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Drug Coverage Transitions and Non-adherence to Medication for Hypertension

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Abstract

Background:

Non-adherence to hypertension medication results in poorer health outcomes and higher health care costs. Cost of medication, complexity of therapy regime and the asymptomatic nature of hypertension have been identified as factors that affect adherence to medication. However, research has not examined if transitions between drug coverage plans affect medication adherence.

Objective: To measure the relationship between drug coverage transitions and non-adherence to medication.

Data Source: Prescription drug utilization records for antihypertensive medication from the Veterans Health Administration (VA) and Medicaid prescription drug claim files from 1999 and 2000.

Research Design: This was a retrospective observational study using secondary data from administrative sources. The dependent variable was the number of days without medication divided by the number of treatment days over a one year period. The main explanatory variable of interest was whether an individual switched between the VA and Medicaid for prescription drugs. Ordinary least squares and instrumental variables regressions examined the effect of switching systems on gaps in medication controlling for health status and demographics.

Results: In ordinary least squares regressions, switching systems was positively and significantly associated with more gaps in medication. The effect remains significant for beta-blockers and borders on significant for angiotensin converting enzyme inhibitors and calcium channel blockers when using instrumental variables regressions.

Conclusions: This study provides some evidence that there is a significant and positive relationship between changes in drug coverage and medication non-adherence. The differences between OLS and IV estimates suggest that transitions and non-adherence are jointly determined.

Key Words: Medication non-adherence, hypertension, drug coverage transitions

Introduction

Uncontrolled hypertension leads to undesirable outcomes, such as increased healthcare costs and increased risk of cardiovascular and cerebrovascular disease.¹⁻³ If used consistently and properly, hypertension medication can adequately control blood pressure and decrease the likelihood of experiencing health complications, resulting in lower health care costs.³ Despite the therapeutic success of antihypertensives, studies suggest that blood pressure control is not achieved in most cases.^{1,2,4,5}

The failure of patients to adhere to a prescribed medication regime is a principal reason behind failed blood pressure control.^{2,5,6} Sixteen to fifty percent of patients terminate hypertension treatment within a year.⁶ Research has focused on several factors that affect adherence including the asymptomatic nature of hypertension, which causes patients to think treatment is unnecessary,² and socioeconomic factors, such as out-of-pocket costs for hypertension medications.^{7,8}

One factor that has been largely overlooked in adherence research is gaps in drug coverage or changes in drug coverage. Stuart, Shea, and Briesacher (2001) found that 35% of respondents to the Medicare Current Beneficiary Survey (MCBS) either had gaps in prescription drug coverage in 1995 or 1996 (30.4%) or switched between drug prescription plans (4.8%).⁹ Updated analyses found that 26% of MCBS respondents in 1998-2000 had one or more gaps in prescription drug coverage.⁸

When individuals experience gaps in drug coverage or change drug coverage, unexpected problems could occur. Patients need to enroll in the new plan and may have to adjust to new drug cost control policies, formularies or cost-sharing. Limited survey data suggests that these transitions can make it difficult to adhere to medications. In a Kaiser Family Foundation survey

of seniors, 34% of the individuals who had used their new Medicare Part D plan reported a problem using the plan, such as not getting enrollment cards, paying unexpected costs or leaving the pharmacy without a prescription because the drug was not affordable or the drug was not covered.¹⁰ West et al. (2007) focused on Medicare and Medicaid dual-eligibles with psychiatric conditions and found that about 22% of their study population either discontinued medication use or temporarily stopped taking medication due to access problems related to the implementation of Medicare Part D.¹¹ This study extends this limited research by using administrative data for a national sample of patients with hypertension. Specifically, we focus on low-income or disabled veterans who rely on the Department of Veteran Affairs (VA) and/or Medicaid for drug coverage.

The reasons why a veteran would choose one program over another for drug coverage are largely related to cost and convenience. The VA provides outpatient prescription drugs to enrolled veterans at low out-of-pocket costs, but it is a closed network that requires veterans to see a VA doctor to get prescriptions. This may require traveling long distances or confronting long waits for appointments, so many veterans choose to go elsewhere.¹²⁻¹⁵ Low-income veterans may also obtain drugs through Medicaid, which could be more convenient because a patient can see a local provider. However, Medicaid programs vary widely in the restrictiveness of eligibility requirements and the generosity of benefits.^{16, 17} As well, due to low reimbursement rates not all providers accept Medicaid.¹⁸⁻²⁰

Thus, depending on an individual's specific healthcare needs, it may be more convenient and affordable to rely on one system or another. For example, if a veteran is using services that the VA specializes in, such as substance abuse services, he may choose to obtain all of his care in the VA, including prescription drugs. However, as healthcare needs change, the program that

best fits these needs may also change. For example, if an uninsured low-income veteran has an acute episode and obtains services at a local hospital, she may be subsequently enrolled in Medicaid and begin obtaining prescription drugs through Medicaid.

This study takes advantage of drug utilization data for veterans who use VA, Medicaid or both programs to examine the relationship between changing drug coverage and medication non-adherence. Due to start up costs (e.g. learning new drug coverage policies) and the administrative burden involved with obtaining care through new programs (e.g. getting enrolled), we hypothesize that veterans who transition between programs for drug coverage will be at higher risk of experiencing gaps in medication compared to veterans who only receive prescription drugs from one program or who routinely use both.

Methods

Study Population and Prescription Drug Utilization Data

The study population included low-income or disabled VA enrollees who enrolled in Medicaid for at least one month in 1999 or 2000, had at least one diagnosis of hypertension between January 1, 1999 and June 30, 1999 (baseline period), and received hypertension medication from either the VA, Medicaid, or both from July 1, 1999 to June 30, 2000 (outcome period). Hypertension diagnoses were identified based on ICD-9 codes from the Medical Inpatient and Outpatient Data Sets in the VA and inpatient and outpatient claims in Medicaid (inpatient and other non-institutional claim files) or Medicare (Inpatient, Outpatient and Carrier SAF claim files). Records for the same individual were linked between the VA, Medicaid and Medicare using social security numbers.

Prescription drug records came from the Pharmacy Benefit Management data set in the VA and the prescription drug claim file from Medicaid. By selecting a sample of low-income

and disabled veterans who used VA or Medicaid coverage for drugs, we minimized the likelihood that individuals in the sample had drug coverage from other sources, including commercial insurance or Medicare HMOs. All prescription drug records for alpha-blockers, beta-blockers, calcium channel blockers, diuretics and angiotensin converting enzyme (ACE) inhibitors that were filled by the pharmacy between July 1, 1999 and June 30, 2000 (outcome period) were extracted for the identified individuals. Prescription drugs from each of these classes were identified in the VA using brand and generic names and using the National Drug Code (NDC) in Medicaid. We combined historical NDCs (NDCs that had gone off the market since 1997 obtained from Medical Coding.Net) with a 2007 FDA current list of NDCs to extract a comprehensive list of hypertension drugs in these classes. Due to potential recycling of NDCs the historical NDCs were given preference if there was duplication in codes between the historical file and the 2007 FDA current file.

Outcome

The outcome of interest is hypertension medication non-adherence, operationalized as the continuous multiple-interval measure of medication gaps (CMG), which is a common measure used in previous studies examining medication adherence.^{21, 22}

CMG = the number of days without drugs/total number of treatment days

The CMG is calculated for each individual within each class of hypertension drugs. Prescription drug utilization records from VA and prescription drug claims from Medicaid were combined for each individual so all prescription fills were taken into account regardless of source. The numerator is the number of days that an individual does not have a needed hypertension drug. In our case the total number of treatment days in the outcomes period (July 1, 1999-June 30, 2000) is 366 (2000 was a leap year). An individual who always has

medication has a $CMG=0$, and as the percentage of days without medication increases the CMG increases from 0 to 1.

Several adjustments to this basic calculation are necessary. Days spent in the hospital or in a nursing home are subtracted from the number of treatment days since outpatient drugs are not needed while an individual is admitted to these institutions. Similarly, if an individual stops receiving a prescription during the year, the number of treatment days will only include the number of days until the last prescription runs out because it is assumed that this drug regime was discontinued for that patient.

Finally, oversupply from the previous prescription must be accounted for. There are two cases when it may not be appropriate to carry over the remaining supply from a previous prescription: 1) drug changes or 2) dose changes. A drug or dose change likely indicates a treatment change. It is unknown whether the individual discards the remaining pills from the previous prescription or uses these pills before starting the new treatment. Therefore, the CMG measure was specified three different ways: 1) always include oversupply from a previous prescription, 2) discard oversupply if a drug change occurs or 3) discard oversupply if either a drug or dose change occurs. Table 1 gives examples of how CMG was calculated taking these various adjustments into account.

We also excluded individuals who had three or more drug or dose changes within a class of drugs. This helped ensure that changes in drugs or dosage were due to actual treatment changes rather than an individual being routinely prescribed multiple drugs or multiple doses of the same drug in a class. In such cases, CMG ought to be calculated separately for each drug or dose. Finally, we excluded individuals who died during the outcome period (July 1, 1999-June

30, 2000) because some individuals may continue to receive prescription drugs through mail order pharmacies after death, leading to inaccurate CMG measures.

Defining Switches in Drug Coverage

Transitioning or switching drug coverage was defined based on prescription drug claims during the outcome period (July 1, 1999-June 30, 2000). Individuals were categorized as receiving prescriptions from one program (VA or Medicaid), switching between programs once, or using both programs. The descriptive statistics in Table 2 indicate that individuals who switched once had significantly more medication gaps than those in the other two groups. This is consistent with our hypothesis that adjustment to new eligibility requirements and/or cost controls contributes to non-adherence. Therefore, we defined switchers (switch=1) as those who switched once in contrast to everyone else (switch=0). To isolate the population that is at highest risk of experiencing a new change in drug coverage, we excluded individuals who had both VA and Medicaid prescription drug records during the baseline period (January 1, 1999-June 30, 1999). These individuals had already successfully managed both programs.

Risk Adjustment

Models were risk adjusted to control for observable differences in prior individual health status based on similar models in the literature.²³ Explanatory variables included age, gender, VA determined priority status that indicates which veterans have precedence for VA care and the percentage of the population that was non-white in the individual's Zip Code as a proxy for race. Following Elixhauser et al. (1998),²³ we created indicator variables for 28 health conditions based on ICD-9 codes from all inpatient and outpatient claims in VA, Medicare and Medicaid during the baseline period. These were used as risk adjustors for health status.

Analyses

Data were analyzed using STATA 9.0.²⁴ Initial analyses predicted CMG using ordinary least squares (OLS) regression with explanatory variables that included switching drug coverage once, age, gender, VA priority status, percentage of residents in the Zip Code who were non-white and indicator variables for the 28 health conditions (Table 3).

A potential complication arises because switching drug coverage and medication gaps (CMG) may be simultaneously determined. For example, an uninsured veteran who experiences an acute episode may use the local hospital and enroll in Medicaid, which allows him to switch to Medicaid for prescription drugs. The acute episode may at the same time disrupt his medication regime and increase his likelihood of having medication gaps. If this simultaneity is not addressed, part of the effect of the acute episode on CMG would be erroneously attributed to switching. To address this potential difficulty we used instrumental variables (IV) regression to isolate the causal relationship between switching and CMG (Tables 4 and 5).

The first stage equation in the IV regression was a logit model that predicted switching. Instruments included whether the individual experienced an inpatient hospitalization during the baseline period (January 1-June 30, 1999) and several Medicaid policy and VA facility characteristics variables. Medicaid restrictiveness is a constructed summary measure of how restrictive different Medicaid programs' enrollment policies are. States with more restrictive enrollment policies enroll fewer beneficiaries as a proportion of their low-income populations (see Pizer, Gardner, and Wolfsfeld (2007) for a detailed explanation of this measure).¹⁷ VA medical center facility characteristics included distance from the center of the veteran's Zip Code to the nearest VA medical center and the completeness of geriatric, medical, and mental health services available at the medical center. VA outpatient clinic characteristics included the

distance from the center of the veteran's Zip Code to the nearest VA outpatient clinic, and whether the outpatient clinic offered pharmacy, lab, psychiatry, psychology, and substance abuse treatment services. Finally, the first stage equation also included the indicators for health status, gender, age, VA priority status, and the percentage of the residents in the veteran's Zip Code who were non-white.

Our expectations were that veterans living closer to VA services or who had access to more comprehensive services within the VA would be less likely to switch to Medicaid for drug coverage, and veterans living in states with less restrictive Medicaid enrollment policies would be more likely to do so. Although the VA has an extensive mail-order pharmacy system that lessens the burden of living far from the VA when using the VA for prescriptions, appropriate prescription management still requires physician appointments so distance may continue to be a factor.

An important and frequently overlooked requirement of IV models is to determine whether instruments are appropriate by examining whether they are correlated with the unobservable term in the outcome equation. Consistent with standard practice,²⁵ we conducted over-identifying restrictions tests to ensure that the instruments in the first stage were not correlated with CMG except through their relationship with switching. Separate tests were performed for each class of drugs since each class had a unique disturbance term. Particular instruments that failed the test for a specific class were excluded from the first stage model for that class (see Table 4 for exclusions). After narrowing down the list of instruments in the first equation for all classes, the overidentifying restrictions test indicated that our remaining instruments were appropriate (Table 5). Table 4 presents the estimated coefficients from models using the refined set of instruments in the first stage equation.

Using the estimates from this first stage equation we constructed the predicted probability of switching programs for drug coverage and replaced actual switching with the predicted probability in the second stage equation, retaining age, gender, VA priority status, the percentage of the residents in the Zip Code who were non-white and the indicators for health status as control variables. This approach is known as the “dummy endogenous variable” technique.²⁶

Finally, because we used a two-step technique that estimated the first and second stage equations separately, bootstrapping of the standard errors was required. We used 400 bootstrap iterations for each class of drugs.

Results

Table 2 reports the quartiles, median and mean CMG for all five drug classes for individuals who used only one program for drug coverage during the outcome period compared to individuals who switched once and individuals who used more than one program. Individuals who used more than one program had the lowest CMG rates. On average, these individuals did not have hypertension medication between 9 and 13% of their needed days. Individuals in the top quartile among this group went without medication between 11% and 22% of the time. Individuals who received drugs from one program only had slightly higher CMG rates with mean gaps in medication about 12-14% of the days and individuals in the top quartile among this group had gaps in medication 19% to 23% of the time. In contrast, individuals who switched once had much higher CMG rates. The mean percent of days without medication was 17-21% and individuals in the top quartile among this group went without medication 27-37% of the time. As expected, the table shows that as oversupply from previous prescriptions is ignored because of assumed treatment changes (either drug or dose) the CMG rates are higher compared to the CMG measure that assumes individuals use all oversupply from previous prescriptions.

Table 3 shows the estimated coefficients on the switch indicator variable in OLS regressions that predict CMG with age, gender, race, VA priority status, and the indicators for health status included as control variables. Switch is equal to 1 if an individual switched between the programs for drugs once and 0 if an individual stayed in one program for drugs or used both programs multiple times for drugs. Switch has a significant positive relationship with CMG among all drug classes. A person on beta-blockers who switches once is predicted to have CMG rates that are about 6% higher compared to individuals who stay in one program or switch more than once. This number is 5% for individuals on alpha-blockers, and 7% for individuals on calcium channel blockers, diuretics or ACE inhibitors. The control variables also have expected relationships with adherence. For example, there is a positive and significant relationship between being diagnosed with alcohol abuse and CMG among all classes of drugs. Similarly, there is a negative and significant relationship between age and CMG for all classes except alpha-blockers and being diagnosed with diabetes and CMG for all classes except ACE inhibitors (data not shown).

Tables 4 and 5 present the results from the first and second stage equations of the IV regression models. For all five classes of drugs, individuals who experienced a hospitalization during the six-month baseline period were significantly more likely to switch compared to individuals who did not experience a hospitalization. Also for all five classes of drugs, there was a significant and negative relationship between the restrictiveness of the Medicaid programs and the likelihood of switching-individuals who live in states with more restrictive programs were less likely to switch. The availability of outpatient substance abuse services (beta-blockers, ACE inhibitors), pharmaceutical services (alpha-blockers) and the outpatient clinic distance (diuretics, ACE inhibitors) also had significant effects on the likelihood of switching programs for drug

coverage. The availability of VA services is expected to have positive effects on switching from Medicaid to VA and negative effects on switching from VA to Medicaid. Therefore, the aggregate effect measured in these models can be positive or negative. Overall, the first stage equation explains about 3 to 5% of the variation in the switch indicator.

Table 5 reports the estimated coefficients on the predicted probability of switching in the second stage equation, bootstrapped standard errors, and the P -values for the overidentifying restriction tests. For all classes except alpha-blockers, there is a positive relationship between the predicted probability of switching and CMG. For beta-blockers, this relationship is significant at the $P<0.05$ level for all variations of CMG except when assuming oversupply from previous prescriptions is always used which borders on significance at $P<0.10$. The estimated effect of switching programs is to increase the percent of days without drugs by 16 to 18%. The coefficient on the predicted probability of switching borders on significance at $P<0.10$ for calcium channel blockers when oversupply from a drug and dose change is ignored. The estimated effect of switching once is to increase the percent of days without drugs by 16%. All variations of CMG border on significance ($P\leq 0.10$) for ACE Inhibitors. The estimated effect of switching once is to increase the percent of days without drugs by 10 to 13%.

The relationship between the predicted probability of switching and CMG for alpha-blockers and diuretics is small and not statistically significant when using IV regression in contrast to the significant and positive relationship found using OLS regression. As in the OLS regressions, the control variables have the expected relationships with CMG (data not shown).

Discussion

To our knowledge this is the first study to use administrative data to examine whether changes in drug coverage cause medication non-adherence. Basic descriptive statistics (Table 2)

and results from OLS regressions are strongly suggestive that transitioning between health care financing programs for drug coverage is associated with a greater risk of experiencing medication gaps. For all classes of drugs, there is a positive and significant association between switching health care programs and gaps in medication (Table 3).

However, there is a simultaneity problem in the relationship between switching and adherence. Individuals who are switching health care programs may be doing so because of a recent acute episode that requires new types of health care services and at the same time affects the ability to adhere to medication regimes. IV estimators are robust to this type of endogeneity if appropriate instruments can be found, but precision is typically affected. Even when using IV regressions, switching increases the likelihood of experiencing gaps in medication among individuals on beta-blockers ($P < 0.05$). In addition, there is weak evidence in some specifications that switching increases the likelihood of experiencing gaps in medication for calcium channel blockers and ACE inhibitors ($P < 0.10$). In contrast, there is no evidence that switching causes medication gaps among individuals on alpha-blockers or diuretics. The fact that IV and OLS point estimates were so different for these two classes suggests that joint determination was a significant problem in the OLS model.

These results indicate that transitions in drug coverage may increase the risk of experiencing medication gaps. The difference between classes in the likelihood of experiencing adherence problems suggests that drug cost control policies may contribute to non-adherence more than enrollment delays do. For this sample, changing prescription drug coverage initially requires enrolling and seeing a doctor in the other program. If enrollment delays were the problem, the transition should affect non-adherence in all drug classes in the same way.

The characteristics of the diuretics and alpha-blockers suggest that drug cost control policies may be playing a role. Thiazide diuretics are believed to be the most effective first line of treatment for high blood pressure and are cheaper than other antihypertensives.^{27, 28} Alpha-blockers are not as commonly prescribed as the other drug classes.^{27, 29} Drug cost control policies may not focus on diuretics due to their effectiveness and low-cost or on alpha-blockers due to their rarity. Instead these policies may target the other classes of hypertension drugs. Further research that relates drug cost control policies to specific drugs and an individual's risk of experiencing medication gaps is needed.

From a VA perspective, policymakers and clinicians should pay particular attention to veterans who are entering or exiting the VA system from other health care systems. However, the negative effect of switching drug plans is also significant outside of the VA. The Medicare Modernization Act of 2003 (Medicare Part D) provides consumers with more options than ever before for prescription drug coverage, including the option to change plans if desired. All Medicare beneficiaries have the option to switch plans on a yearly basis, and individuals dually eligible for Medicaid and Medicare can switch plans on a monthly basis.^{30, 31} Thus, the introduction of Part D in 2006 likely increased switching between drug coverage plans.

Finally, if changes in prescription drug coverage can lead to medication gaps, further research is needed on how to minimize these gaps. The links between adherence to hypertension medication and improved blood pressure control, fewer health complications and lower health care costs are well established,¹⁻³ so investments in ways to decrease medication gaps that are caused by changes in coverage are important. For example, if adherence problems are found to be related to drug cost control policies and changes in costs when drug coverage, policymakers

may choose to limit the use of copayments, prior authorization, or other cost control policies for particular drugs or drug classes.

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Table 1: Calculation of Continuous Multiple-interval Measures of Medication Gaps (CMG)

Prescription fill date	Days supply	Days in hospital	Number of days without drugs (numerator)	Treatment Days (denominator)	CMG
<u>Basic scenario</u>					
July 1, 1999	90	0	2		
October 1, 1999	90	0	2		
January 1, 1999	90	0	1		
April 1, 1999	90	0	1		
			Total=6	366*	0.016
<u>Exclude days in hospital</u>					
July 1, 1999	90	0	2		
October 1, 1999	90	2	0		
January 1, 1999	90	0	1		
April 1, 1999	90	0	1		
			Total=4	364	0.011
<u>Exclude days after last refill if last refill is before the end of the outcome period</u>					
July 1, 1999	90	0	2		
October 1, 1999	90	0	0		
			Total=2	184	0.011
<u>Account for oversupply from previous prescriptions-no treatment changes</u>					
July 1, 1999	30	0	0- Surplus=10		
July 21, 1999	30	0	0^		
August 29, 1999	30	0	0		
			Total=0	90	0
<u>Account for oversupply from previous prescriptions-drug change</u>					
July 1, 1999 (old drug)	30	0	0-no surplus±		
July 21, 1999 (new drug)	30	0	10		
August 29, 1999 (new drug)	30	0	0		
			Total=10	90	0.111

*The outcome period was July 1, 1999 through June 30, 2000. If an individual had hypertension prescriptions throughout the entire outcome period, they will have 366 treatment days. 2000 was a leap year.

^ Despite the 40-day gap between July 21, 1999 and August 29, 1999 the individual never went without drugs because there was a 10-day supply left over from the July 1, 1999 prescription.

± If there is a drug or dose change, this specification assumes that the surplus from the old treatment regime is not used since it is unknown if individuals finish all the pills from the old treatment regime or discard the pills from an old treatment regime.

Table 2: Descriptive Statistics of Continuous Multiple-interval Measures of Medication Gaps (CMG) Using Different Assumptions of Oversupply; 1999-2000

	Used one program [^]				Switched programs				Used both programs			
	25%	50%	75%	Mean	25%	50%	75%	Mean	25%	50%	75%	Mean
<u>Beta-blockers (n=24,483)</u>												
Always use oversupply	0.000	0.041	0.197	0.124	0.000	0.072	0.291	0.178	0.000	0.012	0.132	0.089
Ignore oversupply when drug change	0.000	0.043	0.199	0.125	0.000	0.077	0.291	0.179	0.000	0.025	0.142	0.096
Ignore oversupply when drug or dose change	0.000	0.048	0.205	0.128	0.000	0.082	0.303	0.184	0.000	0.034	0.153	0.106
				n=22,782				n=1,231				n=470
<u>Alpha-blockers (n=14,282)</u>												
Always use oversupply	0.000	0.041	0.197	0.125	0.000	0.055	0.274	0.167	0.000	0.000	0.112	0.093
Ignore oversupply when drug change	0.000	0.041	0.199	0.125	0.000	0.063	0.274	0.168	0.000	0.008	0.118	0.097
Ignore oversupply when drug or dose change	0.000	0.058	0.219	0.137	0.000	0.081	0.295	0.181	0.000	0.021	0.147	0.106
				n=13,449				n=625				n=208
<u>Calcium Channel Blockers (n=30,578)</u>												
Always use oversupply	0.000	0.044	0.192	0.122	0.000	0.081	0.331	0.191	0.000	0.025	0.163	0.103
Ignore oversupply when drug change	0.000	0.046	0.195	0.124	0.000	0.091	0.334	0.196	0.000	0.033	0.173	0.110
Ignore oversupply when drug or dose change	0.000	0.053	0.204	0.129	0.000	0.102	0.336	0.201	0.000	0.041	0.185	0.116
				n=28,679				n=1,390				n=509
<u>Diuretics (n=30,887)</u>												
Always use oversupply	0.000	0.046	0.219	0.134	0.000	0.086	0.359	0.201	0.000	0.009	0.167	0.109
Ignore oversupply when drug change	0.000	0.050	0.221	0.137	0.000	0.097	0.363	0.207	0.000	0.027	0.184	0.120
Ignore oversupply when drug or dose change	0.000	0.055	0.226	0.139	0.000	0.105	0.368	0.211	0.000	0.042	0.206	0.129
				n=28,783				n=1,572				n=532
<u>ACE Inhibitors (n=34,554)</u>												
Always use oversupply	0.000	0.038	0.189	0.119	0.000	0.072	0.306	0.181	0.000	0.023	0.170	0.111
Ignore oversupply when drug change	0.000	0.040	0.191	0.120	0.000	0.081	0.310	0.184	0.000	0.033	0.184	0.120
Ignore oversupply when drug or dose change	0.000	0.052	0.202	0.128	0.000	0.094	0.325	0.192	0.000	0.046	0.219	0.131
				n=32,273				n=1,750				n=531

[^] Individuals who had all drug claims in one program (VA or Medicaid) were categorized as “used one program.” Individuals who had drug claims in one program and then had all subsequent drug claims in the other program were categorized as “switched programs.” Individuals who had drug claims in both the VA and Medicaid multiple times were categorized as “used both programs.”

Table 3: Coefficient on Switching Indicator Using OLS Regression Predicting Continuous Multiple-interval Measures of Medication Gaps (CMG) Using Different Assumptions of Oversupply; 1999-2000*

Switched systems once (ref=no switch or repeatedly used both)^	β	Standard Error	T	P-value
<u>Beta-blockers (n=24,483)</u>				
Always use oversupply	0.0600	0.0051	11.81	<0.001
Ignore oversupply when drug change	0.0597	0.0051	11.74	<0.001
Ignore oversupply when drug or dose change	0.0612	0.0051	12.00	<0.001
<u>Alpha-blockers (n=14,282)</u>				
Always use oversupply	0.0481	0.0072	6.66	<0.001
Ignore oversupply when drug change	0.0488	0.0072	6.76	<0.001
Ignore oversupply when drug or dose change	0.0510	0.0074	6.88	<0.001
<u>Calcium Channel Blockers (n=30,578)</u>				
Always use oversupply	0.0737	0.0047	15.65	<0.001
Ignore oversupply when drug change	0.0767	0.0047	16.22	<0.001
Ignore oversupply when drug or dose change	0.0763	0.0048	16.06	<0.001
<u>Diuretics (n=30,887)</u>				
Always use oversupply	0.0728	0.0048	15.22	<0.001
Ignore oversupply when drug change	0.0759	0.0048	15.79	<0.001
Ignore oversupply when drug or dose change	0.0776	0.0048	16.09	<0.001
<u>ACE Inhibitors (n=34,554)</u>				
Always use oversupply	0.0668	0.0042	15.87	<0.001
Ignore oversupply when drug change	0.0694	0.0042	16.45	<0.001
Ignore oversupply when drug or dose change	0.0702	0.0043	16.52	<0.001

*Models also included percentage of residents in Zip Code that are non-white, VA priority status, age, gender and whether the individual was diagnosed with any of 28 conditions (e.g. alcohol abuse, congestive heart failure).

^Switching systems was operationalized based on drug claims.

Table 4: Coefficients on Instruments of Logistic Regression Used in First Stage Equation For Instrumental Variables Regression Predicting Switching; 1999-2000*

	Pseudo R ²	β	Standard Error	z	P
<u>Beta-blockers (n=24,483)[^]</u>	0.0318				
Inpatient hospitalization during baseline period (ref=no)		0.3181	0.0724	4.39	<0.001
Medicaid restrictiveness		-3.7441	0.6317	-5.93	<0.001
Medical center distance		-0.0008	0.0006	-1.26	0.208
Outpatient clinic distance		0.0022	0.0017	1.33	0.184
Percent of medical center clinics that are geriatric		-0.2505	0.2257	-1.11	0.267
Percent of medical center clinics that are medical		-0.1764	0.1462	-1.21	0.228
Outpatient clinic has substance abuse services (ref=no)		0.2168	0.0809	2.68	0.007
Outpatient clinic has lab services (ref=no)		-0.0089	0.0794	-0.11	0.910
Outpatient clinic has pharmacy services (ref=no)		0.0502	0.0722	0.69	0.487
<u>Alpha-blockers (n=14,282)[@]</u>	0.0482				
Inpatient hospitalization during baseline period (ref=no)		0.4731	0.1017	4.65	<0.001
Medicaid restrictiveness		-3.4803	0.8612	-4.04	<0.001
Medical center distance		-0.0008	0.0009	-0.94	0.349
Outpatient clinic distance		0.0026	0.0021	1.24	0.214
Percent of medical center clinics that are geriatric		-0.5387	0.3163	-1.70	0.089
Percent of medical center clinics that are medical		0.1137	0.2109	0.54	0.590
Outpatient clinic has psychiatry services (ref=no)		-0.0495	0.1177	-0.42	0.674
Outpatient clinic has psychology services (ref=no)		0.1068	0.1274	0.84	0.402
Outpatient clinic has lab services (ref=no)		-0.1139	0.1118	-1.02	0.308
Outpatient clinic has pharmacy services (ref=no)		0.2338	0.1044	2.24	0.025
<u>Calcium Channel Blockers (n=30,578)[§]</u>	0.0295				
Inpatient hospitalization during baseline period (ref=no)		0.4399	0.0689	6.39	<0.001
Medicaid restrictiveness		-2.5976	0.5780	-4.49	<0.001
Medical center distance		-0.0004	0.0005	-0.71	0.480
Outpatient clinic distance		0.0014	0.0014	1.01	0.312
Percent of medical center clinics that are geriatric		-0.2970	0.2204	-1.35	0.178
Percent of medical center clinics that are medical		0.0782	0.1456	0.54	0.591
Percent of medical center clinics that are mental health		-0.1851	0.2126	-0.87	0.384
Outpatient clinic has psychiatry services (ref=no)		0.0278	0.0782	0.36	0.722
Outpatient clinic has psychology services (ref=no)		0.0042	0.0842	0.05	0.961
Outpatient clinic has pharmacy services (ref=no)		-0.0253	0.0700	-0.36	0.718
<u>Diuretics (n=30,887) ‡</u>	0.0310				
Inpatient hospitalization during baseline period (ref=no)		0.3672	0.0652	5.63	<0.001
Medicaid restrictiveness		-3.4352	0.5584	-6.15	<0.001
Outpatient clinic distance		0.0031	0.0011	2.82	0.005
Percent of medical center clinics that are geriatric		-0.2120	0.2093	-1.01	0.311
Percent of medical center clinics that are medical		-0.2589	0.1338	-1.93	0.053
Percent of medical center clinics that are mental health		-0.0570	0.2019	-0.28	0.778
Outpatient clinic has psychiatry services (ref=no)		0.0128	0.0755	0.17	0.866
Outpatient clinic has psychology services (ref=no)		-0.0533	0.0856	-0.62	0.534
Outpatient clinic has substance abuse services (ref=no)		0.0875	0.0862	1.02	0.310
Outpatient clinic has pharmacy services (ref=no)		0.0255	0.0659	0.39	0.698
<u>ACE Inhibitors (n=34,554)</u>	0.0309				
Inpatient hospitalization during baseline period (ref=no)		0.4586	0.0616	7.45	<0.001
Medicaid restrictiveness		-2.8227	0.5333	-5.29	<0.001
Medical center distance		-0.0001	0.0004	-0.33	0.738
Outpatient clinic distance		0.0033	0.0011	3.01	0.003
Percent of medical center clinics that are geriatric		-0.1204	0.2017	-0.60	0.550
Percent of medical center clinics that are medical		-0.2208	0.1294	-1.71	0.088
Percent of medical center clinics that are mental health		0.3225	0.1951	1.65	0.098
Outpatient clinic has psychiatry services (ref=no)		-0.0447	0.0727	-0.62	0.538

Outpatient clinic has psychology services (ref=no)	0.0659	0.0824	0.80	0.423
Outpatient clinic has substance abuse services (ref=no)	0.1807	0.0803	2.25	0.024
Outpatient clinic has lab services (ref=no)	-0.0402	0.0672	-0.60	0.550
Outpatient clinic has pharmacy services (ref=no)	-0.0338	0.0643	-0.53	0.599

*Switching systems was operationalized based on drug claims. Models also included percentage of residents in Zip Code that are non-white, VA priority status, age, gender and whether the individual was diagnosed with any of 28 conditions (e.g. alcohol abuse, congestive heart failure).

^The percent of medical center clinics that are mental health and whether the outpatient clinic offers psychology or psychiatry services were excluded instruments.

@ The percent of medical center clinics that are mental health and whether the outpatient clinic offers substance abuse services were excluded instruments.

§ Whether the outpatient clinic offers substance abuse services and lab services were excluded instruments.

‡ Medical center distance and whether the outpatient clinic offers lab services were excluded instruments.

Table 5: Coefficient on Switching Indicator Using IV Regression Predicting Continuous Multiple-interval Measures of Medication Gaps (CMG) Using Different Assumptions of Oversupply; 1999-2000*

Switched systems once (ref=no switch or repeatedly used both)±	β	Standard Error [@]	<i>P</i>	<i>P</i> -value for OID test [^]
<u>Beta-blockers (n=24,483)</u>				
Always use oversupply	0.1608	0.0847	0.058	0.551
Ignore oversupply when drug change	0.1721	0.0839	0.040	0.487
Ignore oversupply when drug or dose change	0.1824	0.0834	0.029	0.515
<u>Alpha-blockers (n=14,282)</u>				
Always use oversupply	-0.0270	0.0897	0.763	0.654
Ignore oversupply when drug change	-0.0347	0.0879	0.693	0.721
Ignore oversupply when drug or dose change	-0.0140	0.0901	0.876	0.648
<u>Calcium Channel Blockers (n=30,578)</u>				
Always use oversupply	0.1194	0.0862	0.166	0.185
Ignore oversupply when drug change	0.1403	0.0890	0.115	0.176
Ignore oversupply when drug or dose change	0.1558	0.0900	0.084	0.270
<u>Diuretics (n=30,887)</u>				
Always use oversupply	0.0312	0.0811	0.700	0.247
Ignore oversupply when drug change	0.0302	0.0845	0.721	0.483
Ignore oversupply when drug or dose change	0.0259	0.0777	0.739	0.798
<u>ACE Inhibitors (n=34,554)</u>				
Always use oversupply	0.1010	0.0614	0.100	0.141
Ignore oversupply when drug change	0.1150	0.0682	0.092	0.117
Ignore oversupply when drug or dose change	0.1280	0.0679	0.060	0.157

*Models also included percentage of residents in Zip Code that are non-white, VA priority status, age, gender and whether the individual was diagnosed with any of 28 conditions (e.g. alcohol abuse, congestive heart failure).

±Switching systems was operationalized based on drug claims.

[@]Standard errors were bootstrapped with 400 replications.

[^]OID=overidentifying restriction test