acute myocardial infarction
PC	Other and ill-defined cerebrovascular disease
PC	Pulmonary heart disease
PC	Aortic; peripheral; and visceral artery
PC	Cardiac arrest and ventricular fibrilla
PC	Diabetes or abnormal glucose tolerance

Note: MH=mental health condition, PC=physical health condition

Table 4.9.2: Example adherence calculation

Example adherence calculation

	1-Jul-08	8-Jul-08	15-Jul-08	22-Jul-08	29-Jul-08	5-Aug-08	12-Aug-08	19-Aug-08	26-Aug-08	2-Sep-08	9-Sep-08	16-Sep-08	23-Sep-08	Total days
Antipsychotic														
Claim 1														28
Claim 2														0
Claim 3														0
PDC														0.31
Antidepressant														
Claim 1														28
Claim 2														21
Claim 3														21
Claim 2 overlap														7
PDC														0.84

Table 4.9.3: Sample Sizes According to Inclusion Method

Sample Definition

At least one MH and PC drug	At least one MH ICD9 and at least one PC ICD9	Having both the ICD9 and the drugs (Col 1 & Col 2)	Total Enrolled over 2-year period with at least one drug claim
2,846	2,213	1,385	7,883
36%	28%	18%	

Table 4.9.4: Example Individuals' Chronic Conditions

Example Individuals' Chronic Conditions

Person 1	**Person 2**
Disorders of lipid metabolism	Disorders of lipid metabolism
Other nervous system disorders	Other endocrine disorders
Heart valve disorders	Other upper respiratory disease
Cardiac dysrhythmias	Adjustment disorders
Mood disorders	Mood disorders

Table 4.9.6: Regression results, mental health classes, odds ratios with 95% confidence intervals.

Variable	Antidepressants	Anxiolytics	Anticonvulsants	Antipsychotics	CNS Stimulants
Time trend	0.76***	0.81***	0.84***	0.79***	0.77***
	[0.729 - 0.795]	[0.774 - 0.848]	[0.795 - 0.881]	[0.726 - 0.860]	[0.708 - 0.845]
Number of chronic conditions	1.01	1.01	1.01	1.02	0.99
	[0.997 - 1.031]	[0.995 - 1.030]	[0.986 - 1.026]	[0.986 - 1.051]	[0.960 - 1.031]
Policy change	**1.1**	**0.71*** **	**0.84***	**0.93**	**1.13**
	[0.914 - 1.327]	**[0.577 - 0.867]**	**[0.690 - 1.023]**	**[0.662 - 1.314]**	**[0.775 - 1.654]**
CC * Policy change	0.98**	1.03***	1.01	0.98	0.99
	[0.964 - 0.999]	[1.013 - 1.055]	[0.992 - 1.026]	[0.947 - 1.011]	[0.952 - 1.035]
Post-time trend	1.21***	1.27***	1.17***	1.37***	1.19**
	[1.120 - 1.306]	[1.169 - 1.372]	[1.069 - 1.271]	[1.177 - 1.601]	[1.038 - 1.367]
CC * Post-time trend	1.01**	1	1	0.99	1
	[1.001 - 1.013]	[0.990 - 1.003]	[0.994 - 1.005]	[0.982 - 1.006]	[0.990 - 1.012]
Age	1.02***	1	1	1	0.99
	[1.014 - 1.028]	[0.992 - 1.007]	[0.991 - 1.009]	[0.989 - 1.017]	[0.982 - 1.007]
Gender (male, reference)	1.21**	0.87	0.86	0.9	0.98
	[1.026 - 1.423]	[0.730 - 1.048]	[0.694 - 1.060]	[0.641 - 1.267]	[0.697 - 1.386]
Plan type ($500 PPO, reference)					
MHIP+	0.87	1.1	1.24*	1.06	0.98
	[0.733 - 1.033]	[0.916 - 1.316]	[0.998 - 1.536]	[0.797 - 1.409]	[0.696 - 1.391]
$1000 PPO	0.97	0.87	0.94	1.75***	1.17
	[0.781 - 1.192]	[0.676 - 1.110]	[0.729 - 1.212]	[1.187 - 2.587]	[0.757 - 1.822]
HDHP	0.72***	1.01	0.8	1.3	1.03
	[0.581 - 0.888]	[0.770 - 1.315]	[0.591 - 1.073]	[0.799 - 2.106]	[0.594 - 1.783]
HMO	0.68***	0.84	0.81	1.94**	0.77
	[0.517 - 0.882]	[0.626 - 1.118]	[0.568 - 1.164]	[1.115 - 3.371]	[0.396 - 1.511]
Constant	1.66***	1.28	2.17***	1.96*	3.68***
	[1.155 - 2.387]	[0.820 - 1.986]	[1.352 - 3.484]	[0.997 - 3.870]	[1.883 - 7.173]
Observations	13722	10079	7387	2918	2535
Number of subid	1832	1386	1023	395	342

Robust CI in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 4.9.6: Regression results, cardiovascular-related classes, odds ratios with 95% confidence intervals.

Variable	Antihypertensives	Antihyperlipidemics	Antidiabetics	ACE inhibitor	CCBs
Time trend	0.74***	0.71***	0.88***	0.71***	0.77***
	[0.673 - 0.816]	[0.669 - 0.748]	[0.805 - 0.963]	[0.654 - 0.780]	[0.716 - 0.838]
Number of chronic conditions	0.98	0.99	0.98	0.98	1.01
	[0.946 - 1.010]	[0.974 - 1.015]	[0.955 - 1.016]	[0.946 - 1.008]	[0.981 - 1.030]
Policy change	0.82	0.9	0.71	0.87	0.92
	[0.510 - 1.321]	[0.696 - 1.165]	[0.446 - 1.141]	[0.564 - 1.344]	[0.664 - 1.280]
CC * Policy change	1.02	1	1.01	0.99	1
	[0.980 - 1.058]	[0.979 - 1.027]	[0.973 - 1.056]	[0.957 - 1.029]	[0.971 - 1.028]
Post-time trend	1.38***	1.43***	1.12	1.28***	1.25***
	[1.134 - 1.679]	[1.292 - 1.582]	[0.943 - 1.342]	[1.091 - 1.496]	[1.094 - 1.430]
CC * Post-time trend	0.99	1	1	1.01	1
	[0.975 - 1.003]	[0.992 - 1.008]	[0.988 - 1.015]	[0.995 - 1.015]	[0.992 - 1.011]
Age	1.01	1.03***	1.04***	1.03***	1.03***
	[0.991 - 1.032]	[1.019 - 1.043]	[1.025 - 1.058]	[1.011 - 1.041]	[1.019 - 1.048]
Gender (male, reference)	0.92	0.63***	0.69**	0.84	0.85
	[0.665 - 1.279]	[0.524 - 0.768]	[0.488 - 0.982]	[0.624 - 1.129]	[0.645 - 1.114]
Plan type ($500 PPO, reference)					
MHIP+	0.88	0.94	0.79	0.96	0.99
	[0.622 - 1.232]	[0.773 - 1.153]	[0.553 - 1.118]	[0.708 - 1.294]	[0.751 - 1.300]
$1000 PPO	0.95	1.11	0.86	1.05	1.22
	[0.602 - 1.512]	[0.879 - 1.391]	[0.563 - 1.300]	[0.729 - 1.515]	[0.880 - 1.700]
HDHP	0.92	0.75**	0.61*	1.4	1.29
	[0.560 - 1.504]	[0.582 - 0.954]	[0.368 - 1.001]	[0.925 - 2.123]	[0.883 - 1.894]
HMO	0.56*	1.04	0.66	1	1.01
	[0.312 - 1.002]	[0.728 - 1.492]	[0.346 - 1.275]	[0.595 - 1.686]	[0.506 - 2.028]
Constant	6.67***	2.40**	1.46	3.36***	0.89
	[2.072 - 21.472]	[1.230 - 4.682]	[0.607 - 3.491]	[1.395 - 8.074]	[0.411 - 1.944]
Observations	3344	9727	3983	3752	4347
Number of subid	446	1298	527	508	587

Robust CI in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 4.9.8: Regression results, other classes, odds ratios with 95% confidence intervals

Variable	Beta Blockers	Diuretics	Sex hormones	Thyroid hormones	Bronchodilators	Leukotrine Modifiers
Time trend	0.67*** [0.587 - 0.757]	0.68*** [0.623 - 0.742]	0.71*** [0.658 - 0.760]	0.73*** [0.665 - 0.798]	0.76*** [0.685 - 0.833]	0.73*** [0.640 - 0.839]
Number of chronic conditions	0.98 [0.953 - 1.008]	0.97** [0.944 - 0.997]	0.99 [0.961 - 1.020]	1.01 [0.983 - 1.047]	1.04*** [1.013 - 1.061]	1 [0.960 - 1.038]
Policy change	0.71 [0.448 - 1.126]	0.82 [0.552 - 1.209]	1.03 [0.739 - 1.430]	0.99 [0.654 - 1.486]	0.63** [0.417 - 0.958]	1.22 [0.717 - 2.073]
CC * Policy change	1 [0.970 - 1.038]	1.01 [0.977 - 1.038]	0.99 [0.953 - 1.019]	0.99 [0.947 - 1.031]	1 [0.967 - 1.033]	0.98 [0.937 - 1.021]
Post-time trend	1.52*** [1.255 - 1.832]	1.36*** [1.191 - 1.550]	1.38*** [1.217 - 1.572]	1.33*** [1.127 - 1.571]	1.31*** [1.102 - 1.561]	1.13 [0.903 - 1.415]
CC * Post-time trend	1 [0.985 - 1.008]	1 [0.992 - 1.008]	0.99 [0.983 - 1.005]	1.01 [0.993 - 1.022]	1 [0.992 - 1.017]	1.01 [0.995 - 1.031]
Age	1.03*** [1.007 - 1.049]	1.03*** [1.008 - 1.049]	0.99** [0.981 - 1.000]	1.02*** [1.010 - 1.039]	1.02*** [1.009 - 1.032]	1.03*** [1.011 - 1.047]
Gender (male, reference)	0.58** [0.382 - 0.883]	0.79 [0.566 - 1.101]	2.94*** [2.048 - 4.234]	1.32 [0.901 - 1.943]	0.86 [0.648 - 1.139]	0.95 [0.579 - 1.559]
Plan type ($500 PPO, reference)						
MHIP+	1.09 [0.678 - 1.754]	0.98 [0.679 - 1.412]	0.9 [0.681 - 1.197]	0.69** [0.489 - 0.964]	1.39* [0.951 - 2.032]	1.13 [0.711 - 1.787]
$1000 PPO	1.47 [0.858 - 2.525]	0.79 [0.512 - 1.213]	0.91 [0.673 - 1.228]	0.93 [0.631 - 1.363]	1.35 [0.875 - 2.097]	1.32 [0.756 - 2.302]
HDHP	1.19 [0.674 - 2.094]	1.03 [0.648 - 1.634]	0.66** [0.472 - 0.929]	0.73 [0.457 - 1.177]	1.32 [0.887 - 1.976]	0.79 [0.378 - 1.635]
HMO	1.07 [0.545 - 2.085]	1.4 [0.788 - 2.501]	0.68 [0.427 - 1.095]	0.76 [0.355 - 1.647]	1.67* [0.991 - 2.800]	0.99 [0.333 - 2.926]
Constant	3.13* [0.909 - 10.750]	2.12 [0.670 - 6.742]	4.16*** [2.270 - 7.609]	2.99*** [1.367 - 6.548]	0.22*** [0.112 - 0.432]	1 [0.354 - 2.794]
Observations	2231	3200	4899	4128	4068	1323
Number of subid	306	439	669	546	585	183

Robust CI in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 4.9.8: Predicted probability of being adherent (marginal effects), quarterly, mental health medication classes.

	Number of chronic conditions							
Drug Class	**0**	**2**	**4**	**6**	**8**	**10**	**12**	**14**
Antidepressants, Q4 (pre)	**0.61**	**0.62**	**0.63**	**0.63**	**0.64**	**0.65**	**0.65**	**0.66**
Difference (Q5 vs. Q4)	0.00	0.00	-0.01	-0.01	-0.02	-0.02 *	-0.03 *	-0.03 *
Difference (Q8 vs Q4)	-0.06	-0.05	-0.05	-0.04	-0.04	-0.03 **	-0.03 **	-0.03 **
Anxiolytics	**0.33**	**0.33**	**0.34**	**0.34**	**0.35**	**0.35**	**0.36**	**0.36**
Difference (Q5 vs. Q4)	-0.07 ***	-0.05 ***	-0.04 ***	-0.03 ***	-0.02	-0.01	0.01	0.02
Difference (Q8 vs Q4)	-0.05 ***	-0.04 ***	-0.04 ***	-0.03 **	-0.02	-0.01	0.00	0.00
Anticonvulsants	**0.49**	**0.50**	**0.50**	**0.50**	**0.50**	**0.51**	**0.51**	**0.51**
Difference (Q5 vs. Q4)	-0.05 *	-0.04 *	-0.04 *	-0.04 *	-0.03 *	-0.03	-0.02	-0.02
Difference (Q8 vs Q4)	-0.07 *	-0.06 *	-0.06 *	-0.06 *	-0.05 *	-0.05	-0.04	-0.04
Antipsychotics	**0.50**	**0.51**	**0.52**	**0.53**	**0.54**	**0.55**	**0.56**	**0.57**
Difference (Q5 vs. Q4)	0.00	-0.01	-0.02	-0.04 *	-0.05 ***	-0.07 ***	-0.08 ***	-0.09 ***
Difference (Q8 vs Q4)	0.06	0.04	0.02	-0.01 *	-0.03 ***	-0.05 ***	-0.08 ***	-0.10 ***
CNS Stimulants	**0.51**	**0.51**	**0.51**	**0.50**	**0.50**	**0.50**	**0.50**	**0.49**
Difference (Q5 vs. Q4)	0.01	0.01	0.00	0.00	0.00	-0.01	-0.01	-0.01
Difference (Q8 vs Q4)	-0.05	-0.05	-0.05	-0.06	-0.06	-0.06	-0.06	-0.06

Table 4.9.9: Predicted probability of being adherent (marginal effects), quarterly, cardiovascular classes.

	Number of chronic conditions							
Drug Class	**0**	**2**	**4**	**6**	**8**	**10**	**12**	**14**
Antihypertensives	**0.76**	**0.75**	**0.75**	**0.74**	**0.73**	**0.72**	**0.71**	**0.70**
Difference (Q5 vs. Q4)	-0.03	-0.03	-0.03	-0.03	-0.02	-0.02	-0.02	-0.02
Difference (Q8 vs Q4)	-0.02	-0.03	-0.04	-0.05	-0.07	-0.08	-0.10	-0.11
Antihyperlipidemics	**0.71**	**0.70**	**0.70**	**0.70**	**0.70**	**0.69**	**0.69**	**0.69**
Difference (Q5 vs. Q4)	-0.02	-0.02	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01
Difference (Q8 vs Q4)	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00
Antidiabetics	**0.83**	**0.83**	**0.82**	**0.82**	**0.81**	**0.81**	**0.80**	**0.80**
Difference (Q5 vs. Q4)	-0.05	-0.05	-0.04 *	-0.04 *	-0.04 **	-0.03 **	-0.03 *	-0.02
Difference (Q8 vs Q4)	-0.06	-0.05 *	-0.05 *	-0.04 **	-0.03 **	-0.03 **	-0.02 *	-0.02
ACE inhibitor	**0.77**	**0.76**	**0.75**	**0.74**	**0.74**	**0.73**	**0.72**	**0.71**
Difference (Q5 vs. Q4)	-0.04	-0.04	-0.05	-0.05	-0.05 *	-0.05 **	-0.05 **	-0.06 *
Difference (Q8 vs Q4)	-0.10	-0.10	-0.09	-0.09	-0.08 *	-0.08 *	-0.08 **	-0.07 **
CCB	**0.66**	**0.66**	**0.66**	**0.66**	**0.66**	**0.67**	**0.67**	**0.67**
Difference (Q5 vs. Q4)	-0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
Difference (Q8 vs Q4)	-0.05	-0.04	-0.04	-0.04	-0.04	-0.03	-0.03	-0.03
Beta-blocker	**0.69**	**0.69**	**0.68**	**0.67**	**0.66**	**0.65**	**0.64**	**0.63**
Difference (Q5 vs. Q4)	-0.07	-0.07	-0.07 *	-0.07 **	-0.07 **	-0.08 ***	-0.08 ***	-0.08 **
Difference (Q8 vs Q4)	-0.06	-0.07	-0.08 *	-0.08 **	-0.09 **	-0.09 ***	-0.10 ***	-0.10 **

*** p<0.10, ** p<0.05, * p>0.01.

Table 4.9.10: Predicted probability of being adherent (marginal effects), quarterly, other classes.

	Number of chronic conditions							
Drug Class	**0**	**2**	**4**	**6**	**8**	**10**	**12**	**14**
Diuretics	**0.64**	**0.62**	**0.61**	**0.59**	**0.58**	**0.57**	**0.55**	**0.54**
Difference (Q5 vs. Q4)	-0.07	-0.06	-0.06	-0.06	-0.05	-0.05	-0.05	-0.04
Difference (Q8 vs Q4)	-0.12	-0.12	-0.12	-0.12	-0.11	-0.11	-0.11	-0.11
Sex hormones	**0.60**	**0.60**	**0.59**	**0.59**	**0.58**	**0.58**	**0.57**	**0.57**
Difference (Q5 vs. Q4)	0.00	-0.01	-0.02	-0.03	-0.04	-0.05	-0.06	-0.07
Difference (Q8 vs Q4)	-0.01	-0.03	-0.05	-0.07	-0.09	-0.11	-0.13	-0.15
Thyroid	**0.75**	**0.76**	**0.76**	**0.77**	**0.77**	**0.78**	**0.78**	**0.79**
Difference (Q5 vs. Q4)	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02
Difference (Q8 vs Q4)	-0.03	-0.02	-0.01	-0.01	0.00	0.01	0.01	0.02
Bronchodilators	**0.19**	**0.20**	**0.21**	**0.23**	**0.24**	**0.25**	**0.27**	**0.28**
Difference (Q5 vs. Q4)	-0.06 **	-0.06 ***	-0.07 ***	-0.07 ***	-0.07 ***	-0.07 ***	-0.07 ***	-0.07 ***
Difference (Q8 vs Q4)	-0.06 *	-0.06 **	-0.06 **	-0.06 ***	-0.06 ***	-0.06 ***	-0.05 ***	-0.05 ***
Leukotriene modifiers	**0.54**	**0.54**	**0.54**	**0.54**	**0.54**	**0.54**	**0.54**	**0.54**
Difference (Q5 vs. Q4)	0.00 ns	0.00	-0.01	-0.01	-0.02	-0.02	-0.02	-0.03
Difference (Q8 vs Q4)	-0.13	-0.12	-0.10	-0.09	-0.08	-0.06	-0.05	-0.03

*** p<0.10, ** p<0.05, * p>0.01.

Table 4.9.11: Regression results, generics (tier 1) antidepressants and antihyperlipidemics, odds ratios with 95% confidence intervals

Variable	Antidepressants	Antihypertensives
Time trend	0.71***	0.65***
	[0.68 - 0.75]	[0.59 - 0.73]
Number of chronic conditions	1	0.98
	[0.98 - 1.02]	[0.95 - 1.02]
Policy change	1.15	0.93
	[0.94 - 1.42]	[0.64 - 1.35]
CC * Policy change	0.99	0.99
	[0.97 - 1.01]	[0.95 - 1.04]
Post-time trend	1.25***	1.33***
	[1.15 - 1.36]	[1.13 - 1.56]
CC * Post-time trend	1	1
	[1.00 - 1.01]	[0.99 - 1.02]
Age	1.02***	1.03***
	[1.02 - 1.03]	[1.01 - 1.04]
Gender (male, reference)	1.20**	0.96
	[1.02 - 1.41]	[0.73 - 1.25]
Plan type ($500 PPO, reference)		
MHIP+	0.24***	0.26***
	[0.18 - 0.31]	[0.18 - 0.39]
$1000 PPO	0.86	0.93
	[0.70 - 1.06]	[0.63 - 1.39]
HDHP	0.76***	0.78
	[0.62 - 0.93]	[0.53 - 1.15]
HMO	0.68***	0.44***
	[0.52 - 0.91]	[0.29 - 0.67]
Constant	1.96***	5.49***
	[1.34 - 2.85]	[2.11 - 14.30]
Observations	10711	4363
Number of subid	1751	697

Robust CI in brackets

*** p<0.01, ** p<0.05, * p<0.1

4.10 Figures

Figure 4.10.1: Barriers to adherence

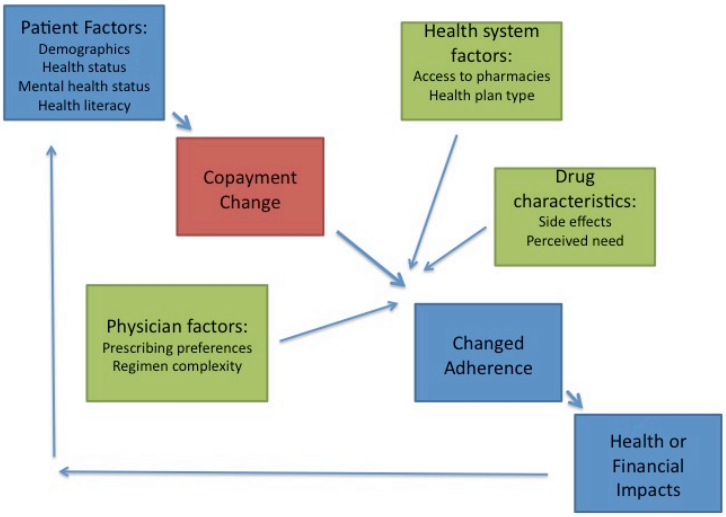


Figure 4.10.3: Yearly proportion of days covered across sample definitions.

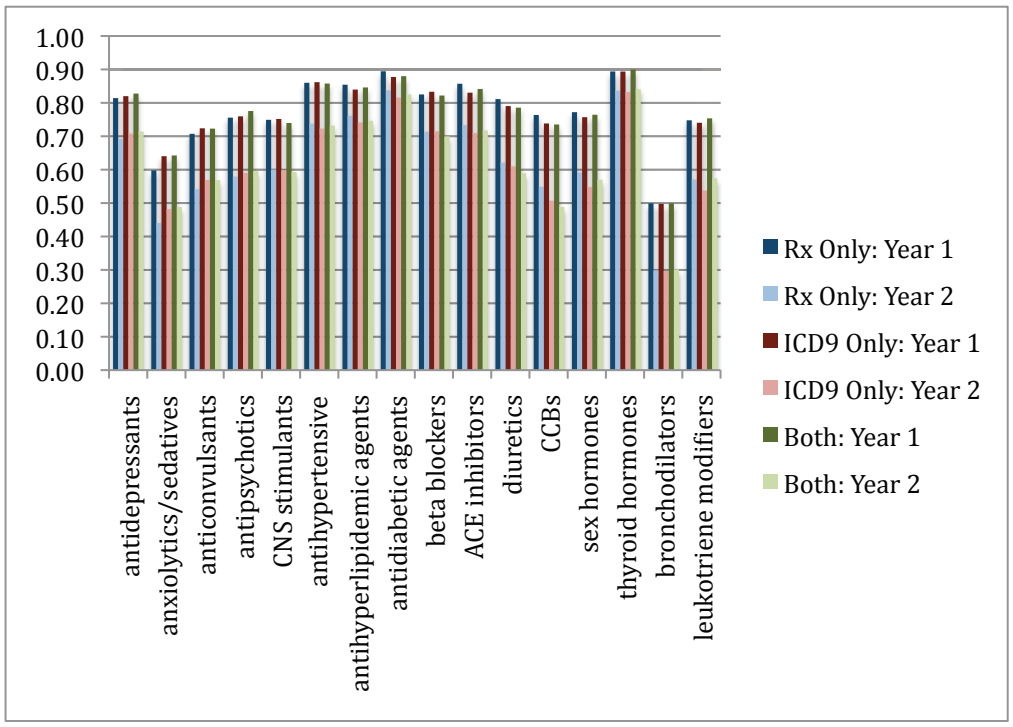


Figure 4.10.5: Average proportion of days covered per quarter for mental health medications

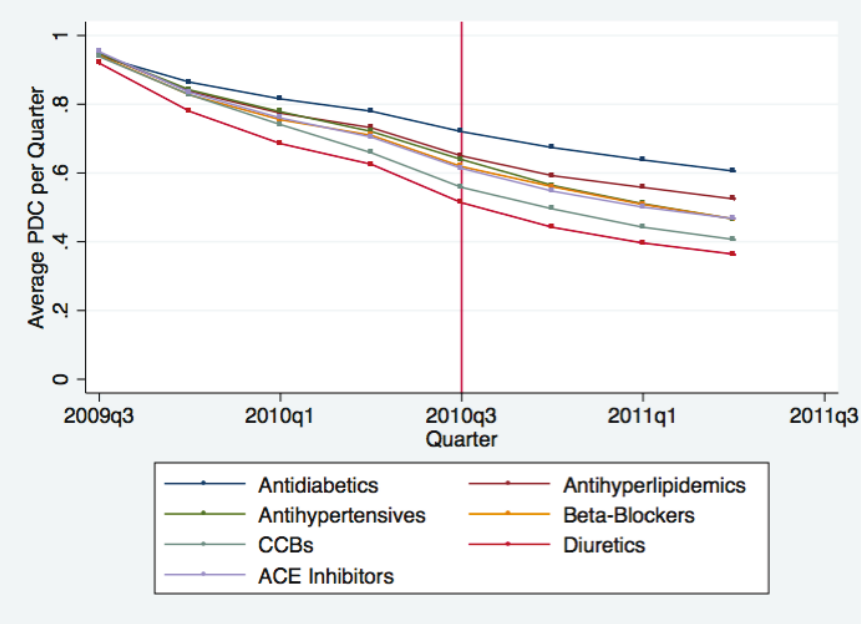


Figure 4.10.4: Average proportion of days covered per quarter for cardiovascular diseases and diabetes

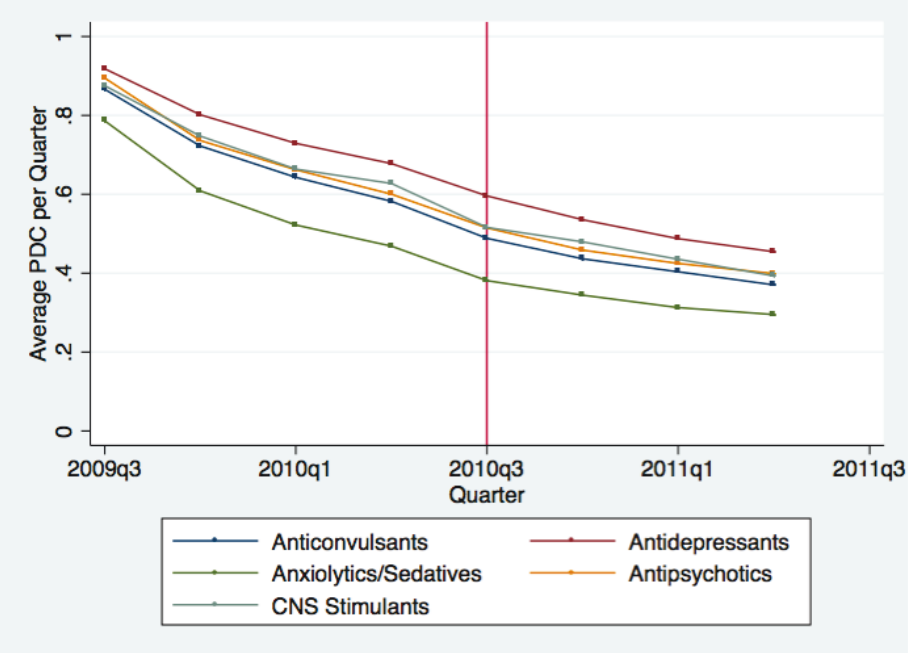
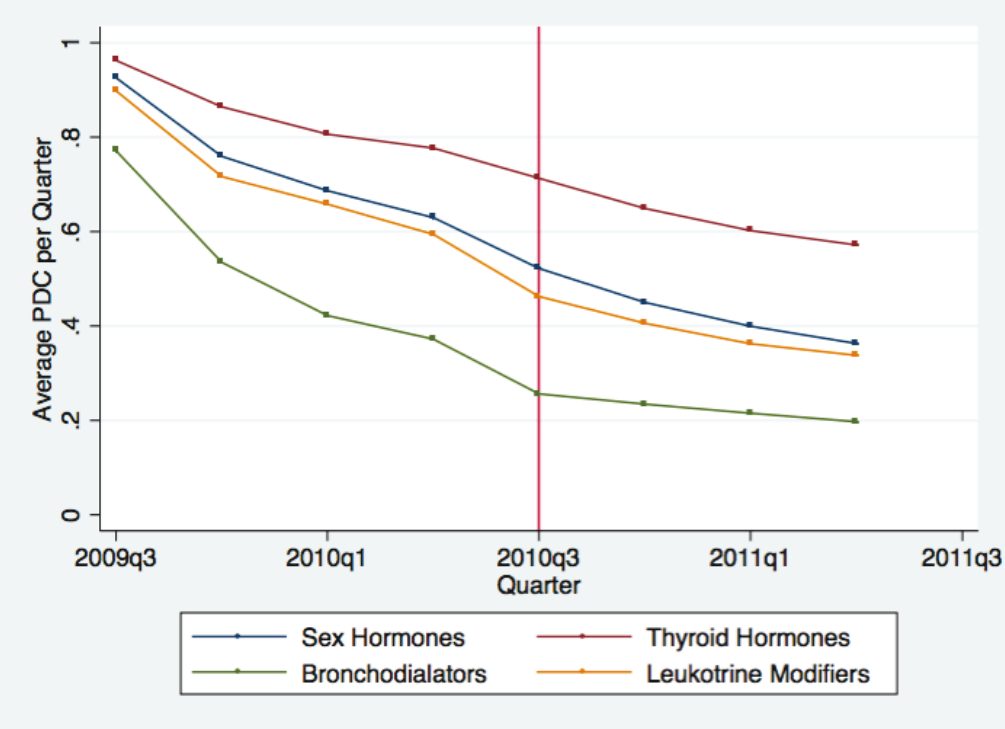


Figure 4.10.7: Average proportion of days covered for hormones and lung disease



4.11 Appendix

Table 4.11.1: Regression results, mental health medications, sample with both medical and mental health conditions (ICD9 defined), odds ratios and 95% confidence intervals.

Variable	Antidepressants	Anxiolytics	Anticonvulsants	Antipsychotics	CNS Stimulants
Time trend	0.75***	0.81***	0.88***	0.79***	0.79***
	[0.705 - 0.791]	[0.766 - 0.860]	[0.823 - 0.931]	[0.725 - 0.871]	[0.713 - 0.887]
Number of chronic conditions	0.99	0.99	0.99	1	0.98
	[0.970 - 1.011]	[0.971 - 1.013]	[0.969 - 1.015]	[0.970 - 1.039]	[0.936 - 1.025]
Policy change	1.1	0.9	0.81*	1.14	1.34
	[0.846 - 1.421]	[0.679 - 1.204]	[0.639 - 1.029]	[0.770 - 1.685]	[0.717 - 2.501]
CC * Policy change	0.98	1.01	1.01	0.97*	0.98
	[0.961 - 1.007]	[0.988 - 1.039]	[0.995 - 1.034]	[0.933 - 1.005]	[0.919 - 1.038]
Post-time trend	1.23***	1.19***	1.09	1.29***	1.16
	[1.111 - 1.366]	[1.073 - 1.327]	[0.977 - 1.209]	[1.092 - 1.524]	[0.941 - 1.429]
CC * Post-time trend	1.01**	1	1	1	1
	[1.001 - 1.016]	[0.994 - 1.009]	[0.993 - 1.007]	[0.985 - 1.011]	[0.985 - 1.016]
Age	1.03***	1	1	1	0.99
	[1.017 - 1.034]	[0.994 - 1.014]	[0.994 - 1.015]	[0.987 - 1.016]	[0.978 - 1.008]
Gender (male, reference)	1.24**	0.88	0.92	1.02	1.04
	[1.011 - 1.513]	[0.703 - 1.095]	[0.724 - 1.179]	[0.711 - 1.472]	[0.704 - 1.531]
Plan type ($500 PPO, reference)					
MHIP+	0.91	1.14	1.17	1.22	1.06
	[0.753 - 1.107]	[0.916 - 1.418]	[0.917 - 1.482]	[0.866 - 1.720]	[0.711 - 1.593]
$1000 PPO	1.09	0.75	0.98	1.83***	1.14
	[0.856 - 1.379]	[0.526 - 1.062]	[0.723 - 1.335]	[1.226 - 2.731]	[0.606 - 2.142]
HDHP	0.76**	1	0.83	2.15***	1.05
	[0.581 - 0.988]	[0.724 - 1.387]	[0.579 - 1.196]	[1.280 - 3.612]	[0.549 - 2.008]
HMO	0.70*	0.84	0.81	2.51***	0.77
	[0.474 - 1.022]	[0.543 - 1.298]	[0.505 - 1.286]	[1.299 - 4.840]	[0.349 - 1.687]
Constant	1.81**	1.44	1.83**	2.00*	3.87***
	[1.141 - 2.861]	[0.829 - 2.510]	[1.052 - 3.188]	[0.924 - 4.318]	[1.729 - 8.646]
Observations	8810	6315	5385	2602	1784
Number of subid	1181	868	746	352	242

Robust CI in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 4.11.2: Regression results, cardiovascular medications, sample with both medical and mental health conditions (ICD9 defined), odds ratios and 95% confidence intervals.

Variable	Antihypertensives	Antihyperlipidemics	Antidiabetics	ACE inhibitor	CCBs
Time trend	0.80***	0.72***	0.88**	0.79***	0.75***
	[0.709 - 0.894]	[0.670 - 0.766]	[0.792 - 0.969]	[0.716 - 0.874]	[0.683 - 0.826]
Number of chronic conditions	0.96**	0.99	0.99	0.99	0.99
	[0.928 - 0.998]	[0.963 - 1.011]	[0.954 - 1.023]	[0.966 - 1.023]	[0.950 - 1.022]
Policy change	0.68	0.93	1.07	0.82	1.08
	[0.393 - 1.181]	[0.663 - 1.310]	[0.587 - 1.960]	[0.525 - 1.278]	[0.663 - 1.774]
CC * Policy change	1.01	1	0.99	1	0.98
	[0.970 - 1.051]	[0.968 - 1.025]	[0.943 - 1.039]	[0.965 - 1.036]	[0.943 - 1.019]
Post-time trend	1.34**	1.41***	1.08	1.25**	1.21**
	[1.069 - 1.686]	[1.248 - 1.595]	[0.875 - 1.323]	[1.028 - 1.516]	[1.032 - 1.421]
CC * Post-time trend	0.99	1	1	1	1
	[0.973 - 1.003]	[0.993 - 1.010]	[0.990 - 1.019]	[0.988 - 1.014]	[0.995 - 1.014]
Age	1.02*	1.03***	1.02**	1.03***	1.03***
	[0.999 - 1.042]	[1.013 - 1.041]	[1.002 - 1.039]	[1.011 - 1.049]	[1.009 - 1.043]
Gender (male, reference)	0.91	0.56***	0.64**	0.85	0.89
	[0.615 - 1.340]	[0.448 - 0.706]	[0.437 - 0.936]	[0.615 - 1.186]	[0.635 - 1.262]
Plan type ($500 PPO, reference)					
MHIP+	0.89	0.89	0.83	1.04	1.15
	[0.584 - 1.361]	[0.708 - 1.121]	[0.539 - 1.271]	[0.729 - 1.498]	[0.792 - 1.683]
$1000 PPO	1.06	1.25	0.98	1.1	1.52*
	[0.610 - 1.843]	[0.952 - 1.643]	[0.618 - 1.542]	[0.750 - 1.621]	[0.987 - 2.348]
HDHP	1.16	0.67***	0.61*	1.07	1.65**
	[0.631 - 2.115]	[0.496 - 0.903]	[0.357 - 1.053]	[0.668 - 1.706]	[1.012 - 2.678]
HMO	0.81	0.94	1.11	0.93	1.31
	[0.421 - 1.568]	[0.615 - 1.422]	[0.517 - 2.387]	[0.467 - 1.869]	[0.746 - 2.288]
Constant	3.93**	3.13***	3.25**	1.26	1.75
	[1.149 - 13.462]	[1.483 - 6.617]	[1.242 - 8.487]	[0.408 - 3.873]	[0.649 - 4.708]
Observations	2379	6532	2759	2904	2683
Number of subid	318	877	365	393	367

Robust CI in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 4.11.3: Regression results, other medications, sample with both medical and mental health conditions (ICD9 defined), odds ratios and 95% confidence intervals.

Variable	Beta Blockers	Diuretics	Sex hormones	Thyroid hormones	Bronchodilators	Leukotrine Modifiers
Time trend	0.63***	0.70***	0.69***	0.80***	0.73***	0.75***
	[0.549 - 0.727]	[0.622 - 0.779]	[0.619 - 0.766]	[0.710 - 0.906]	[0.653 - 0.822]	[0.631 - 0.890]
Number of chronic conditions	0.96**	0.97*	0.97	1.02	1.05***	0.99
	[0.927 - 0.999]	[0.935 - 1.002]	[0.936 - 1.006]	[0.972 - 1.063]	[1.019 - 1.080]	[0.933 - 1.043]
Policy change	0.87	0.83	1.04	1.11	0.99	1.02
	[0.498 - 1.513]	[0.494 - 1.380]	[0.640 - 1.694]	[0.602 - 2.041]	[0.580 - 1.691]	[0.501 - 2.067]
CC * Policy change	1.01	1.01	0.98	0.97	0.98	0.99
	[0.968 - 1.048]	[0.974 - 1.054]	[0.940 - 1.022]	[0.914 - 1.025]	[0.933 - 1.019]	[0.938 - 1.044]
Post-time trend	1.61***	1.39***	1.29***	1.15	1.25**	1.25
	[1.271 - 2.051]	[1.169 - 1.663]	[1.068 - 1.562]	[0.903 - 1.459]	[1.010 - 1.549]	[0.933 - 1.686]
CC * Post-time trend	0.99	0.99	1.01	1.01	1.01	1.01
	[0.978 - 1.009]	[0.983 - 1.004]	[0.992 - 1.021]	[0.991 - 1.029]	[0.993 - 1.023]	[0.982 - 1.030]
Age	1.03**	1.03***	0.99	1.04***	1.01**	1.02
	[1.005 - 1.054]	[1.009 - 1.055]	[0.980 - 1.007]	[1.019 - 1.056]	[1.001 - 1.028]	[0.995 - 1.039]
Gender (male, reference)	0.60**	0.85	2.18***	1.26	0.85	1.16
	[0.369 - 0.974]	[0.580 - 1.247]	[1.397 - 3.394]	[0.786 - 2.007]	[0.594 - 1.219]	[0.629 - 2.136]
Plan type ($500 PPO, reference)						
MHIP+	1.53	0.87	1.47**	0.65*	1.05	1.31
	[0.907 - 2.578]	[0.546 - 1.371]	[1.031 - 2.093]	[0.421 - 1.008]	[0.645 - 1.703]	[0.757 - 2.285]
$1000 PPO	1.49	0.76	1.18	0.91	1.1	1.21
	[0.820 - 2.694]	[0.437 - 1.335]	[0.765 - 1.807]	[0.561 - 1.460]	[0.617 - 1.975]	[0.650 - 2.250]
HDHP	1.29	0.8	0.94	0.98	1.27	1.22
	[0.667 - 2.511]	[0.457 - 1.387]	[0.581 - 1.525]	[0.496 - 1.926]	[0.779 - 2.077]	[0.462 - 3.236]
HMO	0.93	1.03	1.13	0.74	1.01	0.83
	[0.423 - 2.053]	[0.539 - 1.951]	[0.538 - 2.361]	[0.291 - 1.865]	[0.493 - 2.076]	[0.222 - 3.122]
Constant	3.36	1.49	4.37***	1.27	0.34***	1.22
	[0.759 - 14.874]	[0.399 - 5.532]	[1.852 - 10.321]	[0.481 - 3.330]	[0.152 - 0.743]	[0.344 - 4.334]
Observations	1531	2110	2647	2676	2712	865
Number of subid	211	293	364	354	390	119

Robust CI in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 4.11.4: Regression results, mental health medications, sample 3, drug use and ICD9-defined conditions, odds ratios and 95% confidence intervals.

Variable	Antidepressants	Anxiolytics	Anticonvulsants	Antipsychotics	CNS Stimulants
Time trend	0.77***	0.83***	0.90***	0.79***	0.79***
	[0.724 - 0.821]	[0.782 - 0.885]	[0.846 - 0.967]	[0.709 - 0.874]	[0.696 - 0.893]
Number of chronic conditions	0.99	0.99	0.99	1.01	0.99
	[0.973 - 1.017]	[0.969 - 1.016]	[0.969 - 1.019]	[0.969 - 1.043]	[0.940 - 1.038]
Policy change	1.1	0.86	0.75**	1.28	1.42
	[0.816 - 1.486]	[0.637 - 1.163]	[0.572 - 0.984]	[0.802 - 2.049]	[0.731 - 2.767]
CC * Policy change	0.98	1.02	1.02	0.96**	0.98
	[0.954 - 1.004]	[0.992 - 1.044]	[0.995 - 1.037]	[0.917 - 1.000]	[0.915 - 1.044]
Post-time trend	1.19***	1.19***	1.06	1.32***	1.16
	[1.062 - 1.337]	[1.060 - 1.333]	[0.938 - 1.202]	[1.087 - 1.600]	[0.914 - 1.464]
CC * Post-time trend	1.01*	1	1	1	1
	[1.000 - 1.016]	[0.991 - 1.007]	[0.992 - 1.007]	[0.981 - 1.012]	[0.984 - 1.018]
Age	1.03***	1.01	1	1	0.99
	[1.016 - 1.035]	[0.994 - 1.016]	[0.991 - 1.014]	[0.986 - 1.019]	[0.976 - 1.010]
Gender (male, reference)	1.22*	0.77**	0.9	1.02	1.1
	[0.983 - 1.526]	[0.602 - 0.988]	[0.690 - 1.185]	[0.671 - 1.559]	[0.702 - 1.725]
Plan type ($500 PPO, reference)					
MHIP+	0.84*	1.26*	1.22	1.21	1.16
	[0.679 - 1.034]	[0.990 - 1.596]	[0.915 - 1.625]	[0.857 - 1.704]	[0.729 - 1.861]
$1000 PPO	0.96	0.78	0.91	1.78***	1.2
	[0.738 - 1.246]	[0.533 - 1.132]	[0.643 - 1.285]	[1.155 - 2.756]	[0.602 - 2.377]
HDHP	0.66***	1.03	0.87	2.05**	1.08
	[0.497 - 0.886]	[0.721 - 1.482]	[0.582 - 1.295]	[1.134 - 3.702]	[0.501 - 2.333]
HMO	0.64**	1.03	0.74	2.37**	0.76
	[0.429 - 0.959]	[0.688 - 1.549]	[0.449 - 1.226]	[1.151 - 4.878]	[0.304 - 1.880]
Constant	1.79**	1.33	1.84*	2.10*	3.12**
	[1.084 - 2.960]	[0.708 - 2.503]	[0.964 - 3.499]	[0.872 - 5.067]	[1.273 - 7.655]
Observations	7491	5337	4434	2059	1391
Number of subid	1000	729	617	279	188

Robust CI in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 4.11.5: Regression results, cardiovascular medications, sample 3, drug use and ICD9-defined conditions, odds ratios and 95% confidence intervals.

Variable	Antihypertensives	Antihyperlipidemics	Antidiabetics	ACE inhibitor	CCBs
Time trend	0.83**	0.69***	0.84***	0.83***	0.79***
	[0.725 - 0.960]	[0.638 - 0.746]	[0.741 - 0.946]	[0.741 - 0.933]	[0.699 - 0.886]
Number of chronic conditions	0.99	1	0.99	1	0.99
	[0.942 - 1.031]	[0.968 - 1.026]	[0.945 - 1.035]	[0.968 - 1.038]	[0.953 - 1.030]
Policy change	0.68	1.07	1.04	0.67	0.8
	[0.320 - 1.460]	[0.708 - 1.604]	[0.525 - 2.072]	[0.402 - 1.108]	[0.432 - 1.478]
CC * Policy change	1	0.99	0.99	1.02	1
	[0.952 - 1.061]	[0.957 - 1.024]	[0.940 - 1.049]	[0.980 - 1.060]	[0.951 - 1.041]
Post-time trend	1.49**	1.44***	1.19	1.24*	1.30***
	[1.073 - 2.062]	[1.233 - 1.671]	[0.934 - 1.518]	[0.985 - 1.559]	[1.070 - 1.587]
CC * Post-time trend	0.98**	1	1	1	1
	[0.958 - 0.999]	[0.992 - 1.012]	[0.984 - 1.019]	[0.981 - 1.010]	[0.985 - 1.006]
Age	1.02	1.03***	1.03**	1.03***	1.02*
	[0.991 - 1.040]	[1.012 - 1.045]	[1.004 - 1.050]	[1.008 - 1.049]	[0.999 - 1.039]
Gender (male, reference)	1.18	0.56***	0.53**	0.82	0.81
	[0.749 - 1.851]	[0.426 - 0.732]	[0.327 - 0.870]	[0.555 - 1.215]	[0.533 - 1.223]
Plan type ($500 PPO, reference)					
MHIP+	0.76	0.9	0.75	0.97	0.91
	[0.458 - 1.259]	[0.698 - 1.172]	[0.432 - 1.285]	[0.650 - 1.437]	[0.593 - 1.388]
$1000 PPO	0.86	1.17	0.91	1.16	1.45
	[0.445 - 1.672]	[0.866 - 1.590]	[0.501 - 1.650]	[0.758 - 1.772]	[0.854 - 2.475]
HDHP	0.91	0.67**	0.51*	1.22	1.93**
	[0.449 - 1.836]	[0.477 - 0.947]	[0.253 - 1.033]	[0.694 - 2.130]	[1.107 - 3.369]
HMO	0.69	0.99	0.91	0.91	1.66
	[0.315 - 1.518]	[0.603 - 1.614]	[0.341 - 2.440]	[0.324 - 2.548]	[0.869 - 3.166]
Constant	3.37*	3.10***	3.48**	1.02	2.57
	[0.864 - 13.111]	[1.337 - 7.197]	[1.059 - 11.440]	[0.287 - 3.605]	[0.807 - 8.182]
Observations	1696	4946	1924	2103	1835
Number of subid	227	664	256	286	252

Robust CI in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 4.11.6: Regression results, other medications, sample 3, drug use and ICD9-defined conditions, odds ratios and 95% confidence intervals.

Variable	Beta Blockers	Diuretics	Sex hormones	Thyroid hormones	Bronchodilators	Leukotrine Modifiers
Time trend	0.65***	0.67***	0.66***	0.80***	0.72***	0.75***
	[0.552 - 0.760]	[0.587 - 0.757]	[0.591 - 0.747]	[0.707 - 0.910]	[0.636 - 0.825]	[0.622 - 0.908]
Number of chronic conditions	0.98	0.97*	0.99	1.03	1.04**	0.99
	[0.942 - 1.022]	[0.931 - 1.005]	[0.947 - 1.029]	[0.977 - 1.081]	[1.009 - 1.078]	[0.932 - 1.054]
Policy change	0.86	0.74	1.07	0.96	0.77	1.14
	[0.481 - 1.529]	[0.408 - 1.339]	[0.620 - 1.860]	[0.492 - 1.862]	[0.427 - 1.404]	[0.513 - 2.548]
CC * Policy change	1	1.02	0.98	0.98	1	0.97
	[0.957 - 1.040]	[0.979 - 1.066]	[0.938 - 1.029]	[0.920 - 1.044]	[0.953 - 1.041]	[0.916 - 1.037]
Post-time trend	1.58***	1.42***	1.44***	1.22	1.28**	1.22
	[1.219 - 2.040]	[1.166 - 1.736]	[1.168 - 1.787]	[0.938 - 1.575]	[1.013 - 1.607]	[0.878 - 1.683]
CC * Post-time trend	1	0.99	1	1	1.01	1.01
	[0.979 - 1.012]	[0.984 - 1.006]	[0.984 - 1.016]	[0.985 - 1.025]	[0.991 - 1.022]	[0.982 - 1.040]
Age	1.01	1.02*	0.99	1.03***	1.02**	1.02**
	[0.983 - 1.040]	[0.997 - 1.051]	[0.978 - 1.007]	[1.012 - 1.052]	[1.000 - 1.030]	[1.001 - 1.049]
Gender (male, reference)	0.57**	0.92	2.43***	1.13	0.86	1.08
	[0.330 - 0.996]	[0.582 - 1.448]	[1.487 - 3.967]	[0.666 - 1.922]	[0.574 - 1.295]	[0.571 - 2.044]
Plan type ($500 PPO, reference)						
MHIP+	1.42	0.8	1.25	0.59**	1.1	1.37
	[0.773 - 2.594]	[0.459 - 1.381]	[0.836 - 1.857]	[0.365 - 0.961]	[0.657 - 1.839]	[0.733 - 2.561]
$1000 PPO	1.54	0.66	1.09	1.05	1.18	1.09
	[0.797 - 2.985]	[0.364 - 1.192]	[0.689 - 1.717]	[0.620 - 1.768]	[0.622 - 2.247]	[0.547 - 2.188]
HDHP	1.29	0.85	0.8	1.01	1.25	1.02
	[0.619 - 2.702]	[0.445 - 1.609]	[0.486 - 1.316]	[0.478 - 2.119]	[0.732 - 2.130]	[0.342 - 3.064]
HMO	0.9	0.91	0.78	0.61	0.98	1.04
	[0.364 - 2.247]	[0.415 - 1.981]	[0.342 - 1.763]	[0.238 - 1.543]	[0.423 - 2.264]	[0.265 - 4.042]
Constant	6.79**	2.76	4.63***	1.66	0.36**	0.95
	[1.193 - 38.613]	[0.579 - 13.181]	[1.809 - 11.865]	[0.584 - 4.695]	[0.151 - 0.847]	[0.250 - 3.633]
Observations	1188	1597	2242	2253	2194	730
Number of subid	163	221	307	297	316	100

Robust CI in brackets

*** p<0.01, ** p<0.05, * p<0.1

5 Conclusion

5.1 Summary of Results

This dissertation explores the impacts of a value-based insurance design on the use of prescription drugs, medical services and spending, in a population of those with multiple chronic conditions. The analysis takes advantage of a natural experiment, where Maryland's high-risk pool lowered copayments for generic drugs and raised them on brand name drugs. All three papers use this policy change in an interrupted time series design with individual-level utilization data.

The setting for this study is Maryland's high-risk pool, using pharmacy and medical claims data from 2007-2012. Maryland has one of the country's largest high-risk pools, averaging nearly 20,000 enrollees per year. High-risk pools insure those who tried to acquire insurance coverage on the individual market but were denied because of pre-existing conditions. Nearly 80% of the sample has three or more chronic conditions. This population does not have access to employer-based coverage. They have incomes too high for Medicaid and are not age-eligible for Medicare. High-risk pool enrollees are transitioning to the health insurance exchanges in 2014 and 2015, so examining their utilization of services, as well as methods for controlling spending and improving health will be key to managing costs in the exchanges.

The first paper (Chapter 2) analyzes the big-picture changes to drug utilization in terms of 30-day fills and the number of generic and brand fills. This paper also examines the utilization of outpatient, emergency department and inpatient services, as well as the impacts of the copayment policy change on drug, medical and total spending. Finally, this paper also evaluates the out-of-pocket cost changes for consumers. While drug utilization changed minimally, the out-of-pocket costs for consumers rose significantly. For those with ten or more chronic conditions, their annual out-of-pocket costs rose $50 per quarter. Outpatient visits decreased slightly in the month following the policy change, while inpatient visits declined substantially. It is not clear the policy change is directly impacting inpatient visits, as these were declining prior the policy change.

The second paper (Chapter 3) examines whether generic drug used increased following the policy change. The generic utilization rate for each drug class varied, ranging from 8% for Leukotriene modifiers, to 100% for diuretics. Generic utilization did significantly increase for antidepressants, but not for any of the other classes. This analysis also found that the use of generics decreases as the number of chronic conditions increases. There are a variety of possible reasons this may occur, but this study is not set up to determine why. Those with more chronic conditions could be more risk-averse to changing medication regimens, fearing harmful drug interactions or other perceived or real side effects from generic versions of drugs.

The third paper (Chapter 4) analyzes adherence rates across drug classes for those with both mental health and physical comorbidities. Adherence rates were above 80% for the

cardiovascular-related drugs such as antihypertensives and antihyperlipidemics, and just above 50% for the asthma medications. Adherence for all drug classes investigated declines over time. The policy change did not significantly impact this trend except for anxiolytics. The lack of significant finding may be due to relatively small numbers of individuals in many of the classes studied. The copayments could also be just one factor in maintaining adherence to medications.

5.2 Policy Implications

This unique data set allows the study of a group of people with multiple chronic conditions who will be substantially impacted by health reform as these individuals move into the new health insurance exchanges in 2014 and beyond. While this insurance benefit design change lowered the copayments for generic drugs, increasing the copayments on branded drugs does not impact those with multiple chronic conditions. Using cost as the main criterion for drugs to be placed in given tiers is not necessarily incorporating therapeutic value for the drugs in the upper tiers (Fendrick et al. 2001b). Improved designs for those with multimorbidities may reduce copayments for all drugs, regardless of formulary tier, used for a given constellation of conditions. Some early trials have attempted to lower copayments for particular diseases such as diabetes and heart disease, and have found modest improvements in adherence (Maciejewski et al. 2010; Choudhry, Avorn, et al. 2011). For insurers, these designs targeting particular disease groups are challenging to implement administratively, and are in their infancy (Neumann et al. 2010; Neumann et al. 2011).

The policy implications of this study for health insurance exchanges are that those with multiple chronic conditions may need interventions other than cost sharing to encourage the use of cost-effective substitutes. Early reports are conflicting on the average health status of enrollees coming into the exchanges. A recent Urban Institute/Robert Wood Johnson Foundation report suggests that the enrollees in the exchanges will be similar to those in the employer-sponsored market, while recent anecdotal evidence suggests the opposite (Blumberg and Holahan 2013; Mathews and Weaver 2014). Other interventions to improve care coordination in the hopes of lowering costs may be things like primary care medical homes or accountable care organizations, but these payment incentive models for physicians and hospitals have not been shown effective in reducing costs. Finding efficient ways to lower costs while maintaining the health of insured enrollees will be of paramount importance for those with chronic conditions in the health exchanges.

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Rosen, Priyanka Sista, and Kathleen N Lohr. 2012. “Interventions to Improve Adherence to Self-Administered Medications for Chronic Diseases in the United StatesA Systematic Review.” *Annals of Internal Medicine* 157 (11): 785–95.

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110. West, Joyce C, Donald S Rae, Ramin Mojtabai, Maritza Rubio-Stipec, Julie A Kreyenbuhl, Carol L Alter, and Stephen Crystal. 2012. “Clinically Unintended Medication Switches and Inability to Prescribe Preferred Medications under Medicare Part D.” *Journal of Psychopharmacology* 26 (6): 784–93.
111. Wolff, Jennifer L, Barbara Starfield, and Gerard Anderson. 2002. “Prevalence, Expenditures, and Complications of Multiple Chronic Conditions in the Elderly.” *Archives of Internal Medicine* 162 (20): 2269.
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115. Zweifel, Peter, and Willard G Manning. 2000. “Moral Hazard and Consumer Incentives in Health Care.” *Handbook of Health Economics* 1: 409–59.

7 Curriculum Vitae

CURRICULUM VITAE
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CURRENT STATUS:

PhD Candidate
Department of Health Policy and Management
Economic Evaluation and Policy Track
Johns Hopkins School of Public Health

Advisor: Gerard F. Anderson, PhD

EDUCATION AND TRAINING

1. SANTA CLARA UNIVERSITY, SANTA CLARA, CALIFORNIA
   Degree: Bachelor of Science in Political Science, Bachelor of Arts in Italian Studies
   Year: 2001

2. JOHNS HOPKINS BLOOMBERG SCHOOL OF PUBLIC HEALTH
   Department: Health Policy and Management,
   Track: Health Economics, Economic Evaluation and Policy
   Degree: PhD
   Year: September 2009 – Summer 2014 (expected graduation)

HONORS

2009-2011	Kirschstein - National Research Service Award (NRSA) Fellow, Agency for HealthCare Quality and Research (AHRQ).
2008	Tennessee Associated Press Broadcaster's Association

Staff Award: Best Public Affairs

2007 Public Radio News Directors International
First Place: Coverage of the Nashville Mayoral Race

PREVIOUS POSITIONS

2002- 2009 Reporter, Nashville Public Radio
- Covered government and politics for a member station of National Public Radio.
- Topics included state policy, local government and policy, elections and health care financing

2006-2009 Freelance Reporter, Nashville City Paper
- Covered state policy, local government and policy, elections and health care financing.

2002-2009 Company Dancer, Nashville Ballet
- Performed numerous soloist and principal roles

PROFESSIONAL MEMBERSHIPS

- AcademyHealth
- International Health Economics Association (iHEA)
- International Society of Pharmacoeconomics and Outcomes Research (ISPOR)

PEER-REVIEWED PUBLICATIONS

Published

1. DuGoff ED, Canudas-Romo V, **Buttorff C**, Leff B, Anderson GF. Years off your life: the impact of multimorbidity on life expectancy. Forthcoming: Medical Care.

2. Chan KS, Roberts ET, McCleary R, **Buttorff C**, Gaskin DJ. Community characteristics and mortality: The relative strength of association of different community characteristics. Forthcoming: American Journal of Public Health.

3. **Buttorff C**, Trujillo AJ, Ruiz F, Amaya JL. Low rural health insurance take-up in a universal coverage system: perceptions of health insurance among the uninsured in La Guajira, Colombia. Int J Health Plann Manage. 2013 Sep.

4. **Butorff C**, Tunis SR, Weiner JP. Encouraging value-based insurance designs in state health insurance exchanges. Am J Manag Care. 2013 Jul;19(7):593–600.

5. **Buttorff C**, Hock RS, Weiss HA, Naik S, Araya R, Kirkwood B, Chisholm D, Patel V. Economic evaluation of a task-shifting intervention for common mental disorders in India. Bull. World Health Organ. 2012 Nov 1;90(11):813–21.

6. Zare H, Trujillo AJ, Leidman E, **Buttorff C**. Income elasticity of health expenditures in Iran. Health Policy Plan. 2012.

7. Bridges JFP, Lataille AT, **Buttorff C**, White S, Niparko JK. Consumer preferences for hearing aid attributes: a comparison of rating and conjoint analysis methods. Trends Amplif. 2012 Mar;16(1):40–8.

8. Trujillo A, Ruiz F, Bridges JFP, Amaya JL, **Buttorff C**, Quiroga A. Understanding Consumer Preferences in the Context of Managed Competition: Evidence from a Choice Experiment. Applied Health Economics and Health Policy, 2012 Mar 1;10(2):99-111.

9. Bridges JFP, **Buttorff C**. What outcomes should US policy makers compare in comparative effectiveness research? Expert Rev Pharmacoecon Outcomes Res. 2010 Jun;10(3):217–20.

Under Review

10. **Buttorff C**, Andersen MS, Riggs K, Alexander GC. Federal health insurance exchanges provide lower premiums but less generous pharmacy benefits than employer-sponsored plans. Submitted to: Health Affairs.

11. Davis K, **Buttorff C**, Leff B, Samus QM, Szanton S, Wolff, JL. Payment and care delivery innovations in Medicare: Can they bend the cost curve? Submitted to: American Journal of Managed Care.

12. Riggs K, **Buttorff C**, Alexander GC. Impact of the affordable care act on patients' out-of-pocket burden. Submitted to: Health Affairs.

13. Bridges JFP, Groothius-Oudshoorn K, **Buttorff C**. Estimating preferences for medical devices: Does the number of profile in choice experiments matter? Submitted to Medical Decision Making. Also published as NBER Working Paper #w17482. Online: *www.**nber**.org/papers/w17482.pdf*

In Progress

14. Chan KS, Roberts ET, McCleary R, **Buttorff C**, Gaskin DJ. The impact of individual versus community characteristics on mortality.

15. **Buttorff C**, Trujillo AJ, Miranda J. Preferences for nutrition benefits in a low-income food supplement program in Lima, Peru.

16. Trujillo AJ, **Buttorff C**, Amaya JL, Ruiz F. Benefit preferences in Colombia's low-income vs. standard health insurance programs: Can the government encourage more people to sign up?

17. **Buttorff C**, Castillo R, Trujillo AJ, Vecino-Ortiz A, Anderson GF. Evaluation of an Opioid Prescribing Guideline Implementation in a Workers' Compensation Insurance Pool.

LECTURES/PRESENTATIONS

1. Panel Presentation: Low rural health insurance take-up in a universal coverage system: perceptions of health insurance among the uninsured in La Guajira, Colombia. iHEA, 2013.
2. Seminar: Cost-effectiveness of a lay health worker-led approach to treating depressive and anxiety disorders in primary care in Goa, India: a cluster-randomized trial. Fall 2011, JHSPH Health Economics Seminar.
3. Estimating preferences for medical devices: Does the number of profile in choice experiments matter? iHEA, 2011.
4. Writing for Radio. A guest lecture for a health communications class of the department of Health Behavior and Society, JHSPH Fall 2010.
5. The highs and lows of choosing attribute levels in conjoint analysis: testing attribute recoding in cervical cancer screening. Conjoint Analysis in Health Conference, 2010.

POSTER PRESENTATIONS

1. Impact of the affordable care act on patients' out-of-pocket burden, AcademyHealth 2104.
2. Value-based insurance design: falling short for those with multiple chronic conditions, AcademyHealth 2014.
3. The impact of an opioid prescribing guideline intervention on medical spending and utilization, AcademyHealth 2014.
4. Incentives in Chronic Disease Management, AcademyHealth 2012.
5. Encouraging value-based insurance designs in state health insurance exchanges, AcademyHealth 2012
6. Understanding Consumer Preferences in the Context of Managed Competition: Evidence from a Choice Experiment, American Public Health Association 2011.

SELECT NON-PEER REVIEW PUBLICATIONS

1. Davis K, **Buttorff C**, Leff B, Samus Q, Szanton S, Wolff JL. For High-Risk Medicare Beneficiaries: Targeting CMMI Demonstrations On Promising Delivery Models. Health Affairs Blog, April 2014. Online: http://healthaffairs.org/blog/author/davisgroup/

2. **Buttorff C**. "Cooper Discusses Possibilities for Health Care Reform." *Nashville Public Radio*. 26 June 2009. Online: http://wpln.org/?p=9009.

3. **Buttorff C**. "Mental Health Court Teams Up with Drug Court." *Nashville Public Radio*. 22 May 2009. Online: http://wpln.org/?p=7824.

4. **Buttorff C**. "Even with Cuts, Hospital Authority Still Comes up $1.5 Million Short." 21 May 2009. *Nashville City Paper*. Online: http://nashvillecitypaper.com/content/city-news/even-cuts-hospital-authority-comes-15m-short.

5. **Buttorff C**. "TennCare Enrollees Try Weight Watchers." *Nashville Public Radio*. 2 May 2006. Online: http://wpln.org/?p=9.

TEACHING EXPERIENCE

2013-2014: Teaching Assistant
1. Health Economics II: Faculty: Fred Selck.
2. Innovations in Aging. Faculty: Karen Davis.
3. Introduction to Health Policy. Faculty: Gerard Anderson.

2012-2013: Teaching Assistant
1. Economic Evaluation II. Faculty: Dagna Constenla.
2. Economic Evaluation I (online). Faculty: Kevin Frick.
3. Mathematical Microeconomics. Faculty: John Bridges.

2011-2012: Teaching Assistant
4. Health Economics (Online). Faculty: Kevin Frick.
5. Economic Evaluation III. Faculty: John Bridges, Louis Neissen.
6. Economic Evaluation II. Faculty: Krishna Rao.
7. Health Economics. Faculty: Kevin Frick.
8. Economic Evaluation I. Faculty: Kevin Frick.
9. Introduction to Health Policy. Faculty: Gerard Anderson.

2010-2011: Teaching Assistant
1. Economic Evaluation II. Faculty: Amnesty LeFevre, Krishna Rao.
2. Economic Evaluation I. Faculty: Kevin Frick.

2009-2010: Teaching Assistant
1. Understanding Cost-Effectiveness. Faculty: Kevin Frick.

RESEARCH SUPPORT

Title: Dissertation support grant: Value-based insurance design for those with multiple chronic conditions.
PI: Christine Buttorff
Year: 2014
Source: Jayne Koskinas Ted Giovanis Foundation for Health and Policy.

Title: Medicare at 50.
PI: Karen Davis
Year: 2014
Source: Commonwealth Fund
Role: Research Assistant

Title: Evaluation of an Opioid Prescribing Guideline Implementation in a Workers' Compensation Insurance Pool.
PI: Gerard Anderson
Year: 2013-2014
Source: American International Group
Role: Team Director

Title: Preferences for nutrition benefits in a low-income food supplement program in Lima, Peru.
Year: 2013-2014
Source: International Development Research Centre
Co-PIs: Antonio J. Trujillo, Jaime Miranda
Role: Research assistant

Title: Improving mortality predictions
PI: Gerard Anderson
Year: 2012-2013
Source: American International Group
Role: Project Manager

Title: Understanding Consumer Preferences in the Context of Management Competition: Evidence from a Field Experiment in Rural Colombia

Year: 2011-2012
Source: JHSPH Center for Global Health
Co-PIs: Antonio J. Trujillo, John Bridges
Role: Research assistant

OUTSIDE ACTIVITIES

2013-2014	Adjunct Faculty, Peabody Institute, Johns Hopkins University, Baltimore • Teach ballet, pointe and variations classes to elementary and high-school aged students.
2009-2013	Company Dancer, Carbon Dance Theatre, Philadelphia