The Power of Not Asking : How Does the Presumed Consent Law Affect Patient's Choice of Prescription Drugs

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Abstract

Generic drugs offer substantial savings over brand name alternatives. With the spending on prescription drug expenditure as high as 374 billion dollars, states in the United States have adopted different policies to promote generic substitution of brand name drugs. Two popular type of these policies are mandatory switching laws and presumed patient consent laws. To identify the effect of these policies, I use the variation from states who changed the drug substitution polices between 2006 and 2012. Using the aggregate Medicaid State Drug Utilization data, I find that mandatory switching law has little effect while the presumed patient consent increases the generic substitution ratio. The effect of the presumed patient consent law depends on the disease type and how many years the generic drug has been available. To overcome the limits of aggregate data, I analyze the policies using difference in difference method with Medical Expenditure Panel Survey data. I find that individuals living in states with presumed consent are 1.56 percentage points less likely to buy brand name drugs compared to those living in states with explicit patient consent. To understand the mechanism of the presumed consent, I build a model of patient's choice of prescription drugs. By modeling the presumed patient consent law as an extra cost for patients living in states with such policy to buy brand name drugs, I find the effect of presumed patient law on patient's decision to buy prescription drugs is equivalent to 28 dollar increase in the brand name drugs. The average marginal effect of the policy is that the average probability of purchasing brand name drugs decrease by 11 percent. A welfare calculation indicates that consumer's surplus loss exceeds the insurance's gain by 7.5 dollars per person when all states switch from explicit to presumed consent.

Keywords: Health Economics, Prescription Drug, Consumer Demand, Policy Evaluation

1. Introduction

The rising costs of health care expenditures in the United States have captured the attention of media, academics and policy makers. In 2011, the total national health expenditures sum to 2.7 trillion dollars. This suggests that 17.9 percent of U.S GDP is spent on health care. Ten percent of this spending are used for prescription drugs. With the introduction of Medicare part D that covers prescription drug, finding an effective way to control drug expenditure has become a priority for policy makers.

One effective way to control the drug expenditures is to dispense generic drugs whenever a multi-source drug is prescribed. A multi-source drug is defined as having at least one other drug rated as therapeutically equivalent under the Food and Drug Administration's most recent publication of 'Approved Drug Products with Therapeutic Equivalence Evaluations'. A generic drug is usually priced at 10 to 20 percent of the brand name counterpart. As a result, switching to generic drugs can potentially be an effective way to curb the growth rate of drug expenditure. A report prepared by IMS claimed that in 2013 alone, generic drugs have saved the Americans 239 billion dollars.[1]

Many states have used policy tools to promote generic use at retail level. There are two types of laws involved. First type of law regulates whether it is mandatory or permissive for the pharmacists to switch to a generic drug. The second type of law mandates whether the patient consent is presumed or has to be explicit stated. The presumed consent law means that the pharmacists assume that the patient agree with the generic substitution unless the patient explicitly rejects the substitution. The explicit patient law requires that the pharmacists have to ask for patient's permission to switch to a generic drug. A state can choose any combination from the two type of policy tools.

Intuitively, mandatory switching law and patient consent law should increase the use of generic drugs. But there hasn't been any systematic study to quantify the impact of the laws. The only recent study by Shrank et al. (2010) analyzed the law's impact on the generic substitution ratio for Zocor. They find that states implementing policies that require patient consent prior to generic substitution experienced 25% lower rates of generic substitution. But more questions remain to be answered from this study. For instance, does the presumed patient consent law have the same level of impact on every type of drugs? Why the presumed patient consent law works ? What would happen if all states switch from explicit consent law to presumed patient consent law.

This paper tries to answer these questions. I provide the first comprehensive analysis of the generic substitution law's impacts on the prescription drug market. I collect state laws of generic substitution over the period of 2006 and 2012. I merge the state law data with Medicaid State Drug Utilization (MSDU) data. To capture the potential heterogeneity of the law's impacts, I look at 13 drugs in four type of drugs, statins, anti-depressants/SSRI,

[1] http://blogs.wsj.com/pharmalot/2014/09/11/generic-drugs-saved-americans-how-much-money/

anti-depressants/TCA and PPI. I find the mandatory switching law has little effect in the generic substitution ratio. The patient consent law has a negative impact on the generic substitution ratio. The impact depends on how many years the generic drug has been available on the market and the disease type. Since the MSDU data is aggregated at quarterly state level and patients with Medicaid are not representative of the U.S population, it prevents me from answering questions at more detailed levels. To correct for these problems, I merge the law data with the Medical Expenditure Panel Survey (MEPS) data. The MEPS is a set of large-scale surveys of families and individuals, their medical providers (doctors, hospitals, pharmacies, etc.), and employers across the United States. I focus on the two type of antidepressants, SSRI and TCA. I analyze the policies using difference in difference method. I find that individuals living in states with presumed patient consent are 1.56 percentage points less likely to buy brand name drugs compared to those living in states with explicit patient consent. To understand the mechanism of the presumed patient consent, I model the consumer's choice of drugs as a discrete choice problem. By modeling the presumed patient consent law as an extra cost for patients living in states with such policy to buy brand name drugs, I find the effect of presumed patient law on patient's decision to buy prescription drugs is equivalent to 28 dollar increase in the brand name drugs. The average marginal effect of the policy is that the average probability of purchasing brand name drugs decreases about 11 percent. A welfare calculation indicates that consumer's surplus loss exceeds the insurance's gain by 7.5 dollars per person when all states switch from explicit to presumed consent.

The rest of the paper is organized as the following. Section 2 discusses the related literature and this paper's contributions. Section 3 provides background information of the pharmaceutical market and the state laws regulating the generic substitution. Section 4 presents the empirical results using the aggregate medicaid drug utilization data. Section 5 applies the difference in difference method and the discrete choice model to the MEPS data. Section 6 concludes.

2. Literature Review

This paper is related to several strands of literature. First, there are a few studies that evaluated the impact of the generic drug substitution laws. Shrank et al. (2010) evaluated the relationship between different generic substitution policies and generic simvastatin use after patent expiration of Zocor. They found that states implementing policies that require explicit consent prior to generic substitution experienced 25% lower rates of generic substitution.Kelton et al. (2013) examined the movement to generic fluoxetine following patent expiration for Prozac, a widely prescribed antidepressant. They found large differences in states' responses to generic availability. States took between two and ten calendar quarters to reach 90 percent use of generic rather than brand-name fluoxetine. But they did not explore the potential causes of these variations. These studies suffer several limitations. By limiting to one type of drug, they

could not capture potential heterogeneous effects of the laws. And they did not discuss why the mandatory subsitution does not work and the presumed consent works.

This paper is related to the literature of the choice of prescription drugs. This literature has largely focused on the role of physician's preference and learning. Hellerstein (1998) examined the importance of physicians in the process by which patients receive either brand name or generic drugs. Using a data set on physicians, their patients, and the multisource drugs prescribed, she found that very little of the prescription decision can be explained by observable characteristics of individual patients, but all of the evidence indicates that physicians are indeed an important agent in determining whether patients receive either trade-name or generic drugs. Coscelli (2000) studied the contribution of doctor and patient habit to persistence in market shares in prescription drug markets. He found significant evidence of time-dependence in prescription choices for both doctors and patients. Other works include Coscelli and Shum (2004), Crawford and Shum (2005) and Lundin (2000) .

The presumed consent law is widely applied in other scenarios. Abadie and Gay (2006) studied the impact of presumed consent legislation on cadaveric organ donation. Under presumed consent legislation, a deceased individual is classified as a potential donor in absence of explicit opposition to donation before death. They constructed a data set on organ donation rates and potential factors affecting organ donation for 22 countries over a 10-year period. They found that while differences in other determinants of organ donation explain much of the variation in donation rates, after controlling for those determinants presumed consent legislation has a positive and sizable effect on organ donation rates. Another widely known application of the presumed consent is the default opt-in structure of the 401k savings in the United States. Madrian and Shea (2000) is the first to study the switch to automatic enrollment in 401k dramatically changed the savings behavior of employees. They found that 401(k) participation is significantly higher under automatic enrollment. Thaler and Benartzi (2004) and Chetty et al. (2012) studied similar issues and come to the same conclusions. Carroll et al. (2005) modeled the 401(k) enrollment and derive conditions under which the optimal enrollment regime is automatic enrollment (i.e., default enrollment), standard enrollment (i.e., default non-enrollment), or active decisions. Thaler (2008) provided various other examples of presumed consent. Most of the existing literature of the presumed consent policy use reduced form approach to quantify the effect of presumed consent. I contribute to the literature by modeling the presumed consent as an extra cost item and estimate the size of the cost item.

This paper uses nested logit model with correction of endogenous price pioneered by Berry (1994) , Berry et al. (1995) and Nevo (2000) . These methods have been applied to the demand analysis in the pharmaceutical industry since prescription drugs have a natural way of nesting. Cleanthous (2004) used these methodologies to quantify patient welfare benefits from pharmaceutical innovation in the U.S. antidepressant market.Yu and Gupta (2014) specified a random effect nested logit model of competition that allows for competition between the brand drug and generics, and

among multiple generic drugs.The model is estimated on cross-section time-series data for 49 molecules in which the brand drug lost patent exclusivity between 1992 and 2000. They found strong evidence that the early generic entrant enjoys a substantial market share and profit advantage over the second and the third entrants, after controlling for differences in marketing activities.

3. Background Information of the Pharmaceutical Market and the Generic Substitution Laws

Pharmaceutical industry is one of the most heavily regulated industry in the United States. A firm has to file a New Drug Application (NDA) for FDA approval to be able to market the drug. Once approved, this drug is granted market monopoly under the protection of a patent. A patent usually lasts about 20 years. After the drug's patent expired, other firms could apply for FDA approval to produce generic version of that drug. Before the passage of Hatch-Waxman act in 1984, generic producing firms have to go through the same stage of clinical trials as the brand name firm to prove the drug's efficacy and safety. After 1984, generic firms could simply demonstrate bio-equivalence with branded products by showing that the active ingredient in their product diffused into the human bloodstream in a manner similar to the original product. This act dramatically changed the landscape of the pharmaceutical market. Generic drugs now enjoy about 70 percent the market share, compared to about 10 percent in the 1980s.

At one time laws in most states required the pharmacist to fill a prescription as written, precluding generic dispensing when the physician had written the brand name, but the last of these antisubstitution laws was repealed in 1984 (most were repealed in the mid- to late-1970s). They were replaced by two types of laws regulating the substitution of generic drugs. The first type of law can be classified into two categories, mandatory or permissive. An example of the mandatory switching law is the legislation in Florida:

> A pharmacist who receives a prescription for a brand name drug shall, unless requested otherwise by the purchaser, substitute a less expensive, generically equivalent drug product.

An example of the permissive switching law is the Illinois Legislation :

> A different brand name or nonbrand name drug product of the same generic name may be dispensed by the pharmacist, provided that the selected drug has a unit price less than the drug product specified in the prescription.

The second type includes laws that require explicit patient consent or presume consent for substitution. States can choose any type of combinations of the two type of laws. I take the data from Survey of Pharmacy Laws between year 2006 and 2012. Figure 1 plots the distribution of how states choose the generic drug substitution laws.

Figure 1: State Generic Drug Substitution Laws Atlas

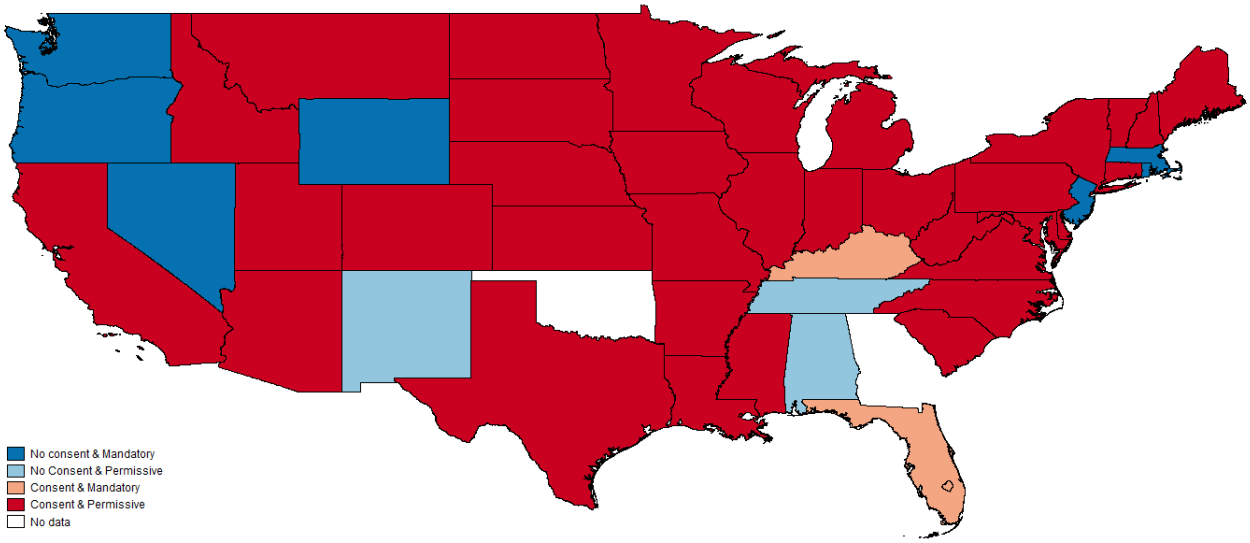


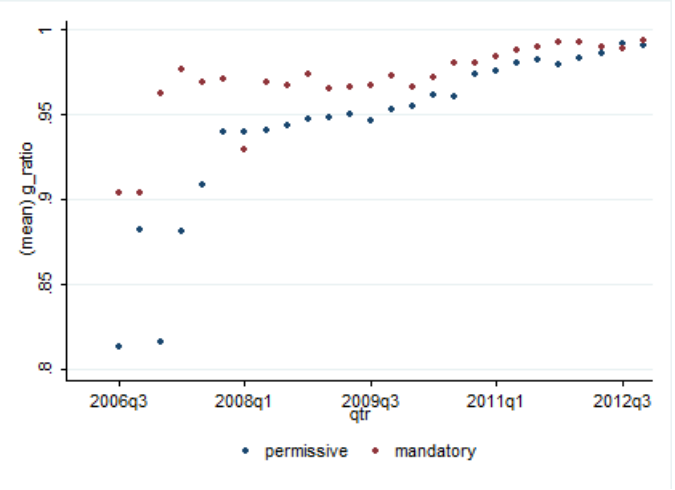
Table 1: State Generic Substitution Laws

Panel A : 2006		
	Mandatory	Permissive
Presumed Consent	7	3
Explicit Consent	3	37
Panel B : 2012		
	Mandatory	Permissive
Presumed Consent	5	7
Explicit Consent	6	32

Note : The data of the state regulations of the generic drug substitution is taken from various years of Survey of Pharmaceutical Laws

From the figure, we can see that the majority of states require explicit patient consent and is permissive towards generic drug substitution. But all four possible combinations of the two laws exist. Table 1 break down the distribution of the law types. In 2006, there are 3 states in both permissive and presumed consent, mandatory and explicit consent group. 7 states belong to the group that presumes consent and is mandatory towards substitution. The dominating group is states that are permissive and require explicit patient consent for substitution. 37 states fall into this group. During the 7 years period between 2006 and 2012, several states changed their generic substitution laws. Panel b in table 1 presents the breakdown of the state laws in 2012. In total , 11 states changed these laws. Changes in both directions exist. For example, Michigan switched from not requiring to requiring consent. And Alabama chose not to require consent in 2009.

Figure 2: Generic Zoloft Substitution Ratio by Mandatory Law



4. Empirical Results from Medicaid State Drug Utilization Data

I begin the empirical analysis by using the aggregate Medicaid State Drug Utilization(MSDU) data. Medicaid drug utilization data are reported by States for covered outpatient drugs that are paid for by State Medicaid Agencies since the start of the Medicaid Drug Rebate Program. It includes number of prescriptions , the medicaid reimburse amount at 11 digits NDC level for each state by quarter and year. I merge the MSDU with the law data described in the last section.

I choose 3 types of drugs that treat major depression , lower cholesterol level and control stomach acid. Each of the three type of drugs has a meaningful share of the total prescriptions in the Medicaid drug program. For instance, central nervous system agents(comprise anti-depressants) comprise 35 percent of the total prescriptions made in the Medicaid program. Cardiovascular drugs(comprise statins) has a share of 10 percent. [2]

The second selection criterion is the drugs should have variations in the year generic drug become available. In the three type of drugs, the earliest year when the generic drug is available is 1987. The latest is 2010. This variations are necessary to identify the potential learning effects of generic drugs.

These three type of drugs also treat very different diseases. This feature helps me to identify whether the generic substitution laws have any heterogeneous effects depending on the disease type. Table 3 shows the brand name, generic name , year when brand name and generic become available by drug type.

The variable of interest is generic substitution ratio. It's defined as the number of prescription for a generic drug , divided by the sum of brand name and generic drug. Figure 2 and 3 shows the average generic substitution ratio for

[2] http://kff.org/report-section/what-drives-spending-and-utilization-on-medicaid-drug-benefits-in-states-issue-brief/

Table 2: Drugs by Type

	Statins			
Generic Name	FLUVASTAT	PRAVASTAT	SIMVASTA	
Brand Name	LESCOL	PRAVACHOL	ZOCOR	
Year Brand Available	1993	1991	1991	
Year Generic Available	2012	2006	2006	
	Anti-Depressants/SSRI			
Generic Name	FLUOX	PAROX	CITALO	SERT
Brand Name	PROZAC	PAXIL	CELEXA	ZOLOFT
Year Brand Available	1989	1982	1982	1982
Year Generic Available	1996	1987	2010	2006
	Anti-Depressants/TCA			
Generic Name	CLOMI	DESI	IMI	TRIMI
Brand Name	ANAFRA	NORPRA	TOFRA	SURMON
Year Brand Available	1989	1982	1982	1982
Year Generic Available	1996	1987	2010	2006
	Stomach Acid/PPI			
Generic Name	LANSOPRAZO	OMEPRAZOLE		
Brand Name	PREVACID	PRILOSEC		
Year Brand Available	1995	1989		
Year Generic Available	2002	2008		

Figure 3: Generic Zoloft Substitution Ratio by Consent Law

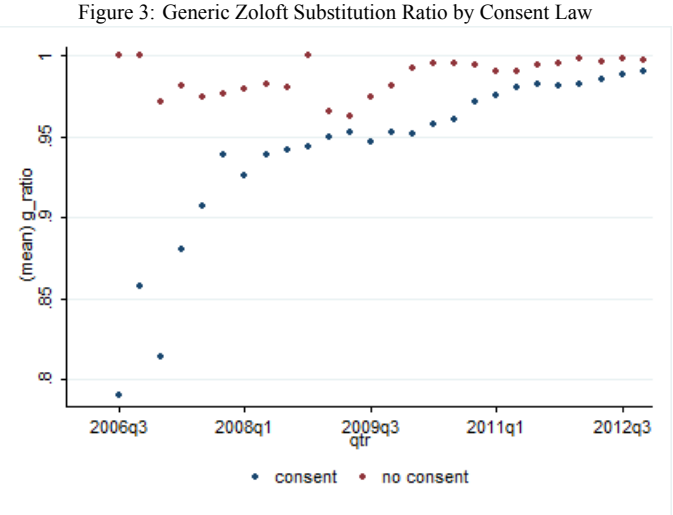


Table 3: The Effect of State Regulations On Generic Drug Substitution Ratio by Drug

	Statins			
	LESCOL	PRAVACHOL	ZOCOR	
Permissive	0.08(0.04)	-0.02(0.012)	0.001(0.007)	
Presumed Consent	0.12(0.04)	0.03(0.014)	0.02(0.007)	
	AntiDepressants/SSRI			
	PROZAC	PAXIL	CELEXA	ZOLOFT
Permissive	0.001(0.003)	0.003(0.005)	-0.0005(0.002)	-0.01(0.008)
Presumed Consent	-0.009(0.004)	0.03(0.005)	0.006(0.002)	0.04(0.009)
	AntiDepressants/TCA			
	ANAFRAN	NORPRAM	TOFRA	SURMON
Permissive	0.01(0.005)	0.002(0.005)	-0.001(0.001)	0.04(0.047)
Presumed Consent	0.02(0.006)	0.02(0.006)	0.002(0.001)	0.10(0.052)
	PPI			
	PREVACID	PRILOSEC		
Permissive	0.01(0.028)	-0.02(0.009)		
Presumed Consent	0.2(0.031)	0.03(0.010)		

Note: All regressions include year fixed effects. Standard errors are clustered at state level.

Zoloft by mandatory and consent law type respectively. A few patterns clearly emerge from the two graphs. First of all , states with mandatory switching and presumed patient consent laws have higher generic substitution rates. This is consistent with the intuition. Second, the generic substitution rate is high and increasing over time. Third, the gap between states that are mandatory or permissive, explicit or presumed consent,becomes smaller over time. At the end of the sample period, this difference has essentially become negligible.

I run a separate regression of the generic substitution ratio on the two type of laws for each drug with year fixed effects. Table 4 presents the regression results. Two findings stand out. First, the mandatory law has a negligible effect on the generic drug substitution rate. Second, the presumed consent law has a consistently positive impact on the substitution rate. This can be seen more clearly from figure 4. Figure 4 plots the value of the estimated coefficients and the 95 percent confidence interval. It's clear from the graph that the coefficients for the variable permissive law is concentrated around 0. The coefficients for patient consent law is centered around the right side of zero.

I then pooled the data for all type of drugs. I implement the same regression form as the individual regression but adding the number of years a generic drug have been available, the number of years a generic drug have been available in the drug class, and the disease type. In the first column, I only include year fixed effects and the two law variables. The coefficient for the mandatory law variable is close to zero and not significant. And the coefficient for the patient consent variable is 0.02 and significant. This suggests that generic substitution ratio is about two percentages higher in states where presumed patient consent is implemented. In the second column, I interact the patient consent laws with year. Patient consent's coefficient becomes 0.035 and the coefficient for the interaction term is -0.0031. Both coefficients are significant. This suggest that when a brandname drug's patent expired, it takes about 10 years for a

Figure 4: Coefficient Plot for Individual Drug Regression

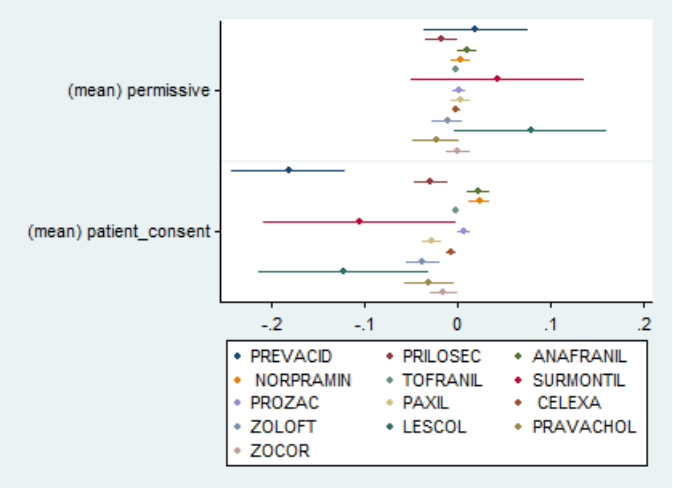


Table 4: The Effect of State Regulations On Generic Drug Substitution Ratio

	Generic Substitution Ratio			
Permissive	0.0011(0.0132)	0.0004(0.003)	0.0018(0.0132)	0.0009(0.0133)
Presumed Consent	0.0224(0.0113)	0.035(0.0086)	0.0441(0.0143)	0.0869(0.0404)
Year		0.0079(0.0016)		
Consent*Year		-0.0031(0.0017)		
Generic Available Years			-0.00169(0.00104)	
G_Years*Consent			-0.0033(0.00112)	
Year Fixed Effects	✓		✓	✓
STATIN				0.0156 (0.0244)
SSRI				0.0548(0.0230)
TCA				0.0198(0.0329)
Consent_STATIN				-0.0526(0.0368)
Consent_SSRI				-0.0694(0.0341)
Consent_TCA				-0.0985(0.0433)
Number of Observations	13,288	13288	13,288	13,288
R Square	0.025	0.019	0.029	0.085

Note : Robust standard errors in parentheses.

states that requires explicit patient consent to have the same level of generic substitution ratio as states without such constraint. In the third column, I add the variable how many years the generic drug has been available and interact it with the patient consent variable. The interaction term is -0.0033 and significant. This suggests that over time, the gap between two type of states closes. Column 4 adds dummies for drug type and interactions of drug type with patient consent law. The omitted drug type is PPI. The coefficient for antidepressant/SSRI and antidepressants/TCA are positively significant. This suggests that the patient consent law has heterogeneous impact depending on the disease type.

5. Empirical results with MEPS data

Though results from section 4 demonstrated the impact of the presumed consent law on generic drug substitution rate, the analysis suffers several short comings. First, the Medicaid data is aggregate at the state level. As a result, it is not clear how the presumed consent law's effect would differ among individuals with different characteristics. For instance, the presumed consent law might have differential impact on patients with different education and income. And the aggregate data does not have enough power to separate the state fixed effect from the treatment effect of the two policies. Second, reduced form estimation does not tell us the mechanisms of the effects of the presumed consent law. It also prevents us from asking questions like what would happen if all states switch from explicit to presumed patient consent. To overcome these drawbacks, I merge the law data with Medical Expenditure Panel Survey(MEPS) and use two different strategies to analyze the data.

5.1. Data Description

MEPS's Household Component (HC) collects data from a sample of families and individuals in selected communities across the United States, drawn from a nationally representative subsample of households that participated in the prior year's National Health Interview Survey. It has a rich set of information in demographic characteristics, health conditions, health status and use of medical services.

In the empirical work below, I focus on two type of anti-depressants, SSRI and TCA. Table 6 shows the name of the brand drug, their corresponding generic drug name , average self payment, average total payment and market share calculated from MEPS. Based on the average self payment, the generic antidepressant is much cheaper compared to the brand name drug. Consumers pay about 13 to 50 percent of the brand name drug price to get generic drugs. Column 6 indicates that even though all brand name antidepressants have much cheaper generic counterparts, they still take up a significant amount of market share. Table 7 breaks down the sample cleaning procedure. There are about 68000 observations for the difference in difference analysis and 19000 for the logit model.

Table 7 presents the demographic information for consumers of anti-depressants, grouped by the type of patient consent law. We can see that the two type of states are almost identical in terms of the demographic factors considered. And people who purchase these antidepressants are more likely to be female, white, old and covered by public health insurance.

5.2. Difference in Difference

To confirm the findings from section 4 but add on causal interpretations, I use the difference in difference method with the MEPS data and estimate the following regression. The dependent variable is whether the purchased drug is

Table 5: Descriptive Statistics For Drug Characteristics

Drug Name	Brand/Generic	Entry Year	Average Self Payment(Dollars)	Average Total Payment(Dollars)	Marke Share(
PROZAC	Brand	1987	56.67	196.12	3.48
FLUOXETINE	Generic	2001	9.61	32.36	16.47
PAXIL	Brand	1992	72.29	158.17	2.78
PAROXETINE	Generic	2003	9.54	34.26	12.01
ZOLOFT	Brand	1991	28.27	76.19	7.09
SERTRALINE	Generic	2006	8.80	27.26	18.54
CELEXA	Brand	1998	19.18	48.14	1.54
CITALOPRAM	Generic	2004	7.40	20.80	18.71
LEXAPRO	Brand	2002	33.65	109.20	17.89
ESCITALOPRAM	Generic	2012	16.89	108.71	1.50

Note: The market share is calculated using the sample for difference in difference analysis.The results are similar when calculated using the sample for the logit model.

Table 6: Number of Observations of the Sample

Selection Rule	Number of Observations
Original Sample	2208624
Keep only drugs purchased for depression	196086
Keep only the ten type of antidepressants(DID Sample)	68704
Drop multiple purchases of one type of drug	49547
Drop if purchases of multiple drug classes (Logit Model Sample)	19152

Table 7: Demographic Characteristics of Consumers of Anti Depressants

	States with Explicit Patient Consent	States with Presumed Patient Consent
Male	0.30	0.30
White	0.86	0.84
Black	0.09	0.10
Age	50.69	50.36
Public Insurance	0.57	0.56
Private Insurance	0.37	0.36

brand name or generic. With state and year fixed effects, the variable of interest is α_1. The estimation result is presented in table 9. In column 1 of table 9, α_1 is -0.0156. This suggests that the presumed consent law reduces the probability of purchasing a brand name antidepressant by 1.56 percentage points. Using the market share of brand name drugs in table 6, this indicates that the presumed consent law decrease the probability of purchasing a brand name drug by 5 percent. This result is robust to clustered standard errors and block bootstrap procedure.

$$Brand = \alpha_0 + \alpha_1 * Treatment_{it} + \beta * x + \alpha_2 * Year_t + \alpha_3 * States_i + \epsilon_{it} \tag{1}$$

In the regression above, the treatment group is the individuals who purchase antidepressants in states switched to presumed consent law and the control group is the individuals who purchase antidepressants in states with explicit consent law. Another way of choosing control group is the individuals who purchase OTC drugs in states who switched to presumed consent law. The argument is that the presumed consent law only applies to prescription drug purchases. As a result, consumer's decision of buying brand or generic OTC drugs should not be affected. Therefore, we can estimate the following equation. But this time , the treatment group is people who purchase prescription drugs and the control group is people who purchase OTC drugs.(In progress)

$$Brand = \alpha_0 + \alpha_1 * Treatment_{it} + \beta * x + \alpha_2 * Year_t + \alpha_3 * States_i + \epsilon_{it} \tag{2}$$

5.3. Model

As mentioned at the beginning of this section, reduced form estimations do not tell us why the presumed patient consent works and can not provide counter factual experiments. To answer these questions, I build a discrete choice model of the prescription drugs. The model is specified as the following.

Consumers choose one drug that gives the highest utility from J types of drugs. The utility derived from drug j is

$$u_{nj} = \sum_k \beta_{i,k} x_{jk} + \alpha * Brand_j * Presumed\_Consent_n + \epsilon_{nj} \tag{3}$$

, where x_{jk} is the product characteristics and interactions between product and individual characteristics. ϵ_{nj} is an i.i.d error term following an extreme value distribution.

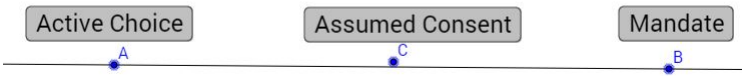
The key element of the model is the term $\alpha * Brand_j * Presumed\_Consent_n$. It's an extra cost item for consumers who would like to buy brand name drug in a state with presumed patient consent. The modeling decision is motivated by the intuition that a policy that mandates the substitution generic drug can be modeled as an positive infinite cost for patients to buy a brand name drug. In this case, a consumer would always choose a generic drug facing the infinite cost

Table 8: DID Regression Results

Independent Variables	Baseline	Add interactions	OTC as control group
Treatment	-0.0156	-0.0932	
	0.0072	0.0326	
Age	-0.0020	-0.0016	
	0.0003	0.0002	
Male	-0.0293	-0.0511	
	0.0126	0.0089	
White	0.0139	0.0958	
	0.0204	0.0201	
Black	-0.0509	0.0558	
	0.0251	0.0240	
Wage	0.0008	0.0006	
	0.0002	0.0001	
Public	0.0050	0.0221	
	0.0182	0.0097	
Private	-0.0017	Omitted	
	0.0179		
Uninsured	Omitted	0.0441386	
		0.0193097	
Year	√	√	
State	√	√	
Consent * Age		0.0005	
		0.0003	
Consent * Male		-0.0254	
		0.0098	
Consent * White		0.0983	
		0.0221	
Consent * Black		0.1269	
		0.0263	
Consent * Wage		-0.0002	
		0.0002	
Consent * Public		-0.0296	
		0.0202	
Consent * Private		-0.0483	
		0.0207	
Number of Observations	68704	68704	
R-Square	0.1459	0.1464	

Note : State and year fixed effects are included in all regressions. Wage is the raw wage in thousands, not inflation adjusted. Standard errors are shown below the coefficient cells.

Figure 5: A continuum of the costs to buy a brand name drug



to buy a brand. Similarly a policy that no pharmacist intervention is allowed can be modeled as no addition costs for a consumer to buy a brand name drug. This intuition can be illustrated by figure 5. Figure 5 plots a continuum of the addition costs to buy a brand name drug in different choice structures. The costs to buy a brand name drug increases when we move to the right of the continuum. Presumed consent should lie between the active choice and mandate to buy generic structure. The goal of the model is to identify the cost difference between the presumed and explicit consent on buying a brand drug.

Using the property of the extreme value distribution, the probability of individual n choosing product j can be succinctly expressed as

$$p_{nj} = \frac{exp(\sum_k \beta_k x_{ijk} + \alpha * brand_j * presumed\_consent_n)}{\sum_j exp(\sum_k \beta_k x_{ijk} \alpha * brand_j * presumed\_consent_n)} \tag{4}$$

The expression of the likelihood for the model is

$$L(\beta, \alpha) = \Pi_{n=1}^{N} \Pi_j (P_{nj})^{y_{nj}} \tag{5}$$

where $y_{nj} = 1$ if person n chooses j and zero otherwise.

The log-likelihood function is then

$$LL(\beta, \alpha) = \sum_{n=1}^{N} \sum_j y_{nj} ln(P_{nj}) \tag{6}$$

I estimate the model with Maximum Likelihood. The result is presented in the first column of table 9. The second column gives the results of a more flexible form of the model discussed above to avoid potential problems of the IIA property caused by the i.i.d error terms.[3] The fact that the value of the coefficients are similar in two specifications allows me to discuss the results using coefficient values from the first column.

Since the model above is non-linear, I can't directly interpret the impact of the presumed consent law based on the sign and magnitude of the coefficients reported above. To help understand the model, I calculate the average marginal

[3]For a more thorough discussion of the IIA property and how mixed logit avoids it, consult Train (2009).

Table 9: Conditional Logit Regression Results

Independent Variable	Baseline	Mixed Logit
Average Price	-0.0071(0.0003)	-0.0071(0.0003)
Brand Name	-0.3585(0.0788)	-0.6815(0.0401)
Brand * Age	-0.0070(0.0009)	
Brand * Male	-0.1531(0.0345)	
Brand * Public	0.0111(0.0595)	
Brand * Private	-0.0548(0.0624)	
Brand * Presumed Consent	-0.2032(0.0428)	-0.1903(0.0426)
Number of Observations	174258	174258

Note : The total number of individuals making choices are 19002.

Table 10: Average Marginal Effect of Change in Consent Law

Drug Type	Predicted Probability of Purchase under Explicit Patient Consent	Predicted Probability of Purchase under Presumed Patient Consent	% Change
PROZAC	0.0641	0.0566	-0.1180
FLUOXETINE	0.1503	0.1599	0.0637
PAXIL	0.0598	0.0527	-0.1191
PAROXETINE	0.1508	0.1604	0.0638
ZOLOFT	0.0835	0.0734	-0.1210
SERTRALINE	0.1512	0.1609	0.0638
CELEXA	0.0817	0.0721	-0.1174
CITALOPRAM	0.1525	0.1622	0.0638
LEXAPRO	0.0755	0.0664	-0.1207
ESCITALOPRAM	0.1183	0.1254	0.0594

effects of all states switching from explicit to presumed patient consent law. The results are presented in table 10. We can see that on average, the switching to presumed consent reduces the average probability of purchasing brandname drug by 11 percent. Using the odds ratio calculated based on column 1 in table 9, the impact of the switch to presumed consent is equivalent of an 28 dollars increase in the brand name drugs.

From a policy maker's perspective, we would like to know the welfare implications of the presumed consent law besides understanding the impact of the policy. There are two parties involved in the welfare calculation, insurance companies and patients. It's clear that insurance companies gain from the presumed consent policy. From column 5 in table 5, the average insurance payment differs by 41 dollars between a brand and generic drug. Therefore after implementing the presumed consent policy, insurance companies gain by paying less for drugs. Based on the predicted share of drugs in explicit and presumed consent scenarios in table 10 and the difference in insurance payments between a brand and generic drug, I calculate that the insurance companies pay 1.69 dollars less per person on average.

On the other hand, consumer's welfare would decrease because of the extra cost term for buying a brand drug. Under the logit assumptions, the consumer surplus associated with a set of alternatives takes a closed form that is easy to calculate. By definition, a person's consumer surplus is the utility, in dollar terms, that the person receives in the

choice situation. The decision maker chooses the alternative that provides the greatest utility. Consumer surplus is therefore $CS_n = (1/\alpha_n)Max_j(U_{nj})$, where α_n is the marginal utility of income. The division by α_n translates utility into dollars. We do not observe U_{nj}. But we observe V_{nj} and knows the distribution of the remaining portion of the utility. Therefore, we can calculate the expected consumer surplus.

$$E(CS_n) = \frac{1}{\alpha_n} E(max_j(V_{nj} + \epsilon_{nj}))$$

Rosen and Small (1979) show that, if each ϵ_{nj} is iid extreme value and utility is linear in income, this expectation becomes

$$E(CS_n) = \frac{1}{\alpha_n} ln(\sum_{j=1}^{J} e^{V_{nj}}) + C \tag{7}$$

where C is a unknown constant that represents the fact that absolute level of utility can not be measured. The change in consumer surplus that results from a change in the consent law can be calculated from equation 7. In particular, $E(CS_n)$ is calculated twice: first under the conditions before the change, and again under the conditions after the change. The difference between the two results is the change in consumer surplus:

$$\triangle E(CS_n) = \frac{1}{\alpha_n} (ln(\sum_{j=1}^{J} e^{V^1_{nj}} - ln(\sum_{j=1}^{J} e^{V^0_{nj}}) \tag{8}$$

where the superscripts 0 and 1 refer to before and after the change. Since the unknown constant C enters expected consumer surplus both before and after the change, it drops out of the difference and can therefore be ignored when calculating changes in consumer surplus.

Using equation 8, I find that the average consumer loss is about 9.17 dollars. Combined with the welfare gain for insurance companies, this model suggests that switching from presumed consent to explicit consent would incur 7.48 dollars loss per person. Some words of caution are necessary. First, this calculation does not consider the supply side's response and do not calculate the welfare change for drug suppliers. It's not clear how the suppliers would react and their welfare would change. As a result, the welfare discussion can only be a partial statement. Second, the welfare calculation considers the psychology costs of switching away from default as real cost. If we ignore this cost and only consider the utility difference of choosing brand and generic drugs, the welfare loss for consumers would be smaller.

5.4. Extenstion-Price Endogeneity

In the estimation in section 5.4, the product price is treated as exogenous. But both producers and consumers might observe product characteristics that are unobservable to econometricians. The presence of the unobserved product

Table 11: Nested Logit Regressions

Independent Variables	One Level Nest
Self Payment	-0.0150(0.0025)
Half Life	0.0093(0.0015)
Log Class Conditional Share	0.8420(0.0249)
Brand Name	0.4160(0.0974)
Patient Consent	-0.0970(0.0445)
Brand Name* Patient Consent	0.2190(0.0749)
Constant	-2.0120
Number of Cells	7109

characteristics in the consumer's utility function will make the price endogenous. And the non-linear feature of the model prevents the use of traditional instruments. To solve this problem, I use a procedure proposed by Berry (1994) to correct for the price endogeneity.

The estimation equation for one level nested logit is

$$ln(Share_{j,g}) - ln(share_0) = \beta_k x_{j,g,k} - \sigma ln(share_{j/g}) + \lambda_1 Brand + \lambda_2 Consent + \lambda_3 Brand * Consent \quad (9)$$

The dependent variable is the log share of product j in group g minus the share of outside good. $x_{j,g,k}$ are product characteristics of good j. $\sigma ln(share_{j/g})$ is the conditional share of product j in group g .

σ in equation 7 provides a falsification test. Only values within 0 and 1 are consistent with utility maximization. The closer to 1 , the more validity the grouping has. Since price is one of the product characteristics and endogenous, the estimation of equation 7 requires a two stage OLS method. I use the number of years a drug has been available to the market and the number of firms producing the drug as instruments. Table 12 discuss results from nested logit models. Based on the coefficients from this regression, we can calculate that the presumed consent law would reduce the share of the brandname drugs by 12.9 percent. This result is consistent with the calculation in section 5.3.

6. Conclusions

Prescription drug spending in the U.S. ballooned in 2014 to nearly $374 billion.[4] With the introduction of the Affordable Care Act, the expenditure of the prescription drug is expected to rise at a faster pace in the next few years. The ability to promote generic drug use for multi-source drugs will be key to control the growth of spending on prescription drugs. State governments and insurance companies have come up various ways of incentivizing patients to buy generic drugs whenever possible. The strategies include mandatory switching laws for pharmacists, presumed patient consent laws, and tiered pricing in health insurances. Consumer's price elasticity for prescription drugs have been widely studied. But there are limited study of the effects of the state laws on pharmacist's ability to switch to generic drugs. This paper tries to fill in the gap of the literature. I use the change of the state laws to identify the impacts of the laws on generic drug use. I find that the mandatory substitution law has little effects. And the effect of presumed patient law on patient's decision to buy prescription drugs is equivalent to 28 dollar increase in the brand name drugs. The average marginal effect of the policy is that the average probability of purchasing brand name drugs decrease by 11 percent. A welfare calculation indicates that consumer's surplus loss exceeds the insurance's gain by 7.5 dollars per person when all states switch from explicit to presumed consent.

Regarding the estimate of the size of the impact, some words of caution are in order. I do not take the supp side's responses into account. It's possible that the brand drug producers decrease the price of the brand drugs in states with presumed patient consent law. Therefore, the impact of the presumed consent law would be smaller compared to my calculations.

[4] http://blogs.wsj.com/pharmalot/2015/04/14/why-did-prescription-drug-spending-hit-374b-in-the-us-last-year-read-this/

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