Web Appendix
Toshiaki Iizuka "Physician Agency and Adoption of Generic Pharmaceuticals"

Appendix 1: Which generic price should be used?

In the main text, I assumed that only one generic and one branded version exist per drug and that the doctor chooses between these two. In reality, however, multiple generics often exist per corresponding brand-name drug. Moreover, although retail prices for generics are identical at the time of entry and set at 70% of the corresponding brand-name drug, their prices in subsequent years may diverge, as generics set different wholesale prices. One way of addressing this problem is to separately estimate a discrete choice model for each drug with all generics and brand names as alternative choices. However, even with the large dataset that I use, some generics show up in the data set only a few times, making this estimation strategy difficult. Moreover, finding common factors that affect generic adoption across different drugs is the main goal of this study, and this approach will not achieve this goal.

The alternative approach chosen in this paper is to estimate the model discussed above by computing the average price and markup differentials between generic and brand-name drugs. One issue here is which price should be used as the price for generics. I use a simple average of retail prices of all generic drugs for which the active ingredient, form, and strength are the same. As for markups, I first computed the markup for each generic drug with the same active ingredient and then take their average. These approaches are consistent with the assumption that doctors may not know the exact price and markup of each generic but have an idea about average prices and use this information in their decisions. Lundin (2000) also makes a similar simplifying assumption and estimates a binary choice model.

Appendix 2: Details on computing ΔP_{ikt}

Computing per-day out-of-pocket cost difference to the patient, ΔP_{ikt}, is relatively straightforward. The government sets the retail price for each drug (i.e., active ingredient), form (e.g., tablet), and strength (e.g., 10 mg), and these prices are publicly available. From the claims data, I know the drug that the patient takes in terms of its active ingredient, form, strength, dosage per day and co-insurance rate. Using these data, I can compute the per day out-of-pocket cost to the patient for both the generic and brand-name versions.[1] A

[1] In rare cases, generic versions do not exist even after a brand-name drug's patent has expired. I excluded such brand-name-only observations from the data.

preliminary analysis found, however, that dosage per day recorded in the claims data is sometimes unusually high. For example, while the maximum dosage per day for pravastatin sodium (a major cholesterol-reducing drug) is two 10-mg tablets, the dosage per day for some patients is recorded as 30, which suggests coding mistakes. To exclude such observations, I first looked at the data and identified for each drug-form-strength combination the most common dosage per day and then excluded observations for which the dosage is more than twice or less than a half of the most common dosage. This reduced observations by 4%.

Appendix 3: 40 drugs included in the analysis with information on ATC code, generic share, and number of observations.

active ingredient	ATC code	generic share	no. of obs
nizatidine	A02B1	9.4%	8,159
famotidine	A02B1	17.5%	57,425
sofalcone	A02B9	24.6%	11,318
voglibose	A10B5	6.3%	5,953
epalrestat	A10X	6.9%	467
cilostazol	B01C4	17.1%	2,398
beraprost sodium	B01C4	11.5%	1,557
pilsicainide hydrochloride hydrate	C01B	4.4%	1,515
amezinium metilsulfate	C01C1	28.1%	1,770
doxazosin mesilate	C02A2	10.9%	8,719
nicergoline	C04A1	23.5%	2,412
celiprolol hydrochloride	C07A	25.2%	1,749
bisoprolol fumarate	C07A	28.2%	6,898
carvedilol	C07A	5.9%	6,897
betaxolol hydrochloride	C07A	13.6%	3,500
nisoldipine	C08A	55.8%	1,229
nilvadipine	C08A	9.6%	4,203
manidipine hydrochloride	C08A	16.1%	3,912
alacepril	C09A	35.6%	1,644
lisinopril hydrate	C09A	21.9%	4,850
trandolapril	C09A	7.0%	2,413
simvastatin	C10A1	25.0%	13,599
pravastatin sodium	C10A1	21.9%	40,730
bezafibrate	C10A2	27.0%	12,491
ethyl icosapentate	C10B	21.6%	1,823
terguride	G02D	21.2%	1,009
propiverine hydrochloride	G04B4	12.3%	940
tamsulosin hydrochloride	G04C	8.7%	1,529
cefixime	J01D1	34.7%	10,106
roxithromycin	J01F	27.3%	2,733
ciprofloxacin	J01G1	72.9%	16,718
itraconazole	J02A	12.2%	2,060
acyclovir	J05B	51.4%	5,730
etodolac	M01A1	17.4%	14,249
zaltoprofen	M01A1	5.1%	11,338
bucillamine	M01C	12.6%	2,349
brotizolam	N05B1	22.7%	22,133
setiptiline maleate	N06A9	3.9%	593
oxatomide	R06A	56.2%	15,811
epinastine hydrochloride	R06A	49.6%	47,025

Lansoprazole, a popular anti-ulcer drug, could have made this list but was excluded from the data. The government did not apply Equation (1) in 2006, because its sales far exceeded the firm’s forecast submitted to the government during the approval process.

Appendix 4: 40 drugs included in analysis by one-digit ATC category

ATC category	no. of drugs	generic share	no. of obs.
A (Alimentary tract and metabolism)	5	16.8%	83,322
B (Blood and blood forming organs)	2	14.9%	3,955
C (Cardiovascular system)	18	20.8%	120,354
G (Genito-urinary system and sex hormones)	3	13.3%	3,478
J (General anti-infectives systemic)	5	52.6%	37,347
M (Musculo-skeletal system)	3	12.0%	27,936
N (Nervous system)	2	22.2%	22,726
R (Respiratory system)	2	51.2%	62,836
total	40	27.7%	361,954

Appendix 5: Alternative Reason for Price Responsiveness

The estimated price coefficients in Model 1 indicate that VI clinics are sensitive to patient out-of-pocket costs, and I argued that information advantage of VI doctors may make them a better agent for the patient.

Another possible reason for the negative coefficient on patient costs is that, holding the price-cost markup constant, choosing a less expensive drug also benefits the doctor by reducing inventory costs. This explanation differs from the above explanation in that the doctor is only concerned about his/her own welfare. Although distinguishing these two explanations is not an easy task, I have constructed a new variable that captures the difference in the markup ratio between the two versions (i.e., $\Delta MarkupRatio = M^{GE}_{ikt} / P^{R\ ,GE}_{ikt} - M^{B}_{ikt}/P^{R,B}_{ikt}$) and re-estimated Model 1. Suppose generics become cheaper, holding all other factors constant. Then, if the inventory explanation is correct, this change should increase generic adoption, since a doctor can reduce inventory costs by choosing cheaper generics. This means that Δ*MarkupRatio* should positively affect generic adoption in the case of VI clinics. The results reported in Model 13 in Table A1, however, do not support this argument. They show that Δ*MarkupRati*o has little impact on generic adoption and that the remaining parameters change little due to this addition, providing a support for the view that VI doctors care about patient costs.

Table A1: Results that include ΔMarkupRatio

	(13)	
	Markup Ratio	
	coeff.	APE
yt_lag1	3.1893***	0.5151***
	(0.1537)	(0.0379)
yt_lag1*VI	-0.0376	0.0294
	(0.1887)	(0.0603)
ΔM	0.2819	0.0247**
	(0.7808)	(0.0098)
ΔM*VI	1.6970*	0.0380**
	(0.9216)	(0.0171)
ΔP	-0.6844	-0.0302***
	(0.6933)	(0.0085)
ΔP*VI	-1.5647*	-0.0375**
	(0.8669)	(0.0162)
ΔMarkupRatio	-0.7129	0.0021
	(1.5463)	(0.0182)
ΔMarkupRatio*VI	0.2923	-0.0092
	(0.9266)	(0.0249)
GEpref	1.2292***	0.0276***
	(0.2912)	(0.0031)
GEpref*VI	0.5136	0.0182***
	(0.3366)	(0.0061)
VI	0.1334	0.0061***
	(0.1882)	(0.0012)
female	0.0797	0.0014
	(0.0559)	(0.0010)
internal medicine	-0.2282***	-0.0042***
	(0.0778)	(0.0015)
dermatology	-0.1148	-0.0020
	(0.1497)	(0.0025)
orthopedics	-0.0644	-0.0011
	(0.1651)	(0.0028)
ear, nose, throat	0.0486	0.0009
	(0.1521)	(0.0028)
surgery	-0.0690	-0.0012
	(0.1306)	(0.0022)
GE_age	-0.7760***	-0.0137***
	(0.2287)	(0.0041)
GE_age2	0.2765***	0.0049***
	(0.0703)	(0.0013)
GE_age3	-0.0204***	-0.0004***
	(0.0060)	(0.0001)

yt_0	2.6848***	0.3309***
	(0.2013)	(0.0350)
yt_0*VI	-0.1812	-0.0127
	(0.2051)	(0.0581)
(mean) ΔM	-0.2178	-0.0208**
	(0.8635)	(0.0104)
(mean) ΔM*VI	-1.4610	-0.0326*
	(0.9651)	(0.0175)
(mean) ΔP	0.9366	0.0308***
	(0.6340)	(0.0082)
(mean) ΔP*VI	1.2278	0.0318**
	(0.7672)	(0.0144)
Observations	45964	
Log likelihood	-1711.65	

Notes: All regressions in this table use Wooldridge's (2005) method described in the text. All regressions include drug fixed effects, and age-category, region, insurer, and year dummies but not shown in the table. Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Appendix 6: Data for the analysis of forward looking doctors

To examine the decisions by forward-looking doctors, I first computed ΔM and ΔP up to March 2008, using the most recent data available and the approach discussed in section 4.5. To obtain ΔMs and ΔPs beyond March 2008, additional assumptions are required. Although estimating a dynamic oligopoly model that allows one to predict future ΔMs and ΔPs is attractive, estimating such a model is beyond the scope of this paper (see Ching, 2010a for such an attempt). Instead, I utilized the price data for the 40 drugs between 2002 and 2008 and computed the average rate of price reduction in each period after patent expiration.[2] Fitting simple regression models to these price reductions in each period, I forecasted price changes after 2008 for each drug.[3] After obtaining the price data, I computed markup differences in the same way as before.

[2] During this period, generic-drug prices declined on-average by 27.8%, 21.7%, 18.8%, 13.9%, and 10.0% in the first to fifth period after generic entry, respectively, while brand-name prices declined by 10.7%, 5.8%, 4.6%, 5.3%, and 3.5% in respective periods.

[3] The regression models that I used to forecast future price reductions are the followings: (1) ΔP^G_t=0.3663*exp(-0.249*t), (2) ΔP^B_t=-0.041*ln(t)+0.099, where ΔP^G_t and ΔP^B_t are the percentage of generic and brand-name price reductions in the t^{th} periods after generic entry, respectively. They fit the data reasonably well. R-squared for the above models are 0.982 and 0.872, respectively.