Online Appendix

Switching Costs, Brand Premia and
Behavioral Pricing in the Pharmaceutical Market

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Contents

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A Additional Institutional Details

A.1 Trade-margins of pharmacies

Table 1: Trade-margins of Pharmacies

Purchasing Price (PP)	Retail Price
$PP \leq 75$	$PP \times 1.20 + 30.50 + 11.50$
$75 < PP \leq 300$	$PP \times 1.03 + 43.25 + 11.50$
$300 < PP \leq 50,000$	$PP \times 1.02 + 46.25 + 11.50$
$PP > 50,000$	$PP + 1,046.25 + 11.50$

Retail prices of pharmaceuticals under generic competition in dependency to purchasing prices since 04/2016 (TLV, 2016). Trade margins are implicitly defined. Note that the 11.50 KR apply due to the generic competition. Prices in SEK; 10 SEK are approximately 1.1 USD.

Purchasing Price (PP)	Retail Price
$PP \leq 75$	$PP \times 1.20 + 31.25 + 10.00$
$75 < PP \leq 300$	$PP \times 1.03 + 44.00 + 10.00$
$300 < PP \leq 6,000$	$PP \times 1.02 + 47.00 + 10.00$
$PP > 6,000$	$PP + 167.00 + 10.00$

Retail prices of pharmaceuticals under generic competition in dependency to purchasing prices before 04/2016 (TLV, 2016). Trade margins are implicitly defined. Prices in SEK; 10 SEK are approximately 1.1 USD.

B Additional Summary Statistics

B.1 Comparison Experts to Non-Experts

In the following I show additional summary statistics in order to first explore the descriptive differences between the general population and informed/expert patients, I show the substitution behavior for the entire population and the subgroup of patients with a medical education.[1] Table 2 show substitution decisions of the general population and the medical experts. Comparing the difference between the entire population and patients with a medical education, one sees that those with a medical education consume the PoM more often in cases of painkillers and antibiotics and less often in the case of antiepileptics. Patients with a medical education oppose substitution less often for painkillers (17%) and antibiotics (6.6%) but more

[1] The experts have undertaken a medical career path (physician). Note that the education does not necessary mean that individuals work as a physician.

Table 2: Summary Statistics for Substitutions

	Painkillers		Antiepileptics		Antibiotics	
	All	Med.	All	Med.	All	Med.
Fraction Consumption PoM	0.734	0.742	0.929	0.909	0.866	0.889
	(0.44)	(0.44)	(0.26)	(0.29)	(0.34)	(0.31)
Fraction Opp. Sub. by Patient	0.209	0.17	0.028	0.031	0.094	0.066
	(0.41)	(0.38)	(0.16)	(0.17)	(0.29)	(0.25)
Fraction Opp. Sub. by Physician	0.024	0.045	0.018	0.026	0.005	0.013
	(0.15)	(0.21)	(0.13)	(0.16)	(0.07)	(0.12)
Fraction Opp. Sub. by Pharmacy	0.034	0.043	0.026	0.034	0.034	0.032
	(0.18)	(0.2)	(0.16)	(0.18)	(0.18)	(0.17)
Income (in k SEK)	225	672	197	535	252	665
	(195)	(365)	(151)	(327)	(244)	(393)

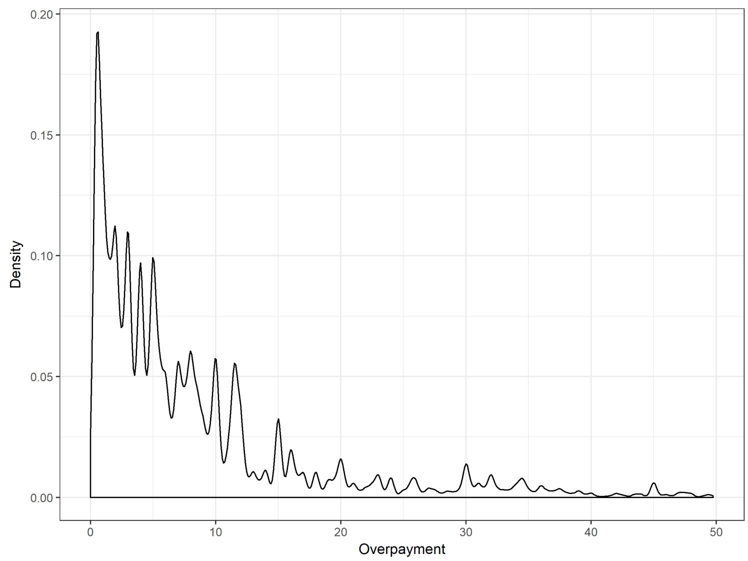
Summary statistics for the three market segments of painkillers, antiepileptics and antibiotics. Within each segment the first column shows statistics for the entire market (All) whereas the second column shows statistics for the patients with a medical education (Med). The fraction of consumption of the PoM describes the fraction of purchase occasions where a patient has consumed the PoM. If a patient does not consume the PoM it is due to one of the three displayed reasons (opposed substitution by the patient, opposed substitution by the physician or opposed substitution by the pharmacy). Income is in SEK per year on average. Standard deviations are displayed in parentheses.

often for antiepileptics (3.1%). It is less likely that physicians or pharmacies oppose substitution (physicians oppose substitution: painkillers 2.4%, antiepileptics 1.8%, antibiotics 0.5%; pharmacy opposes substitution: painkillers 3.4%, antiepileptics 2.6%, antibiotics 3.4%). Note that those patients with a medical education are slightly more likely than their physician or pharmacy to oppose substitution. Finally, those patients with a medical education have on average a higher disposable income than the average of the Swedish population.

B.2 Overpayment Distribution

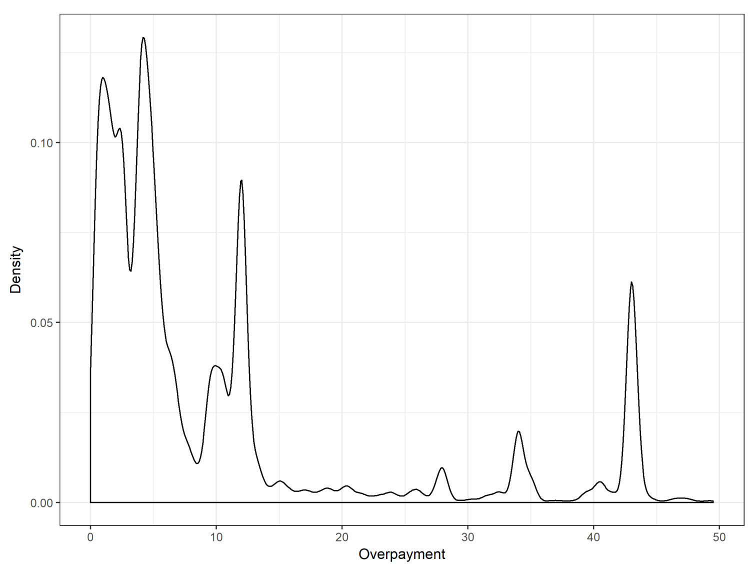
In case patients oppose substiution they pay the price difference to the chosen product. In the following I show the density of overpayments for painkillers, antibiotics and antiepileptics. I show the densities of overpayments over all individuals and all purchases of opposed substitution. Figure 1 shows the the density of painkillers, Figure 2 for antibiotics and 3 for antiepileptics.

Figure 1: Density of Overpayment



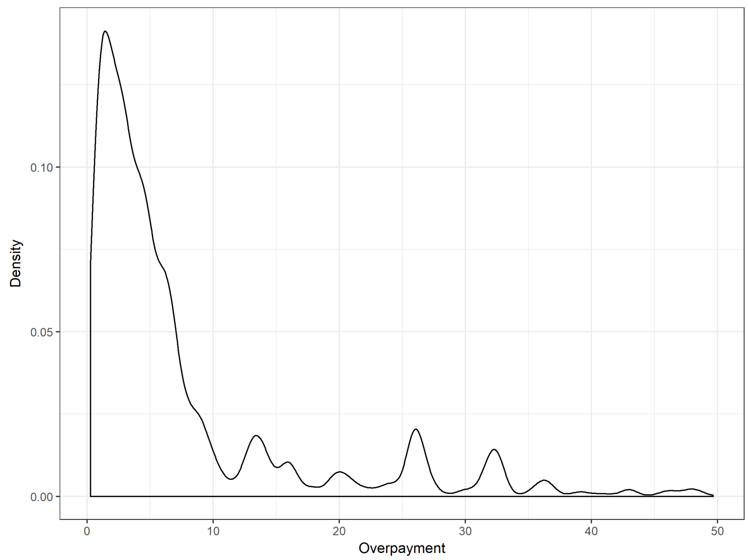
Nores Density of overpayments in SEK (10 Sek approx. 1 USD) for all painkillers. The density is truncated at 50 SEK.

Figure 2: Density of Overpayment



Density of overpayments in SEK (10 Sek approx. 1 USD) for all antibiotics. The density is truncated at 50 SEK.

Figure 3: Density of Overpayment



Density of overpayments in SEK (10 Sek approx. 1 USD) for all antiepileptics. The density is truncated at 50 SEK.

C Reduced Form: Switching Costs and Brand Premia

C.1 Main Analysis, Model Build Up

In the following I present additional results from the major regression model presented in the main analysis. Within the main analysis I showed results for the most preferred specification (including fixed effects as well as controlling for unobserved heterogeneity). Now, I show less rich models. The following three tables show the results for the subgroups of painkillers, antibiotics and antiepileptics separately. Within each Table, model 1 is a specification without fixed effects and controls while model 2 includes only subgroup times time fixed effects. In model 3 I further add controls such that the specification corresponds to the one presented in the main analysis.

C.2 Different Definition of State Dependence

I redefine the definition of the dummy variable D_{ijt-1}. In my main specification D_{ijt-1} takes the value one if patient i has purchased product j in the last purchase occasion within the last month. Now I use a dummy D^2_{ijt-1} which takes the value one if a patient has consumed a product j in the last purchase occasion, independent of the time. Similar to the last presentation of results, the following three tables show the results

Table 3: Regression Evidence, Probability of Opposed Substitution, Painkillers

	(1)	(2)	(3)
	'Opp.'	'Opp.'	'Opp.'
D_{t-1}	-0.0188***	0.0330***	0.0332***
	(0.000317)	(0.000262)	(0.000262)
Med	-0.0209***	-0.0540***	-0.0488***
	(0.00186)	(0.00173)	(0.00173)
$D_{t-1} \times Med$	0.0251***	-0.00340	-0.00304
	(0.00478)	(0.00398)	(0.00390)
$log(Inc)$			-0.0000237
			(0.0000909)
$Constant$	0.187***	0.176***	0.108***
	(0.000219)	(0.000159)	(0.00121)
Education	No	No	Yes
Control Heterogeneity	No	No	Yes
Geogr. Fixed Effects	No	No	Yes
Observations	35595027	35595027	32923856
R^2	0.000	0.245	0.264
Fixed Effects	'No'	'SubGroup*Time'	'SubGroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Linear least square regression results for the segment of painkillers. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. D_{t-1} is a dummy that takes the value one if a patient has consumed the product in the previous purchase occasion in the last month. Med is a dummy that takes the value one if an individual has a medical education as a physician. Log(Income) is the logarithm of income. Education indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects. Fixed $Effects$ indicates if the model controls for substitution group $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 4: Regression Evidence, Probability of Opposed Substitution, Antibiotics

	(1) 'Opp.'	(2) 'Opp.'	(3) 'Opp.'
D_{t-1}	-0.00472***	0.00796***	0.0116***
	(0.000609)	(0.000544)	(0.000570)
Med	-0.0240***	-0.0188***	-0.0245***
	(0.000642)	(0.000620)	(0.000676)
$D_{t-1} \times Med$	0.00759*	0.00351	0.00101
	(0.00381)	(0.00352)	(0.00354)
$log(Inc)$			0.000680***
			(0.0000369)
$Constant$	0.0896***	0.0892***	0.0799***
	(0.0000971)	(0.0000893)	(0.000610)
Education	No	No	Yes
Control Heterogeneity	No	No	Yes
Geogr. Fixed Effects	No	No	Yes
Observations	12857251	12857251	12326138
R^2	0.000	0.114	0.121
Fixed Effects	'No'	'SubGroup*Time'	'SubGroup*Time'

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Linear least square regression results for the segment of antibiotics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. D_{t-1} is a dummy that takes the value one if a patient has consumed the product in the previous purchase occasion in the last month. Med is a dummy that takes the value one if an individual has a medical education as a physician. $Log(Income)$ is the logarithm of income. Education indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 5: Regression Evidence, Probability of Opposed Substitution, Antiepileptics

	(1) 'Opp.'	(2) 'Opp.'	(3) 'Opp.'
D_{t-1}	-0.0168***	-0.00295***	-0.00401***
	(0.000491)	(0.000471)	(0.000516)
Med	0.00245	-0.00806*	-0.0107**
	(0.00376)	(0.00379)	(0.00391)
$D_{t-1} \times Med$	0.00309	0.00820	0.00650
	(0.00710)	(0.00655)	(0.00659)
$log(Inc)$			0.0000675
			(0.000128)
$Constant$	0.0301***	0.0271***	-0.00888***
	(0.000410)	(0.000345)	(0.00244)
Education	No	No	Yes
Control Heterogeneity	No	No	Yes
Geogr. Fixed Effects	No	No	Yes
Observations	543738	543738	500363
R^2	0.002	0.058	0.063
Fixed Effects	'No'	'SubGroup*Time'	'SubGroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Linear least square regression results for the segment of antiepileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. D_{t-1} is a dummy that takes the value one if a patient has consumed the product in the previous purchase occasion in the last month. Med is a dummy that takes the value one if an individual has a medical education as a physician. $Log(Income)$ is the logarithm of income. Education indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

for the subgroups of painkillers, antibiotics and antiepileptics separately. The results show that estimates of state dependence due to switching costs are positive. Patients are more likely to oppose substiution after having purchased a product in a last purchase occasion. However, compared to the the purchase occasion within the last month, coefficients are smaller. Intuitively, switching costs decrease over time.

Table 6: Regression Evidence, Probability of Opposed Substitution, Painkillers, Different State Dependence

	(1)	(2)	(3)
	'Opp.'	'Opp.'	'Opp.'
D^2_{t-1}	-0.102***	0.00159***	0.00618***
	(0.000369)	(0.000450)	(0.000443)
Med	-0.0548***	-0.0599***	-0.0539***
	(0.00154)	(0.00140)	(0.00146)
$D^2_{t-1} \times Med$	0.0803***	0.0152**	0.0165***
	(0.00586)	(0.00533)	(0.00495)
$log(Inc)$			-0.0000255
			(0.0000915)
$Constant$	0.226***	0.182***	0.112***
	(0.000185)	(0.000148)	(0.00122)
Education	No	No	Yes
Control Heterogeneity	No	No	Yes
Geogr. Fixed Effects	No	No	Yes
Observations	35595027	35595027	32923856
R^2	0.017	0.244	0.263
Fixed Effects	'No'	'SubGroup*Time'	'SubGroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Linear least square regression results for the segment of painkillers. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. D^2_{t-1} is a dummy that takes the value one if a patient has consumed the product in the previous purchase occasion. Med is a dummy that takes the value one if an individual has a medical education as a physician. $Log(Income)$ is the logarithm of income. Education indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

C.3 Reference Dependence

In my main model specification I include substitution group times time fixed effect to control for price effects. In detail, each patient faces the same price differences between the prescribed and the product of

Table 7: Regression Evidence, Probability of Opposed Substitution, Antibiotics, Different State Dependence

	(1) 'Opp.'	(2) 'Opp.'	(3) 'Opp.'
D^2_{t-1}	-0.0174***	0.00342***	0.00656***
	(0.000473)	(0.000429)	(0.000449)
Med	-0.0245***	-0.0191***	-0.0247***
	(0.000631)	(0.000611)	(0.000668)
$D^2_{t-1} \times Med$	0.0120***	0.00621*	0.00351
	(0.00337)	(0.00306)	(0.00300)
$log(Inc)$			0.000680***
			(0.0000369)
$Constant$	0.0905***	0.0892***	0.0798***
	(0.0000959)	(0.0000886)	(0.000610)
Education	No	No	Yes
Control Heterogeneity	No	No	Yes
Geogr. Fixed Effects	No	No	Yes
Observations	12857251	12857251	12326138
R^2	0.000	0.114	0.121
Fixed Effects	'No'	'SubGroup*Time'	'SubGroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Linear least square regression results for the segment of antibiotics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. D^2_{t-1} *is a dummy that takes the value one if a patient has consumed the product in the previous purchase occasion. Med is a dummy that takes the value one if an individual has a medical education as a physician.* $Log(Income)$ *is the logarithm of income. Education indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects.* $Fixed\ Effects$ *indicates if the model controls for substitution group* $\times$ *month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.*

Table 8: Regression Evidence, Probability of Opposed Substitution, Antiepileptics, Different State Dependence

	(1)	(2)	(3)
	'Opp.'	'Opp.'	'Opp.'
D^2_{t-1}	-0.0351***	-0.0210***	-0.0220***
	(0.000585)	(0.000677)	(0.000749)
Med	-0.00589	-0.0105*	-0.0120**
	(0.00422)	(0.00435)	(0.00445)
$D^2_{t-1} \times Med$	0.00584	0.00285	0.00311
	(0.00488)	(0.00505)	(0.00497)
$log(Inc)$			0.000142
			(0.000126)
$Constant$	0.0437***	0.0368***	-0.0000817
	(0.000507)	(0.000464)	(0.00239)
Education	No	No	Yes
Control Heterogeneity	No	No	Yes
Geogr. Fixed Effects	No	No	Yes
Observations	543738	543738	500363
R^2	0.012	0.061	0.066
Fixed Effects	'No'	'SubGroup*Time'	'SubGroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Linear least square regression results for the segment of antiepileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. D^2_{t-1} is a dummy that takes the value one if a patient has consumed the product in the previous purchase occasion. Med is a dummy that takes the value one if an individual has a medical education as a physician. $Log(Income)$ is the logarithm of income. $Education$ indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

the month and I argue that I control for price difference by introducing fixed effects. However, patients face different aboslut levels of payment due to the co-payment structure. In this section I show that a higher co-payment is associated with a slightly higher probability of opposing substitution, but controlling for the co-payment level does not affect estimates for switching costs and perceived quality differences. Consider the following extended regression model where $\bar{p}_{it}$ is the minimal co-payment for individual i at time t, i.e. the co-payment a patient pays for the product of the month.

$$
\begin{aligned}
P(OpposeSubst_{ijt} = 1) = & \alpha + \lambda_1 \bar{p}_{it} + \beta_1 D_{ijt-1} + \beta_2 Med_{it} + \lambda_2 \bar{p}_{it} \times D_{ijt-1} + \\
& \lambda_3 \bar{p}_{it} \times Med_{it} + \beta_3 D_{ijt-1} \times Med_{it} + \rho X_{it} + D_{ij0} + \gamma_{st} + \varepsilon_{ijt}.
\end{aligned}
$$

Besides using the same variable specification as in the main model, I include interaction between the copayment level and the variables of interests D_{ijt-1} and Med_{it}. In model I present the results, again for the three different subgroups (painkillers, antibiotics and antiepileptics). First consider the coefficients of D_{ijt-1} and Med_{it}. The coefficients are all significant and very close to those in the main specification. Further the regression evidence shows that the co-payment level has small u significant effects. In detail, a one USD increase in co-payment (10 SEK increase of $\bar{p}_{it}$) is associated with a 0.2 percentage points higher probability of opposed substitution in case of painkillers. For antibiotics and antiepileptics the effect is a magnitude lower. Note that previous consumption of the product doubles the impact of higher co-payment level while medical education is associated with a reduction of half the effect size.

C.4 Initial Condition Problem

In the main specification of the reduced form analysis I try to tackle the challenge of identifying true state dependence by controlling for the initial observed purchase. Intuitively, the problem of this approach is that I do not observe the entire medical history of patients. The first observed choice of the six year long panel may be not independent of the unobserved heterogeneity. In the main specification I assume that the initial choice is indeed independent of unobserved heterogeneity. In this robustness check I try to reduce the assumptions by employing a sub-sample analysis of those patients who have not purchased any product in the first two or three years of the panel. The patients in this sub sample either have never purchased a product or they have not purchased a product in the first years of the panel. In the latter case it is likely that

Table 9: Regression Evidence, Probability of Opposed Substitution, Reference Dependence

	(1) 'Opp.'	(2) 'Opp.'	(3) 'Opp.'
$\bar{p}$	0.000243***	0.0000245***	0.0000353***
	(0.00000223)	(0.00000149)	(0.00000191)
Med	-0.0428***	-0.0222***	-0.00848*
	(0.00226)	(0.000917)	(0.00384)
$Med \times \bar{p}$	-0.000137***	-0.0000275**	-0.0000113
	(0.0000177)	(0.00000890)	(0.0000157)
D_{t-1}	0.0277***	0.00966***	-0.00369***
	(0.000258)	(0.000666)	(0.000515)
$D_{t-1} \times \bar{p}$	0.000282***	0.0000370***	0.0000233***
	(0.00000492)	(0.00000620)	(0.00000515)
$log(Inc)$	-0.0000513	0.000700***	0.000116
	(0.0000902)	(0.0000369)	(0.000127)
$Constant$	0.102***	0.0784***	-0.0130***
	(0.00120)	(0.000615)	(0.00245)
Education	Yes	Yes	Yes
Control Heterogeneity	Yes	Yes	Yes
Geogr. Fixed Effects	Yes	Yes	Yes
Observations	32923856	12326138	500363
R^2	0.266	0.122	0.065
Fixed Effects	'SubGroup*Time'	'SubGroup*Time'	'SubGroup*Time'

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Linear least square regression results for the segment of painkillers, antibiotics and antiepileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. D_{t-1} is a dummy that takes the value one if a patient has consumed the product in the previous purchase occasion in the last month. Med is a dummy that takes the value one if an individual has a medical education as a physician. $Log(Income)$ is the logarithm of income. $Education$ indicates if the model controls for the level of education according to the grades in a six-step grid. $Geographical$ indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group $\times$ month fixed effects. $\bar{p}$ is the product unspecific co-payment a patient has to pay when consuming the cheapest available product of the month. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

the correlation between the initial condition and the unobserved heterogeneity is lower.

Using the sub-sample of individuals that have not purchased a product of painkillers, antibiotics, or antiepileptics between 2010 and 2013 or between 2010 and 2012 I estimate the following model that is the same as the one in the main specification:

$$P(OpposeSubst_{ijt}=1) = \alpha + \beta_1 D_{ijt-1} + \beta_2 Med_{it} + \beta_3 D_{ijt-1} \times Med_{it} + \rho X_{it} + D_{ij0} + \gamma_{st} + \varepsilon_{ijt}, \quad (1)$$

I show the results in the following two Tables. Table 10 shows the results for the sample excluding patients with purchases in the initial two years. Note first that the sample size reduces to approximately 10% of the whole sample. Results of the estimates are similar in size to the estimates in the main analysis. However, I do not find significance for the subgroup of antiepileptics due to sample size. In Table **??** I show the results for the same regression evidence when excluding patients who have purchased any product during the first three years of the sample (between 2010 and 2013). The sample size is 5% of the initial sample. The results are similar to the one in Table 10 for painkillers. For antibiotics I find significant results for perceived quality differences and an insignificant but positive coefficient for switching costs. For antiepileptics results are again comparable in size but insignificant. Overall, the robustness check confirms the main analysis. Constraining the sample to those patients where the initial condition is less likely to be correlated with unobserved heterogeneity shows that estimates of switching costs and perceived quality differences are the same.

C.5 Robustness Check: Individual Fixed Effects

Within this section I describe results of the main regression equation when including individual fixed effects. Consider the following regression specification:

$$P(OpposeSubst_{ijt}=1) = \alpha + \beta_1 D_{ijt-1} + \beta_2 Med_{it} + \beta_3 D_{ijt-1} \times Med_{it} + \rho X_{it} + D_{ij0} + \mu_i + \lambda_t + \varepsilon_{ijt},$$

where I introduce patient specific fixed effect μ_i and time fixed effects λ_t. The regression uses variation on the patient level during time. For the estimation of state dependence individual fixed effects reduce threat of unobservable consumer heterogeneity that is time invariant. However, the estimation of quality misconception is now dependent on individual specific variation of the medical education over time. This

Table 10: Prob. to oppose substitution, Sample of patients without purchases in initial two years

	Painkillers 'Opp.'	Antibiotics 'Opp.'	Antiepileptics 'Opp.'
D_{t-1}	0.0278***	0.00977***	-0.000556
	(0.00103)	(0.00199)	(0.000987)
Med	-0.0626***	-0.0381***	-0.00708
	(0.00360)	(0.00242)	(0.00579)
$D_{t-1} \times Med$	0.00874	0.0290	0.00137
	(0.0162)	(0.0210)	(0.0116)
$log(Inc)$	0.000297	0.000806***	0.000243
	(0.000166)	(0.000103)	(0.000226)
$Constant$	0.175***	0.172***	0.00515
	(0.00249)	(0.00183)	(0.00357)
Education	Yes	Yes	Yes
Control Heterogeneity	Yes	Yes	Yes
Geogr. Fixed Effects	Yes	Yes	Yes
Observations	3027383	1989534	172540
R^2	0.218	0.104	0.054
Fixed Effects	'SubGroup*Time'	'SubGroup*Time'	'SubGroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Linear least square regression results for the segment of painkillers, antibiotics and antiepileptics. Sample of patients who have not consumed any product of the respective subgroup between 2010 and 2012 (the first two years of the penal period). One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. D_{t-1} is a dummy that takes the value one if a patient has consumed the product in the previous purchase occasion in the last month. Med is a dummy that takes the value one if an individual has a medical education as a physician. $Log(Income)$ is the logarithm of income. $Education$ indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects. Fixed $Effects$ indicates if the model controls for substitution group $\times$ month fixed effects. In the lower part of the table I show the average fraction of opposed substitution as well as the price and average payment of those that oppose substitution (in USD, 1 USD are 10 SEK). Finally, I also state the percentage increase of opposed substitutions that are associated to past consumption (switching costs) and a medical education (quality misconceptions). Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 11: Prob. to oppose substitution, Sample of patients without purchases in initial three years

	Painkillers 'Opp.'	Antibiotics 'Opp.'	Antiepileptics 'Opp.'
D_{t-1}	0.0276***	0.00306	0.00355
	(0.00150)	(0.00264)	(0.00206)
Med	-0.0653***	-0.0433***	-0.0108
	(0.00501)	(0.00322)	(0.00783)
$D_{t-1} \times Med$	-0.00328	0.0675*	0.0000117
	(0.0230)	(0.0270)	(0.0196)
$log(Inc)$	0.000415	0.000587***	0.000635*
	(0.000215)	(0.000135)	(0.000323)
$Constant$	0.205***	0.196***	0.0111*
	(0.00328)	(0.00254)	(0.00554)
Education	Yes	Yes	Yes
Control Heterogeneity	Yes	Yes	Yes
Geogr. Fixed Effects	Yes	Yes	Yes
Observations	1499375	1040551	59978
R^2	0.226	0.118	0.044
Fixed Effects	'SubGroup*Time'	'SubGroup*Time'	'SubGroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Linear least square regression results for the segment of painkillers, antibiotics and antiepileptics. Sample of patients who have not consumed any product of the respective subgroup between 2010 and 2013 (the first three years of the penal period). One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. D_{t-1} is a dummy that takes the value one if a patient has consumed the product in the previous purchase occasion in the last month. Med is a dummy that takes the value one if an individual has a medical education as a physician. $Log(Income)$ is the logarithm of income. $Education$ indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects. Fixed $Effects$ indicates if the model controls for substitution group $\times$ month fixed effects. In the lower part of the table I show the average fraction of opposed substitution as well as the price and average payment of those that oppose substitution (in USD, 1 USD are 10 SEK). Finally, I also state the percentage increase of opposed substitutions that are associated to past consumption (switching costs) and a medical education (quality misconceptions). Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

is problematic in two dimensions. First, individuals that finish their medical education during the six observable years are only a few. Second, education updates are observable on a yearly level rather than on the monthly level such that precision decreases.

In Table 12 I show results for the specification with individual fixed effects for the three subgroups (painkillers, antibiotics and antiepileptics). For painkillers and antibiotics the estimates of switching costs are smaller but also significant. For antiepileptics past consumption is insignificantly but positive related to opposed substitution. The different result for atiepileptics are in line with the argumentation that individual specific learning patterns drive negative switching costs in the main specification. Considering perceived quality differences the results are insignificant for painkillers and antiepileptics. For antibiotics the results are comparable to the main specification. Due to the lack of power and precision it is not possible to estimate perceived quality differences when including individual fixed effects. However, results for switching costs are robust for individual fixed effects.

C.6 Robustness Check: Substitution between Substitution Groups

One important assumption of the reduced form approach as well as the demand estimation is the separability between substitution group. In case a patient receives a prescription for a specific substitution group, I assume that a patient does not get dispensed a product of a different substitution group, even if another substitution groups contains the same active ingredient and only the size is different. The prescribe determines the substitution group, a pharmacists does not change the group and patients only choose within a group. In the data, I seldom observe inter substitution group substitutions. However, the non-substitution could be due to prices in equilibrium that prevent profitable substitution.

Within this section I challenge the assumption of separate substitution groups. Let s_{sat} be the market share of a substitution group s among substitution groups with active ingredient a at time t. In the following model I evaluate if a lower price of the PoM in a substiution group is correlated with higher market share among the substances:

$$s_{sat} = \beta PricePoM_{sat} + \gamma_{at} + \varepsilon_{sat},$$

where $PricePoM_{sat}$ is the lowest price of a product within a substitution group s. Note, that I use a relative price coefficient, $PricePoM_{sat} / \min_{s \in a}(PricePoM_{sat})$, the price of the PoM in a substitution group divided

Table 12: Regression Evidence, Probability of Opposed Substitution, Individual Fixed Effects

	Painkillers 'Opp.'	Antibiotics 'Opp.'	Antiepileptics 'Opp.'
D_{t-1}	0.0172***	0.00675***	0.000486
	(0.000189)	(0.000661)	(0.000491)
Med	0.00266	-0.0202*	-0.0500
	(0.0180)	(0.00939)	(0.0383)
$D_{t-1} \times Med$	-0.00275	0.000516	-0.00463
	(0.00284)	(0.00416)	(0.00816)
$log(Inc)$	0.00119***	0.000654***	0.000498
	(0.000172)	(0.000117)	(0.000330)
$Constant$	-0.0985***	-0.0181**	-0.0138
	(0.00742)	(0.00677)	(0.0353)
Education	Yes	Yes	Yes
Control Heterogeneity	Yes	Yes	Yes
Geogr. Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Observations	32923856	12326138	500363
R^2	0.361	0.423	0.224

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Linear least square regression results for the segment of painkillers, antibiotics and antiepileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. D_{t-1} is a dummy that takes the value one if a patient has consumed the product in the previous purchase occasion in the last month. Med is a dummy that takes the value one if an individual has a medical education as a physician. Log(Income) is the logarithm of income. Education indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects.Individual and $Time\ Fixed\ Effects$ indicates if the model controls for patient specific or month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

by the lowest prices among all other PoM containing the same substance. γ_{at} are substance/active ingredient times time fixed effects. The fixed effects control external margins such that the regression shows effect on variation within a specific substance (as paracetamol) at a given month. If substitution between the groups is common (either on the prescriber level or on the pharmacy level) one would expect a negative correlation between the price and the share of a substitution group.

In Table 13 I show the results for the segments of painkillers. In models (1) to (3) I use the absolut price of the PoM and in model (4) the relative price of the PoM as a regressor. Without controlling for the substance $\times$ time fixed effect a slight negative correlation is observable. However, the correlation is small and including the fixed effects leads to insignificant results. The result is also insignificant for the relative price specification. Overall, I do not find evidence for correlation between the lowest price in a substitution group and the market share of the substitution group among other substitution groups with the same substance.

Table 13: Regression Substitution between Groups

	Share of Substitution Group			
	(1)	(2)	(3)	(4)
PoM Price	-0.0001^{***}	-0.00003^{**}	0.00000	
	(0.00002)	(0.00001)	(0.00001)	
Relative PoM Price				-0.003
				(0.00001)
Fixed effects	No	Subgroup and Time	Substance $\times$ Time	Substance $\times$ Time
R-Squared	0.026	0.82	0.808	0.809
N	6,941	6,941	6,941	6,941

Notes: ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Notes: Linear least square regression results for the segment of painkillers. One observation corresponds to a substitution group within a month. The outcome variable is a the market share of a substitution group among all substitution groups of the same active ingredients. PoM Price is the price of the product of a month (the lowest price) of a substitution group. Relative PoM Price is the PoM Price divided by the minimal PoM Price among all substitution groups of an ingredient. $Fixed\ Effects$ indicates if the model controls for substitution group and month fixed effects or substance (active ingredient) $\times$ time fixed effects. Standard errors are clustered on the substitution group level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 14: Summary Statistics for Repeated Purchases

	Painkillers	Antiepileptics	Antibiotics
Repeated Consumption in Subgroup	0.897	0.921	0.428
	(0.3)	(0.27)	(0.49)
Repeated Consumption of Product	0.754	0.849	0.562
	(0.43)	(0.36)	(0.5)
Repeated Consumption, same Product as in First Observed Period	0.637	0.851	0.864
	(0.48)	(0.36)	(0.34)
Opposed Substitution	0.209	0.028	0.094
	(0.41)	(0.16)	(0.29)
Opposed Substitution Cond. on Repeated Consumption of Product	0.239	0.024	0.135
	(0.43)	(0.15)	(0.34)
Opposed Substitution Cond. on same Product as in first observed period	0.249	0.027	0.093
	(0.43)	(0.16)	(0.29)

Summary statistics for the three market segments of painkillers, antiepileptics and antibiotics. The fraction of consumption repeated within a substiution group (Subgroup) describes the fraction of purchase occasions where the patient has purchased the same medical substance before. The fraction of repeated purchases of the same product describes the same pattern but with a specific brand. The fraction of repeated consumption of the same product as in the first period refers to the fraction of purchase occasions where consumers buy the same brand as they did the first time they got a specific substance. The last two rows condition the fraction of opposed substitution on (1) the repeated purchase of a product, i.e. solely considering patients who have purchased a brand previously and on (2) the fact that the same brand has been purchased the first time the patient is observable in the data set. Standard deviations are displayed in parentheses.

C.7 Additional Summary Statistics: Switching Costs

In Table 14 I show summary statistics about substitution patterns: 89.7% of the painkiller consumption and 92.1% of the antiepileptic consumption are repeated within a subgroup whereas only 42.8% of purchases of antibiotics are repeated. Further, in the former two substitution groups, a larger part of patients has purchased the exact same product before (75% for painkillers, 85% for antiepileptics and 56% for antibiotics). In the lower part of Table 14 I show how the fraction of opposed substitution is affected by the repeated consumption. For those occasions where the patient purchases the same product of painkillers or antibiotics as in the previous purchase occasion, the fraction of opposed substitution increases compared to the general fraction of opposed substitution. Conditional on a repeated purchase, the fraction of opposed substitutions increases from 20.9% to 23.9% for painkillers and from 9.4% to 13.5% for antibiotics. For the therapeutic subgroup of antiepileptics the relation is opposite and small. Conditional on repeated purchases, the fraction of opposed substitutions for antiepileptics decreases from 2.8% to 2.4%.

C.8 Graphical Analysis: Purchasing Frequencies

The next two figures graphically illustrate the repeated purchasesof painkillers.[2] In detail, Figure 4 shows the density of repeated purchases divided by the days since the last purchase of a painkiller within the same substitution group. The sample is reduced to those purchases that are repeated, that is, another purchase within the same substitution group by the same patient has been observed before. I divide the sample in four different groups. The first group are those purchases of the same product, where patients consume the PoM - and therefore substitute. The second group consists of purchases where patients substitute and consume a different product than in the last occasion. In the third group, patients do not substitute and consume the same product, whereas in the fourth group patients do not substitute and consume a different product than during the last purchase occasion. The densities for the four different groups are stacked.

The results show that those groups that substitute (and consume the PoM) have a cyclicality in their density. The density is higher for a cycle of 7 days since the last purchase (i.e. 7, 14, 21, 28, etc., days after last purchase). For the group that substitutes and consumes the same product as in the last occasion, the density is exceptionally high on the 14th day after the last purchase. For the patients that oppose substitution one does not see a higher density on specific days. One possible explanation is that the patients who purchase very frequently and in specific time spans are less likely to oppose substitution. Nevertheless, repeated purchases are correlated with opposing substitution in general.

I reduce the sample to those situations where a consumer does not have a repeated purchase within the same month and show results in Figure 5. By doing so, I exclude patients who face the same prices with certainty. The basic intuition of the first graph is unchanged. Although repeated purchases are correlated with a higher probability of an opposed substitution, some weekly time spans (7 or 14 days) between purchases are associated with a lower possibility of opposing substitution.

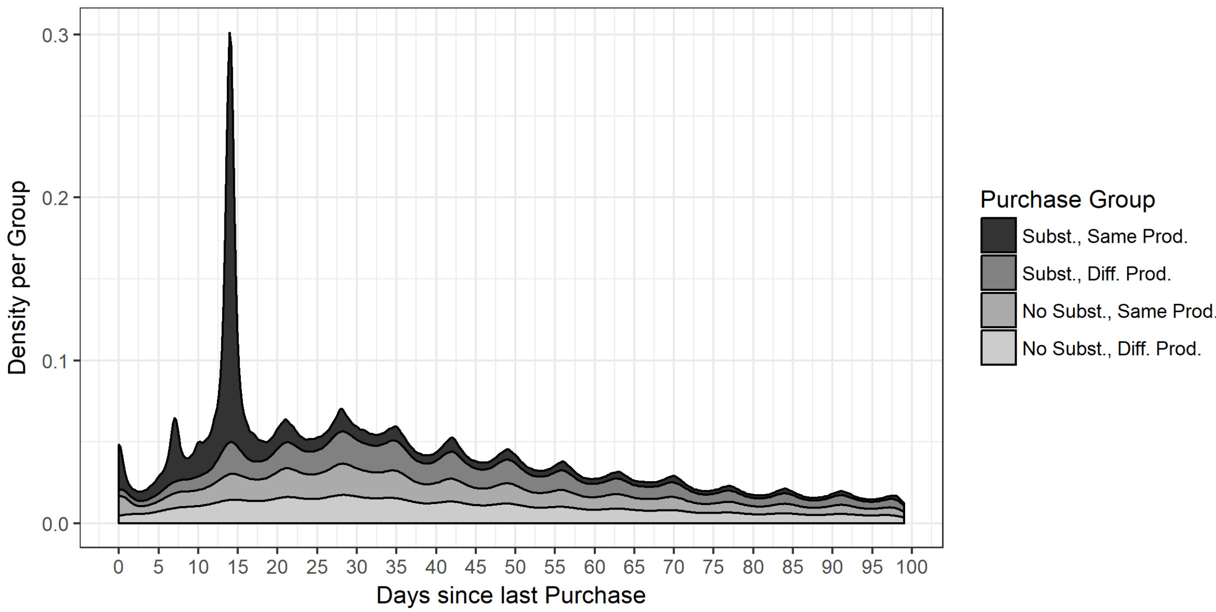
Painkillers:

Antibiotics:

Antiepileptics:

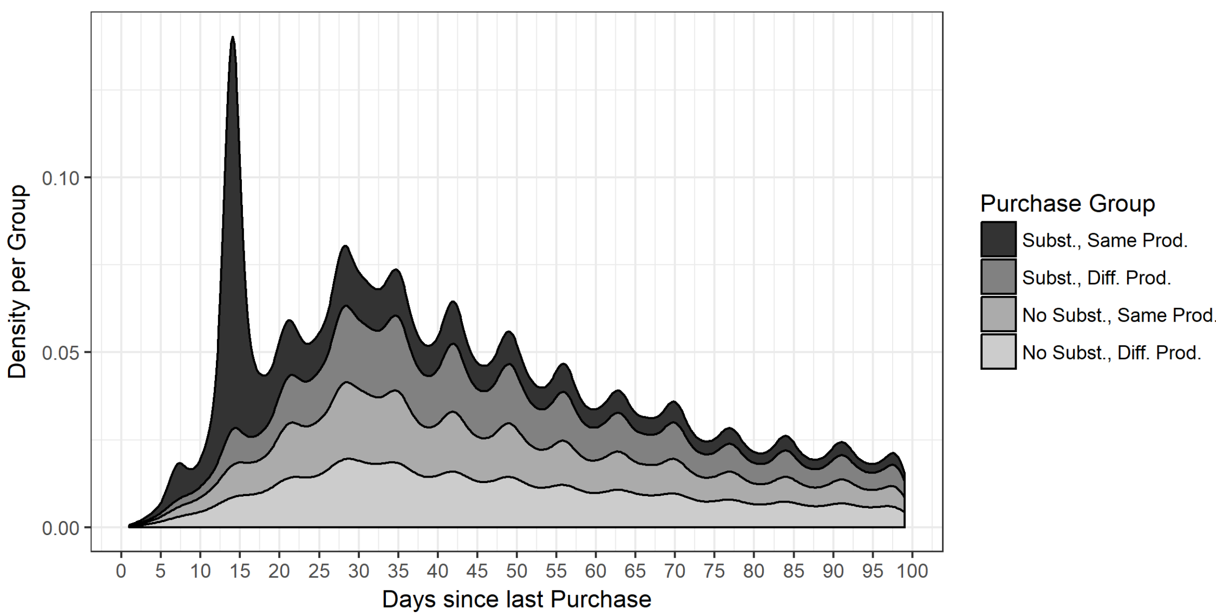
[2]Note that I restrict the graphical analysis to the group of painkillers. I present the same graphical evidence for antibiotics (Figures 6 and 7) and antiepileptics (Figures 8 and 9)

Figure 4: Densities, Days since Last Purchase



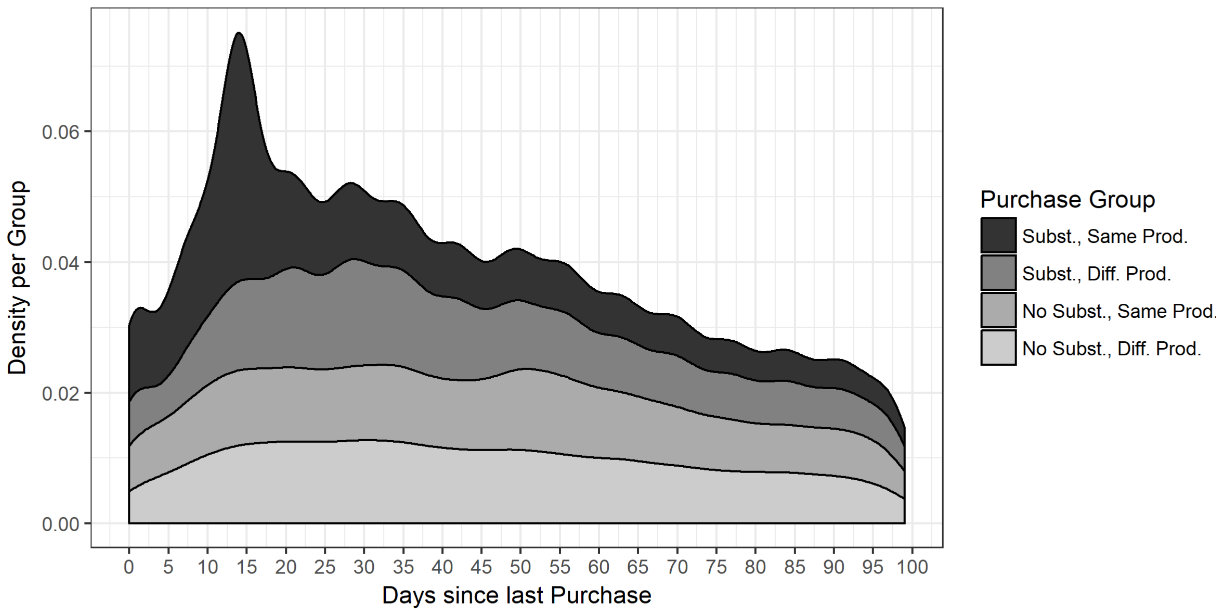
The figure shows the density of the time in days since the last purchase of a painkiller within the same subgroup. The sample is reduced to those purchases that are repeated, i.e. there was another purchase within the same substitution group by the same patient before. Four different groups are considered: (1) The density of time since the last purchase by patients who substitute and take the same product; (2) The density of patients who substitute and consume a different product as their last purchase; (3) The density of patients who do not substitute and consume the same product as their last purchase and (4) The density of time since last purchase by patients who do not substitute and consume different products. The peaks in groups (1) and (2) are exactly at 7, 14 and 21 days. Within their group there is a higher density of patients. The peaks are not observable in groups (3) and (4).

Figure 5: Densities, Days since Last Purchase within Last Month



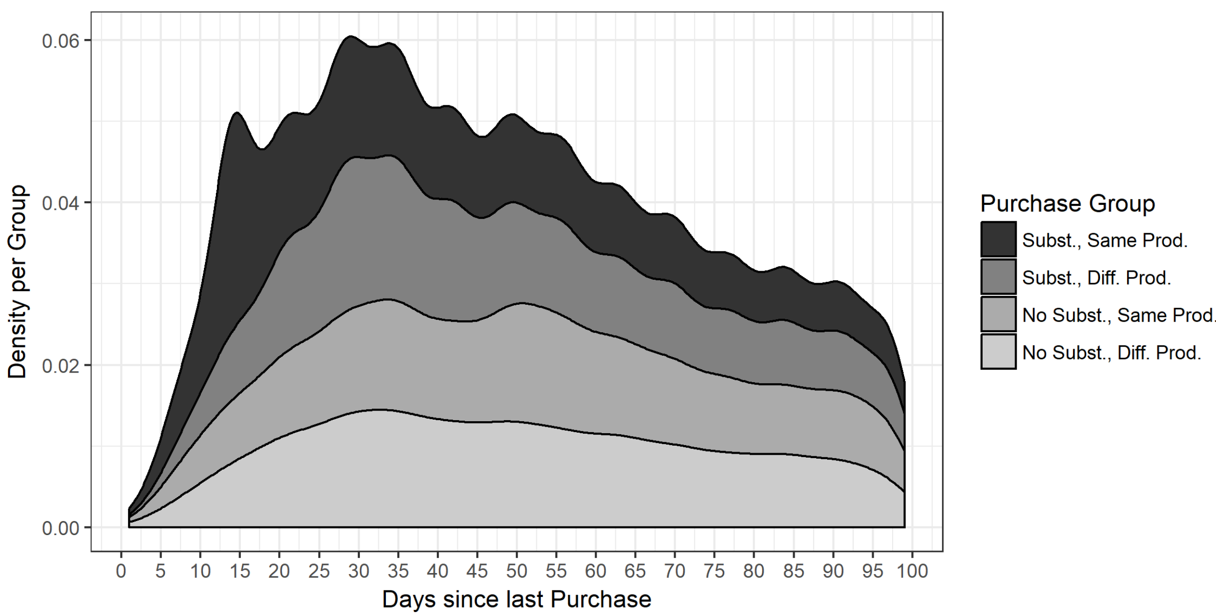
The figure shows the density of the time in days since the last purchase of a painkiller within the same subgroup. The sample is reduced to those purchases that are repeated, i.e. there was another purchase within the same substitution group by the same patient before. Further I reduce the sample to those patients where the previous purchase occasion was in the last calendar month. Four different groups are considered: (1) The density of time since last purchase by patients who substitute and take the same product; (2) The density of patients who substitute and consume a different product as their last purchase; (3) The density of patients who do not substitute and consume the same product as their last purchase and (4) The density of time since last purchase by patients who do not substitute and consume different products. The peaks in groups (1) and (2) are exactly at 7, 14 and 21 days. Within their group there is a higher density of patients. The peaks are not observable in groups (3) and (4).

Figure 6: Densities, Days since Last Purchase



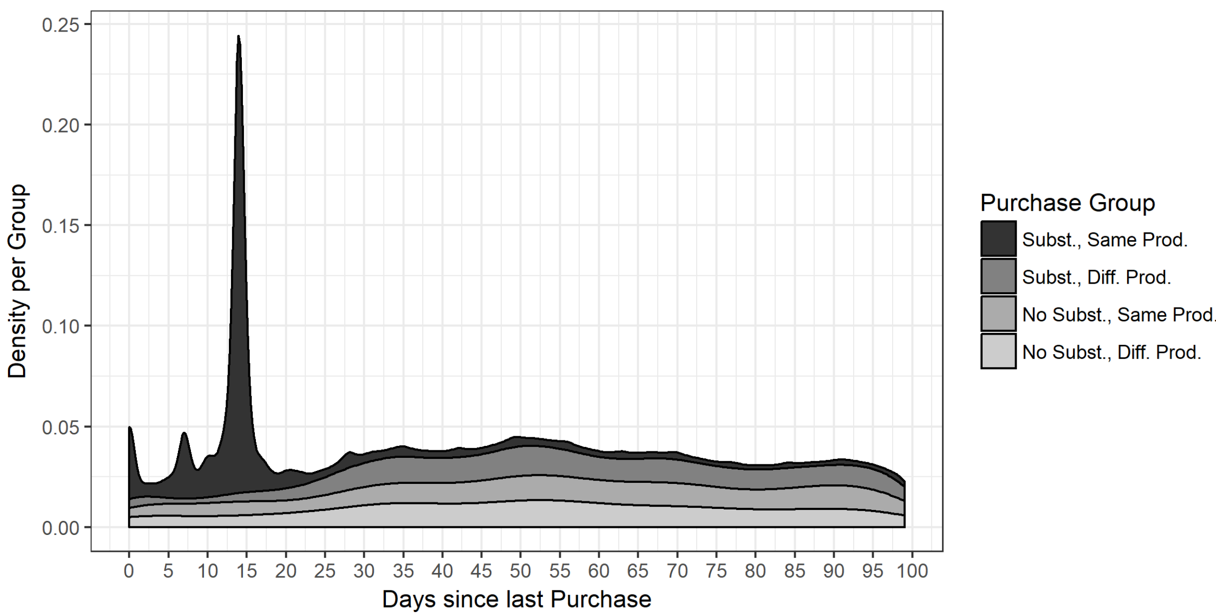
The figure shows the density of the time in days since the last purchase of an antibiotic within the same subgroup. The sample is reduced to those purchases that are repeated, i.e. there was another purchase within the same substitution group by the same patient before. Four different groups are considered: (1) The density of time since last purchase by patients who substitute and take the same product; (2) The density of patients who substitute and consume a different product from their last purchase; (3) The density of patients who do not substitute and consume the same product as their last purchase and (4) The density of time since last purchase by patients who do not substitute and consume different products. The peaks in groups (1) and (2) are exactly at 7, 14 and 21 days. Within their group there is a higher density of patients. The peaks are not observable in groups (3) and (4).

Figure 7: Densities, Days since Last Purchase within Last Month



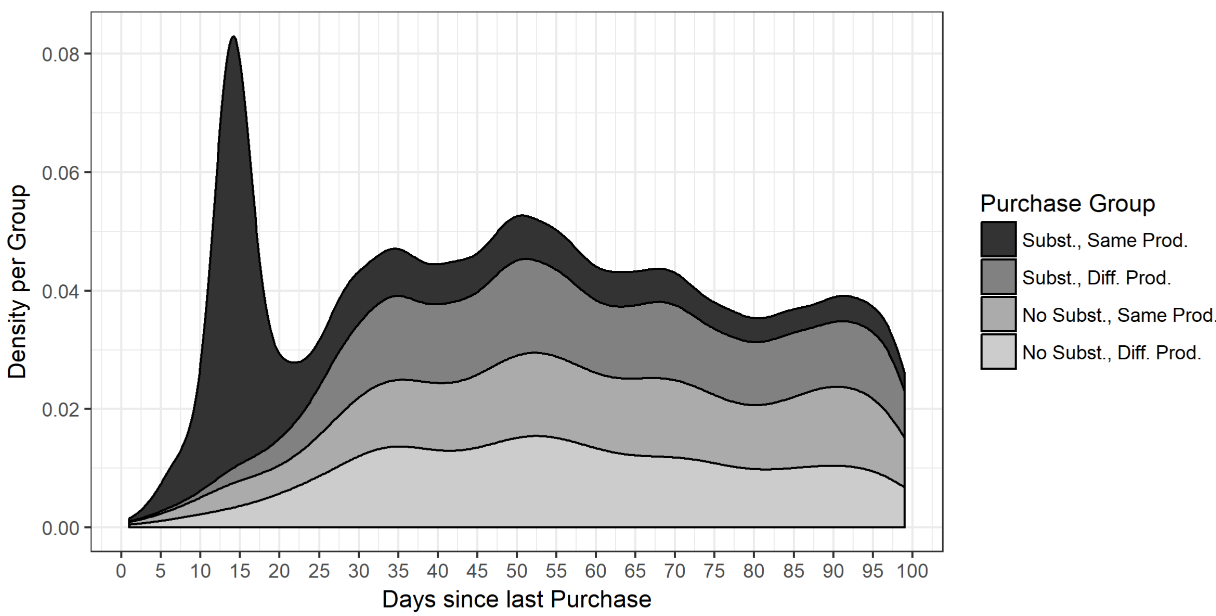
The figure shows the density of the time in days since the last purchase of an antibiotic within the same subgroup. The sample is reduced to those purchases that are repeated, i.e. there was another purchase within the same substitution group by the same patient before. Further I reduce the sample to those patients where the previous purchase occasion was in the last calendar month. Four different groups are considered: (1) The density of time since last purchase by patients who substitute and take the same product; (2) The density of patients who substitute and consume a different product from their last purchase; (3) The density of patients who do not substitute and consume the same product as their last purchase and (4) The density of time since last purchase by patients who do not substitute and consume different products. The peaks in groups (1) and (2) are exactly at 7, 14 and 21 days. Within their group there is a higher density of patients. The peaks are not observable in groups (3) and (4).

Figure 8: Densities, Days since Last Purchase



The figure shows the density of the time in days since the last purchase of an antiepileptic within the same subgroup. The sample is reduced to those purchases that are repeated, i.e. there was another purchase within the same substitution group by the same patient before. Four different groups are considered: (1) The density of time since last purchase by patients who substitute and take the same product; (2) The density of patients who substitute and consume a different product from their last purchase; (3) The density of patients who do not substitute and consume the same product as their last purchase and (4) The density of time since last purchase by patients who do not substitute and consume different products. The peaks in groups (1) and (2) are exactly at 7, 14 and 21 days. Within their group there is a higher density of patients. The peaks are not observable in groups (3) and (4).

Figure 9: Densities, Days since Last Purchase within Last Month



The figure shows the density of the time in days since the last purchase of an antiepileptic within the same subgroup. The sample is reduced to those purchases that are repeated, i.e. there was another purchase within the same substitution group by the same patient before. Further I reduce the sample to those patients where the previous purchase occasion was in the last calendar month. Four different groups are considered: (1) The density of time since last purchase by patients who substitute and take the same product; (2) The density of patients who substitute and consume a different product from the last purchase; (3) The density of patients who do not substitute and consume the same product as their last purchase and (4) The density of time since last purchase by patients who do not substitute and consume different products. The peaks in groups (1) and (2) are exactly at 7, 14 and 21 days. Within their group there is a higher density of patients. The peaks are not observable in groups (3) and (4).

Table 15: IV Regression, Rizatriptan

	First Stage 3 M	β_3	First Stage 6 M	β_6
322	0.49***	0.382*	0.5***	0.559*
	(0.089)	(0.221)	(0.125)	(0.29)
1466	0.50***6	0.511***	0.386***	-0.094
	(0.039)	(0.103)	(0.042)	(0.167)
318	0.623***	0.314***	0.508***	-0.058
	(0.042)	(0.078)	(0.038)	(0.079)
1372	0.547***	0.429***	0.664***	0.262***
	(0.043)	(0.097)	(0.041)	(0.079)
319	0.631***	0.452***	0.559***	0.254***
	(0.036)	(0.067)	(0.051)	(0.096)
2056	0.426***	0.517*	0.278***	-0.11
	(0.087)	(0.303)	(0.082)	(0.435)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results of the Instrumental Variable regression for different substitution groups of Rizatriptan (painkiller, original product Maxalt). The first column differentiates between the substitution groups. The first stage of the IV regression is shown in columns two and four, first for the initial three months and second for months four to six. The coefficients for the second stage are in columns three and six. Standard errors in parentheses.

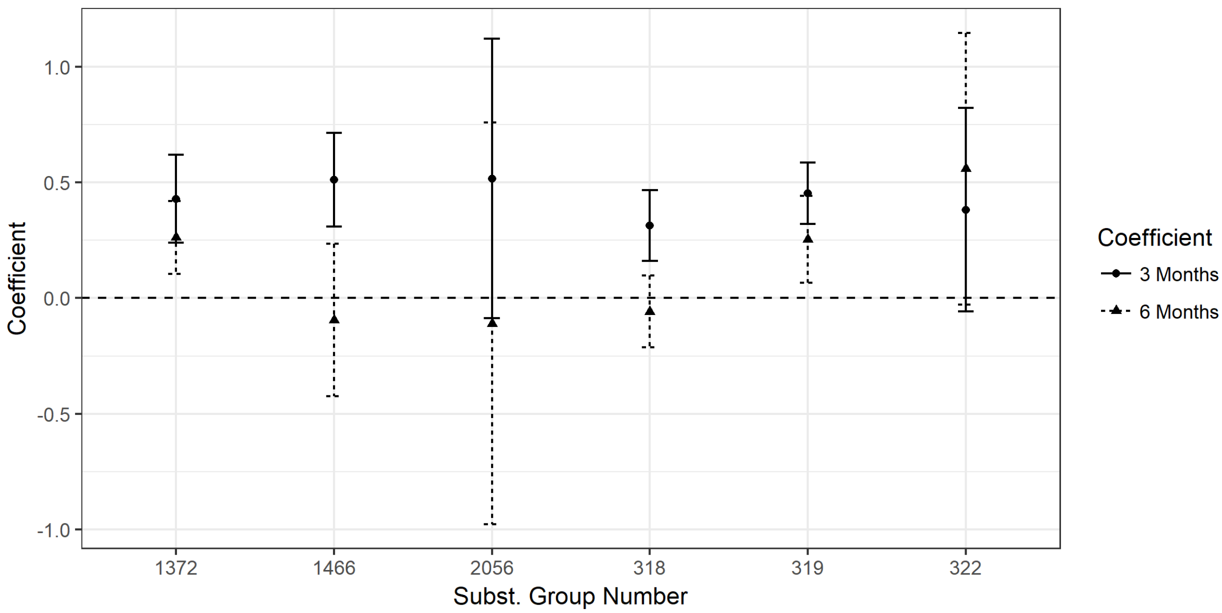
C.9 Robustness Check: Patent Expiries, Additional Substances

Within the following, I present additional substances that ran off patent. As in the main analysis I use the quasi-experimental setting to show causal evidence of switching costs. For Rizatiptan (a painkiller treating migraine) as well as Clindamycin (an antibiotic used against a number of bacterial infections) I present the first and second stage of the IV identification strategy. Table 15 and Figure 10 correspond to Rizatriptan, and Table 16 and Figure 11 describe results for Clindamycin.

C.10 Robustness Check: Price Changes, Discontinuity

Within this subsection I provide an additional robustness check for the evidence of switching costs. In detail, I use a general discontinuity due to the timing of starting a treatment to evaluate switching costs. The basic intuition of this robustness check is described in Figure 12. Consider the subsequent month within a substitution group. Consider two pharmaceuticals $j \in \{1,2\}$ where in the first month $p_1 < p_2$, in the second month $p_2 < p_1$ and in the third month again $p_1 < p_2$. I consider those individuals who started their initial treatment (within the observable data) of the substitution group group who consumed the PoM during the last 10 days

Figure 10: IV Regression, Rizatriptan



Coefficients of second stage for different substitution groups of Maxalt. Coefficients for each substitution group are divided into coefficients for the initial three months and months four to six. A coefficient for the first three months is equal to $\beta_3 = .5$ and says that the initial consumption of a generic increases the possibility of purchasing a generic again during the following three months by 50%. Note that I include 95% confidence intervals.

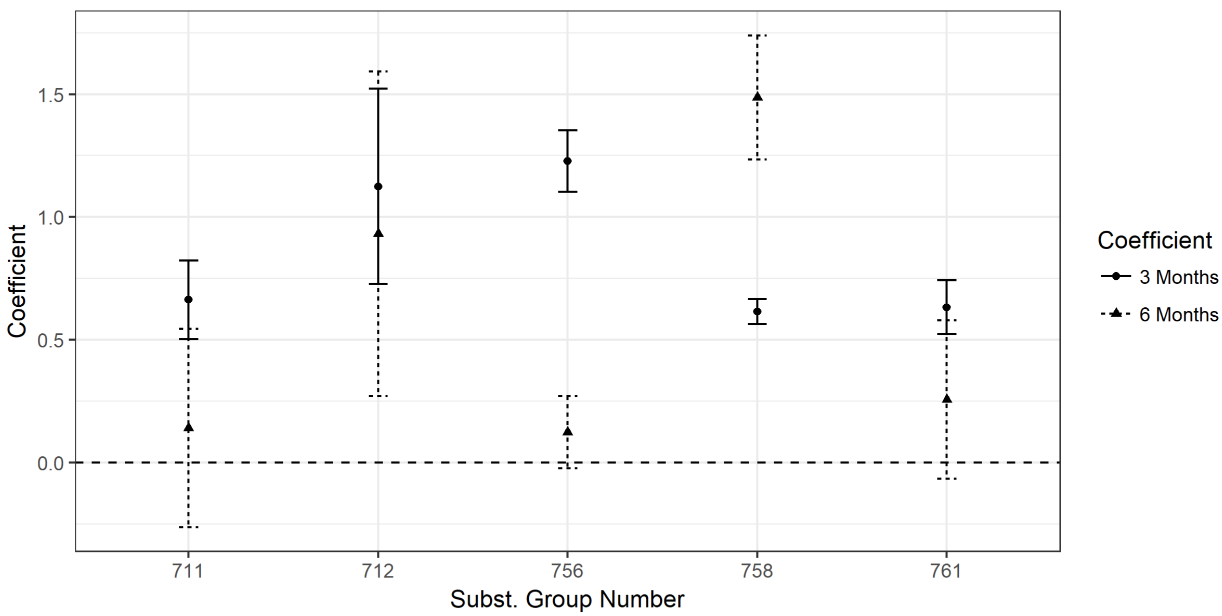
Table 16: IV Regression, Clindamycin

mod3	First Stage 3 M	β_3	First Stage 6 M	β_6
756	0.373***	1.228*	0.348***	0.123
	(0.016)	(0.064)	(0.021)	(0.075)
758	0.173***	0.615***	0.206***	1.487***
	(0.004)	(0.025)	(0.012)	(0.129)
761	0.206***	0.632***	0.199***	0.256
	(0.01)	(0.055)	(0.023)	(0.164)
711	0.287***	0.663***	0.277***	0.14
	(0.019)	(0.082)	(0.038)	(0.205)
712	0.147***	1.124*	0.286***	0.932***
	(0.019)	(0.202)	(0.056)	(0.334)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

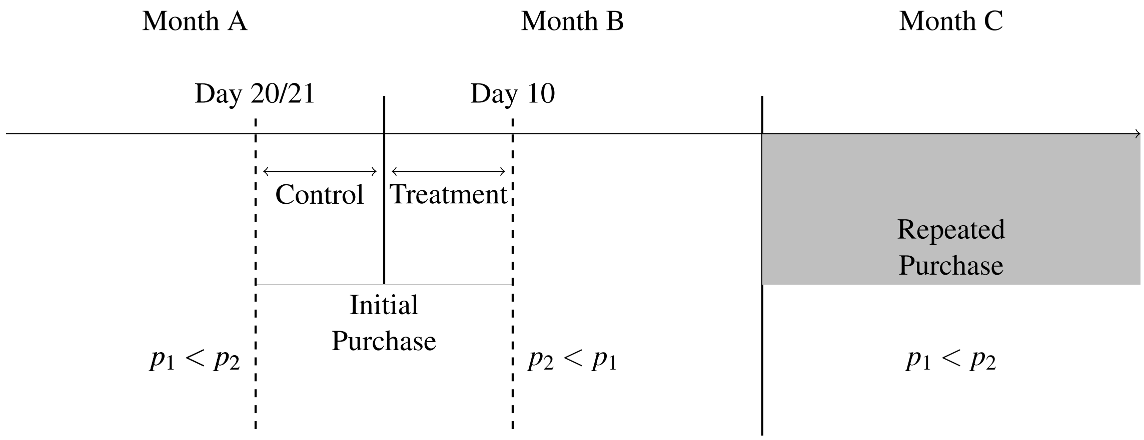
Results of the Instrumental Variable regression for different substitution groups of Clindamycin (an antibiotic). The first column differentiates between the substitution groups. The first stage of the IV regression is shown in columns two and four, first for the initial three months and second for months four to six. The coefficients for the second stage are in columns three and six. Standard errors in parentheses.

Figure 11: IV Regression, Clindamycin



Coefficients of second stage for different substitution groups of Clindamycin. Coefficients for each substitution group are divided into coefficients for the initial three months and months four to six. A coefficient for the first three months is equal to $\beta_3 = .5$ and says that the initial consumption of a generic increases the possibility of purchasing a generic again during the following three months by 50%. Note that I include 95% confidence intervals.

Figure 12: Regression Design, Robustness Check



Sketch of the regression design that is used in the robustness check.

of the first month or the first 10 days of the second month. So, the sample is reduced to patients starting with $j = 1$ in the first month (last 10 days) or $j = 2$ in the second month. The first is the control and the latter is the treatment group. Furthermore, I require that during the remaining 20 (or 21) days of the second month patients do not purchase a product of the substitution group again. I then compare the repeated purchase of the patients in the third month, when $p_2 < p_1$. Overall, I explore if the probability of opposing substitution increases if a patient has been quasi randomly assigned to a previous consumption of the specific product without any additional payments. Note that the sole difference between the treatment and control group is the date of purchasing a product initially. The date difference is at most 20 days. The identifying assumption is that patients do not initially (during the first purchase) adjust the timing of purchases with the intention of receiving a specific product. Given that the drugs are prescription drugs, treatment is usually needed immediately and further price changes are not easily predictable, the assumptions are likely to hold.

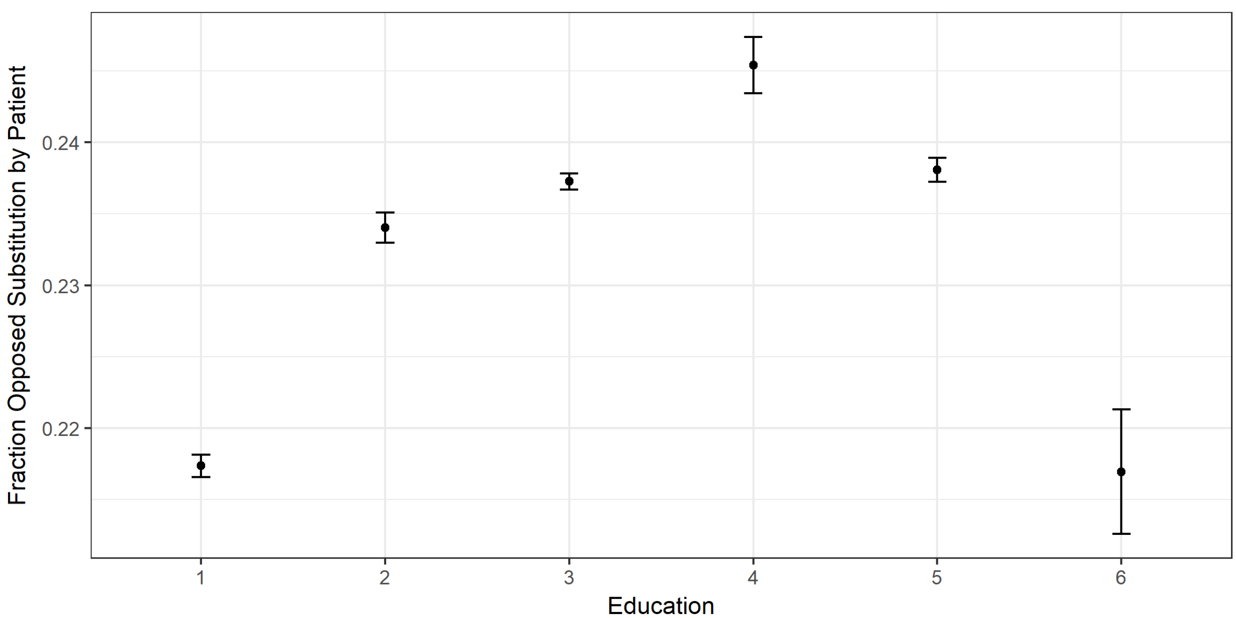
Formally I estimate a regression model similar as in Section 5.

$$P(OpposeSubst_{ijt} = 1) = \alpha + \beta_1 SD_{jit} + \rho_0 FirstPurchase_{ij0} + \rho_1 log(Income_{it} + 1) +$$
$$\rho_4 EduLevel_i + \gamma_{st} + \varepsilon_{jit}$$

SD is a dummy that takes the value 1 if a patient is in the treatment group. In practice this statement is equivalent to saying that *SD* is 1 if a patient has consumed the product before or the patient has consumed any product in the previous month, since I solely consider patients who have purchased the PoM in the second month and oppose substitution in month three. Table **??** shows the result of the least square regression considering painkillers. Model (1) does not include controls and only uses *SD* as a regression. Models (2) and (3) include the logarithm of income and subgroup $\times$ time fixed effects. Model(3) further controls for the education level and unobserved heterogeneity. Results are strong, significant and stable. In the final specification the probability of opposing substitution increases by 15% points if a patient is in the treatment group and therefore purchased the product in the previous month when it was the PoM. The results back up the general regression results and show an even stronger effect considering only the discontinuity.

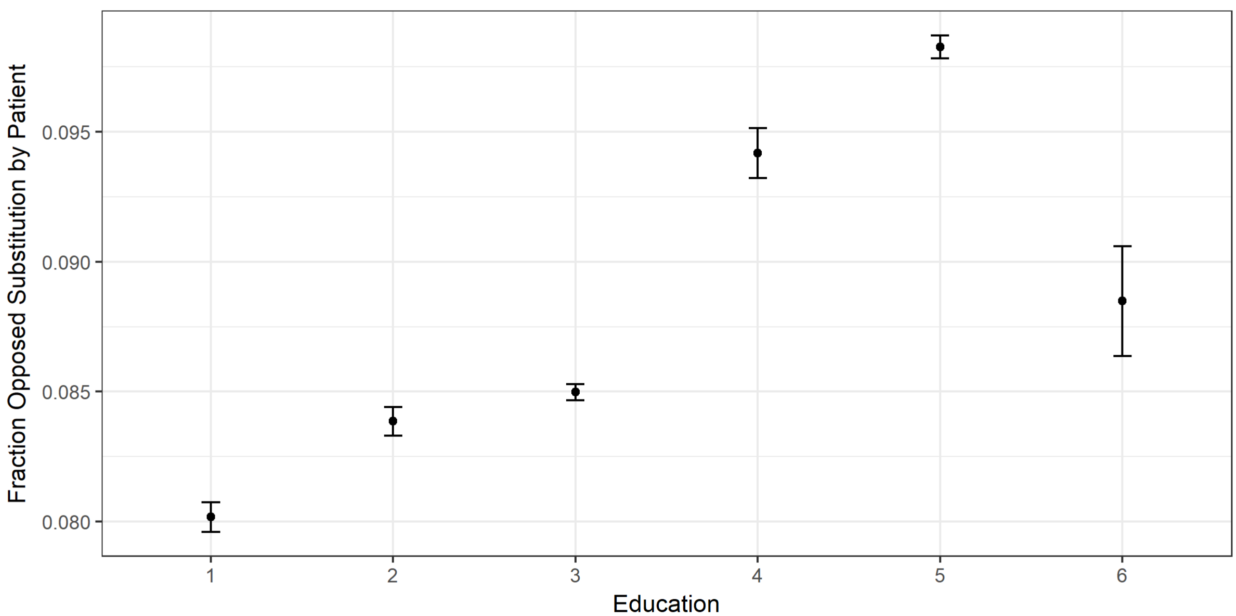
C.11 Graphical Analysis: Education and Substitution

Figure 13: Education and Substitution Decision



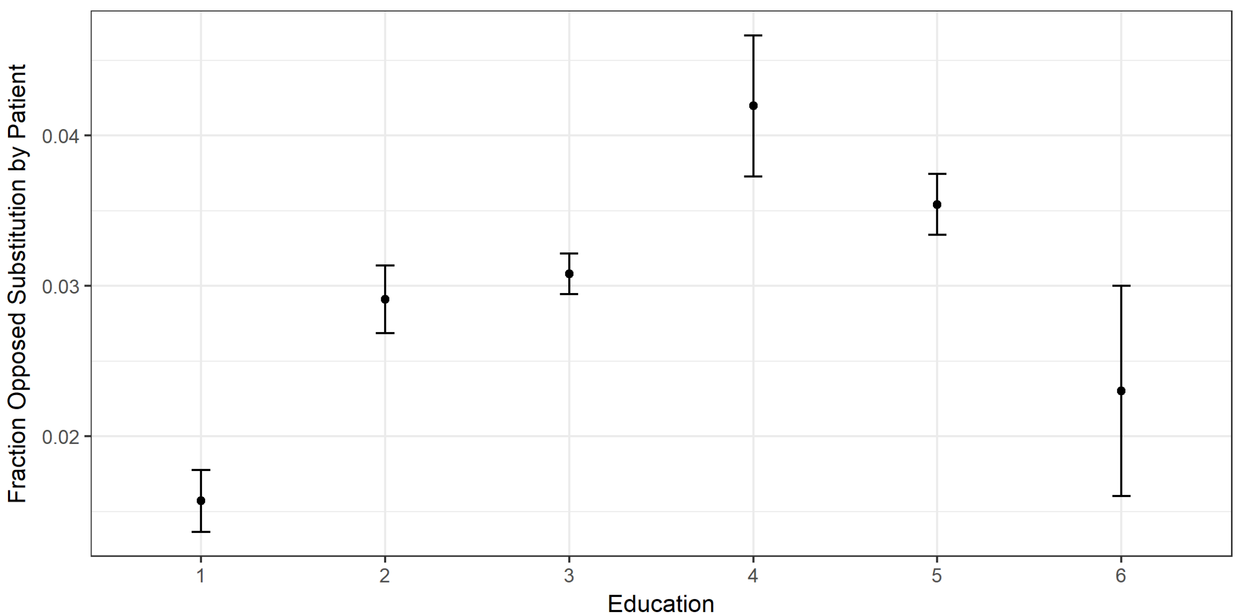
Fraction of patients that oppose substitution when consuming painkillers dependent on the level of education. The education is divided in six difference education segments. 1 for an education less than nine years lower secondary, lower seconday 9 to 10 years (2), upper secondary (3), post secondary less than two years (4), post secondary more than two years (5) and PhD as well as professional degrees (6). The error bars correspond to a 95% confidence interval.

Figure 14: Education and Substitution



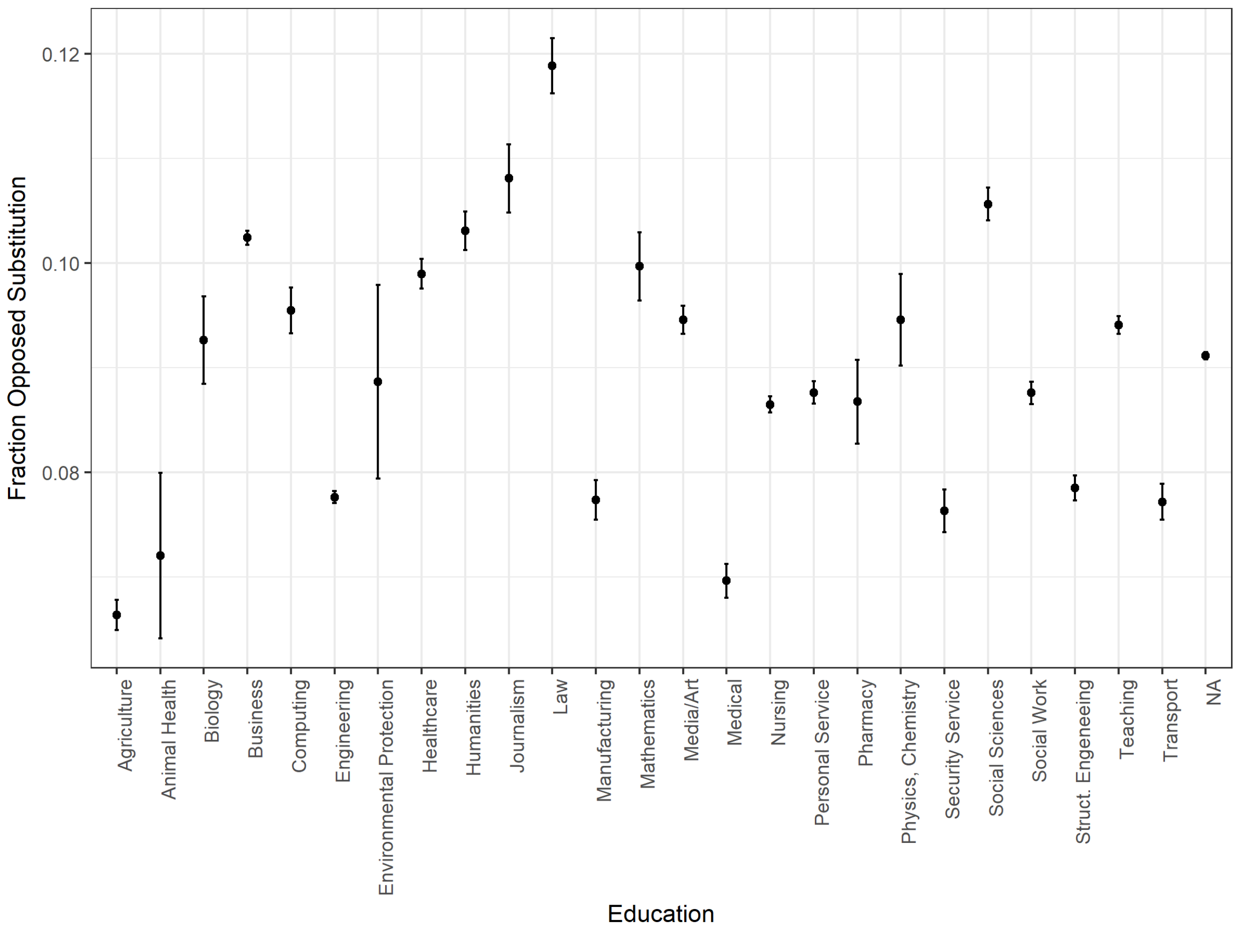
Fraction of patients that oppose substitution when consuming antibiotics, dependent on the patient's level of education. Education is divided into six different segments: (1) lower secondary, an education less than nine years; (2) lower secondary, 9 to 10 years; (3) upper secondary; (4) post-secondary, less than two years; (5) post-secondary, more than two years; (6) PhD and professional degrees. The error bars correspond to a 95% confidence interval.

Figure 15: Education and Substitution



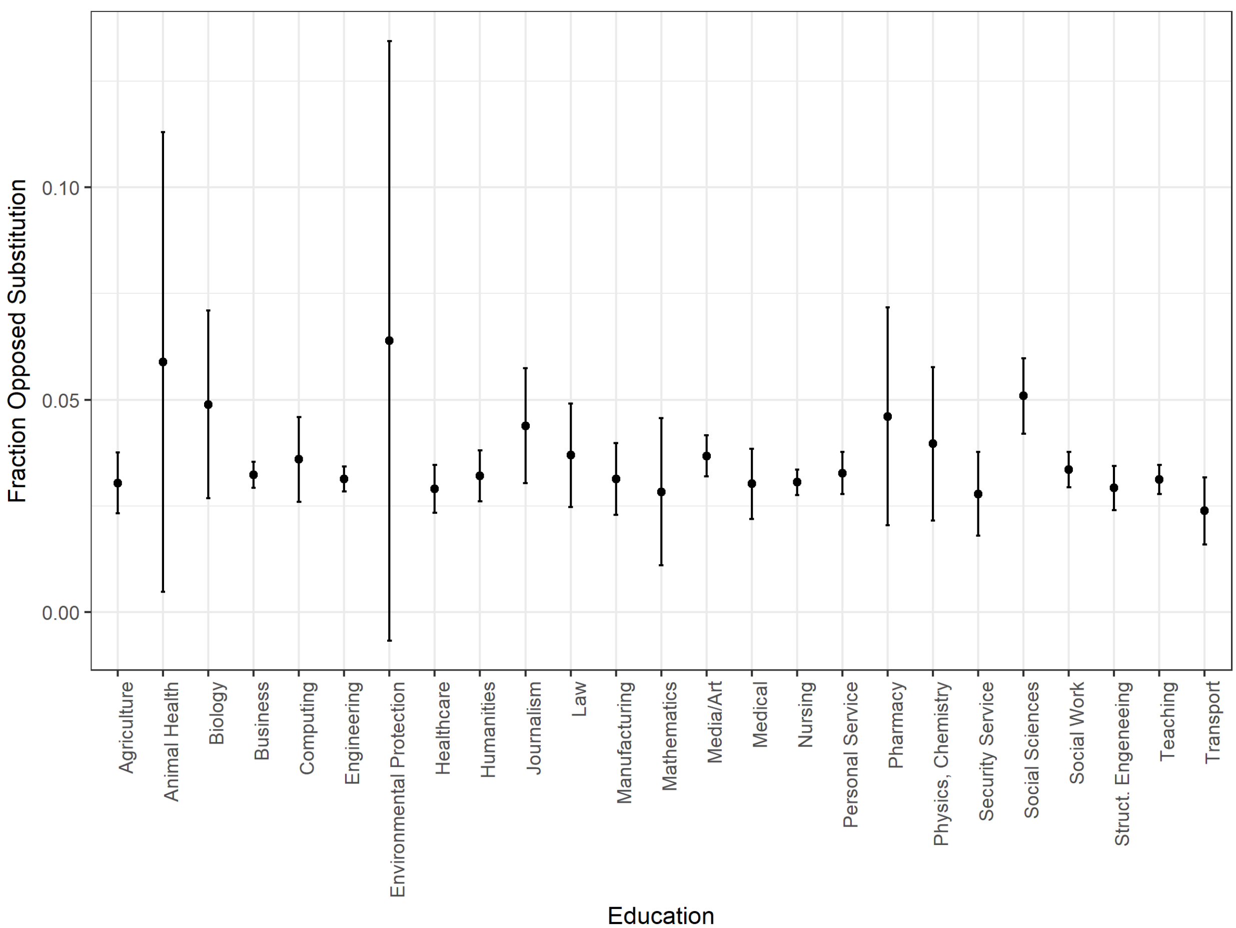
Fraction of patients that oppose substitution when consuming antiepileptics, dependent on the patient's level of education. Education is divided into six different segments: (1) lower secondary, an education less than nine years; (2) lower secondary, 9 to 10 years; (3) upper secondary; (4) post-secondary, less than two years; (5) post-secondary, more than two years; (6) PhD and professional degrees. The error bars correspond to a 95% confidence interval.

Figure 16: Education Subject and Substitution



Fraction of patients that oppose substitution when consuming antibiotics, dependent on the subject of the patient's education. Education is divided into 25 different subjects, ordered alphabetically. The error bars correspond to a 95% confidence interval.

Figure 17: Education Subject and Substitution



Fraction of patients that oppose substitution when consuming antiepileptics, dependent on the patient's subject of education. Education is divided into 25 different subjects, ordered alphabetically. The error bars correspond to a 95% confidence interval.

D The Role of Pharmacies

Within this section I describe the role of pharmacies in the prescription drug market. I further present evidence that pharmacies are not responsible for opposed substitutions by patients. After receiving a prescription from a primary health care provider a patient gets dispensed a product at a pharmacy of the individual's choice. The pharmacy is responsible for explaining the substitutability in case the prescribed drug is not the cheapest available alternative within a substitution group. The pharmacies are required to explain that products are medically equivalent and to explain any price differences that consumers have to pay out of pocket (Sveriges Riksdag, 2002).

Note that the pharmaceutical margins (Appendix A) imply that higher prices are associated with higher profits for pharmacies. It may be possible that pharmacists have an incentive to avoid substitution and dispense more expensive products in order to increase their own profits. However, this is unlikely. First of all, regulation forbids that pharmacists avoid substitution. Second, the market for pharmacies in Sweden would limit this behavior. The market for pharmacies is divided into four approximately equal-share oligopolists which increases the possibility of control. Note that one of the main pharmacy brands is state owned. The organization may play a role as the employee within a pharmacy cannot be legally financially incentivized to maximize profits when dispensing prescription drugs. Finally, I provide two-fold empirical evidence that pharmacies do not maximize their profits by dispensing more expensive products. Pharmacies are able to increase their profits by decreasing the information provision to consumers such that consumers pay the price difference to the cheapest product out of pocket as they do not substitute. Further pharmacies could reduce intentionally the stock of the PoM such that they can dispense more expensive products to patients. In the latter case consumers do not have additional costs. If pharmacies do not provide full information, I could not exclude that inattention is a reason for overpayment. In model terms, pharmacies do not decrease information costs to zero. Perceived quality differences may not be the sole reason for choosing expensive products.

If pharmacies do not provide accurate information they would have a higher incentive to reduce information provision the more expensive a product is. In the following I provide regression evidence on the monthly market share level that there is no strong correlation between prices and the probability of opposed substitution by patients. The model takes the following form:

$$P(OpposeSubst_{jt}) = \alpha + \beta p_{jt} + \gamma_j + \varepsilon_{jt}.$$

Where j is a product, t the time period (month), $OpposeSubst_{jt}$ the fraction of opposed substitution for product j in t, p_{jt} the price and γ_j product fixed effects. Within the least square regressions I partly include polynomials of price to explore the nonlinear correlation between price and the fraction of opposed substitutions. Standard errors are clustered on the product level.

Table 17 shows the results of four different models. Models 1 and 2 show regression evidence without fixed effects and Models 3 and 4 include product fixed effects. While Models 1 and 3 solely include the price as regressors, Models 2 and 4 further use the squared price. The results show that prices are only marginally and negatively correlated with the fraction of opposed substitution. Furthermore, including the fixed effects reduces significance to the 5/

Table 17: Regression Results, Opposed Substitution by Patient

	Fraction Opposed Subst. by Patient			
	(1)	(2)	(3)	(4)
Price	-0.0001^{***}	-0.0002^{***}	-0.00002^{**}	-0.00000
	(0.00001)	(0.00003)	(0.00001)	(0.00002)
Price^2		0.00000^{***}		-0.000
		(0.00000)		(0.000)
Constant	0.215^{***}	0.228^{***}		
	(0.010)	(0.012)		
Fixed effects	No	No	Yes	Yes
N	20,635	20,635	20,635	20,635

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regression of fraction of opposed substitution by patient on the price. One observation is product j at time t. The outcome variable is the fraction of opposed substitutions by patients. Models 3 and 4 use fixed effects on the substitution-group level. Standard errors are clustered on the substitution-group level.

The second test considers the situation that pharmacies could adjust their procurement behavior such that they have a low stock of cheaper products. In cases that the cheapest product is out of stock the pharmacy has the possibility to dispense more expensive products. Patients would get reimbursed according to the price of the dispensed product (i.e. they do not have to pay the price differences). I explore the possible incentive by showing evidence of the following regression:

$$P(PharmOpposeSubst_{jt}) = \alpha + \beta p_{jt} + \gamma_j + \varepsilon_{jt}.$$

Where j is a product, t the time period (month), $PharmOpposeSubst_{jt}$ the fraction of product j that is not the cheapest but dispensed because the cheapest product is out of stock, p_{jt} the price and γ_j is product fixed effects. Within the least square regressions I partly include polynomials of price to explore the nonlinear correlation between price and the fraction of opposed substitutions. Standard errors are clustered on the product level.

Table 18 shows the results of four regressions. Again, Models 1 and 2 show results without fixed effects while I include fixed effects in Models 3 and 4. Further, Models 2 and 4 explore the effect of squared prices. The results show that there is not a linear price effect on the fraction of opposed substitution by the pharmacy. First of all the effects of prices are very small. Second, without including the squared prices the effects of prices are insignificant. Including the polynomial of price shows that there is a nonlinear effect of prices. In detail, there is a concave relationship for prices on the fraction of opposed substitution by pharmacies. One cannot rationalize the effect from profit-maximizing behavior of pharmacies because pharmacies would have a greater interest in opposing substitution for products of higher prices. The results suggest that the effect decreases for higher prices.

Table 18: Regression Results, Opposed Substitution by Pharmacy

	Fraction Opposed Subst. by Pharmacy			
	(1)	(2)	(3)	(4)
Price	0.00002	0.0001***	0.00001	0.0002***
	(0.00001)	(0.00003)	(0.00002)	(0.00004)
Price^2		−0.00000***		−0.00000***
		(0.00000)		(0.00000)
Constant	0.122***	0.105***		
	(0.004)	(0.005)		
Fixed effects	No	No	Yes	Yes
N	20,635	20,635	20,635	20,635

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regression of fraction of opposed substitution by pharmacy on prices. One observation is product j at time t. The outcome variable is the fraction of opposed substitutions by pharmacy (no additional costs for patient). Models 3 and 4 use fixed effects on the substitution-group level. Standard errors are clustered on the substitution-group level.

E The Role of the Prescriber

The institutional setting of the Swedish pharmaceutical market allows for the possibility that a prescriber (a primary health care provider or a specialist) opposes substitution. If a prescriber opposes substitution the patient get dispensed a product without any higher costs. In Table 4 I have shown that the fraction of opposed substitutions by the physician are uncommon (2.4 % of dispenses for painkillers, 0.5 % for antibiotics, and 1.8 % for antiepileptics)). In this section I investigate if being a medical expert itself is associated with a higher probability of a prescriber opposed substitution. The major threat of identifying perceived quality differences is that medical experts do not purchase cheaper drugs but are able to 'play the system' by getting prescrribed expensive product without the possibility of substitution. In the following I first show that perceived quality differences are important. However, I also show that medical experts are more likely to get opposed substitution by their prescriber.

I evaluate the differences in substitution decisions in three different specifications where a patient i purchases product j in substitution group s at month t:

$$\begin{aligned} P(CheapestProd_{ijt}=1) =& \alpha + \beta Med_{it} + \rho_1 Original_{jt} + \rho_2 Generic_{jt} + \rho_3 log(Income_{it}+1) + \\ & \rho_4 EduLevel_{it} + \rho_5 Geograph_{it} + \gamma_{st} + \varepsilon_{ijt} \\ P(OpposeSubst_{ijt}=1) =& \alpha + \beta Med_{it} + \rho_1 Original_{jt} + \rho_2 Generic_{jt} + \rho_3 log(Income_{it}+1) + \\ & \rho_4 EduLevel_{it} + \rho_5 Geograph_{it} + \gamma_{st} + \varepsilon_{ijt} \\ P(DocOpposes_{ijt}=1) =& \alpha + \beta Med_{it} + \rho_1 Original_{jt} + \rho_2 Generic_{jt} + \rho_3 log(Income_{it}+1) + \\ & \rho_4 EduLevel_{it} + \rho_5 Geograph_{it} + \gamma_{st} + \varepsilon_{ijt} \end{aligned}$$

The difference between the three regressions is the outcome variable. $CheapestProd$ takes the value 1 if patients get dispensed the PoM, $OpposeSubst$ takes the value 1 if a patient actively opposes substitution and therefore has additional expenses. $DocOpposes$ takes the value 1 if a physician opposes substitution on their prescription. In these specific cases the patients do not have to pay for the price difference to the cheapest available product. As described in Table 2, all three variables have a different mean. While the majority of the population gets dispensed the cheapest product (the PoM), some patients oppose substitution (almost 21%). The possibility that patients do not substitute and do not pay for it due to the opposed substitution by a pharmacy or doctor is much less likely (3.4% due to pharmacy and 2.4% due to a physician's opposing substitution). Table 2 also shows that patients with a medical education are slightly more likely that their prescribing physician to oppose substitution (Painkillers: 4.5% for medical education, 2.4% whole sample; Antiepileptics: 2.6% to 1.8%; Antibiotics: 1.3% to 0.5%). The three outcome variables allow exploration of the role of education/perceived quality differences on (1) the general consumption and (2) the consumption for which consumers bear additional costs. Finally, it allows me to explore whether patients with medical education are able to get preferred products by physicians who oppose substitution for them such that they do not have additional expenses.

Med is the variable of interest, namely it examines the impact if a patient has a medical education as a physician. Further, I control for the origin of a product (generic, original, parallel import), the logarithm of disposable income as well as general education level (as described before). I partly also include the geographical area (county) as a control.[3] The final specification includes substitution group times time fixed effects. Intuitively, I control for effects of a given substitution group at a specific time. Correspondingly, I exploit variation within a substitution group in a distinct time period. Important factors are therefore excluded as I explore the effect of a medical education given a specific price relation within a month in a market. Note further that the included education length leads to comparison of physicians with patients of a comparable education level.

All three regression specification methods are used for each of the three therapeutic markets. Table 19 shows the results for the first regression where the outcome is *CheapestProd*, the dummy that takes the value 1 if a patient get dispensed the cheapest available product of a substitution group, the PoM. Table 20 shows the results for the second regression where the outcome *OpposeSubst* is 1 if a patient opposes substitution and pays a price difference out of pocket. Finally, Table 21 shows the results for the third regression where the outcome *DocOpposes* is 1 if a physician has opposed substitution. Within each table, Models (1) and (2) show results for painkillers, Models (3) and (4) the results for antibiotics, and Models (5) and (6) the results for antiepileptics. For each therapeutic subgroup the first models show pooled evidence across geographical counties whereas the second models use county fixed effects.[4]

Evaluating the results across tables for painkillers, patients with a medical education are 4.73% points

[3] Sweden consists of 21 counties.

[4] In Appendix C.2 I show additional regression evidence, i.e. without fixed effects and building up a model.

(Table 19, Model 2) less likely to pay to get dispensed another painkiller. Roughly half of the effect is due to a lower frequency of opposing substitution, the other half of the effect is due to a higher possibility that the prescriber opposes substitution. Given that on average 20.9% of patients oppose substitution to the cheapest available product and patients with a medical education are 4.73% points less likely to oppose substitution as well as 2.4% points more likely to get dispensed the cheapest product, there is evidence for perceived quality differences of painkillers.

For antibiotics the effects are significant and go in the same direction as painkillers. However, the effects are smaller in size. Patients with a medical education are 1.42% points more likely to consume the cheapest product (Table 19, Model 4), 2.3% less likely to oppose substitution (Table 20, Model 4) and 0.7% more likely that their doctor opposes substitution (Table 21, Model 4). The smaller size of the estimates compared to the market of antibiotics is in line with the observation that on average 9.4% of patients oppose substitution of antibiotics (20.9% for painkillers). In general, the conclusions for antibiotics are the same as painkillers and there is evidence for perceived quality differences of antibiotics.

For antiepileptics the coefficients are going in the same direction. However, only the coefficients of the outcome variable of opposing substitution by the patient ($OpposeSubst$) are significant. Here medical education decreases the probability of opposing substitution by 0.75% (Table 20, Model 6). Given the lack of significance as well as the size of the coefficients, I do not find evidence for perceived quality differences in the market for antiepileptics.

The estimation has shown the differences in perceived quality differences between the markets of painkillers/antibiotics and antiepileptics. There may be several reasons why patients act differently when purchasing painkillers/antibiotics or antiepileptics. First of all, the difference is not necessarily due to the frequency of purchases. As shown in Table **??**, the average purchase occasion is different between antibiotics and painkillers. However, the frequency of purchases do not differ between painkillers and antiepileptics. One possible reason for the difference is the difference in the underlying disorder. Epilepsy is a long-term neurological disorder that not only requires medication but often also steady contact with physicians. The frequency of contact and treatment may decrease perceived quality differences about the specific pharmaceuticals.

Table 19: Regression Results, Substitution to Cheapest Product

	Painkillers		Antibiotics		Antiepileptics	
	(1)	(2)	(3)	(4)	(5)	(6)
	Cheap.	Cheap.	Cheap.	Cheap.	Cheap.	Cheap.
Med	0.0241***	0.0240***	0.0147***	0.0142***	0.00488	0.00408
	(0.00231)	(0.00234)	(0.000873)	(0.000868)	(0.00935)	(0.00932)
Original	0.113***	0.101***	-0.583***	-0.578***		
	(0.00885)	(0.00888)	(0.00140)	(0.00140)		
Generic	0.400***	0.402***	-0.0250***	-0.0240***	-0.182***	-0.182***
	(0.00884)	(0.00887)	(0.00116)	(0.00116)	(0.00380)	(0.00380)
Log(Inc)	0.000403***	0.000663***	-0.000657***	-0.000568***	0.0000270	0.000113
	(0.000106)	(0.000104)	(0.0000393)	(0.0000392)	(0.000266)	(0.000268)
Constant	0.366***	0.326***	0.974***	0.947***	1.100***	1.096***
	(0.00893)	(0.00897)	(0.00126)	(0.00128)	(0.00515)	(0.00577)
Education	Yes	Yes	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	Yes	No	Yes
Observations	32,923,856	32,923,856	12,326,138	12,326,138	500,363	500,363
R^2	0.442	0.446	0.281	0.282	0.155	0.157
Fixed Effects	'Sub*Time'	'Sub*Time'	'Sub*Time'	'Sub*Time'	'Sub*Time'	'Sub*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of painkillers, antibiotics and antiepileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if a patient consumes the cheapest available option in a substitution group. Med is a dummy that takes the value 1 if an individual has a medical education as a physician. $Log(Income)$ is the logarithm of income. $Education$ indicates if the model controls for the level of education according to the grades in a six step grid. $Geographical$ indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group or substitution $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 20: Regression Results, Opposed Substitution

	Painkillers		Antibiotics		Antiepileptics	
	(1)	(2)	(3)	(4)	(5)	(6)
	Opp.	Opp.	Opp.	Opp.'	Opp.	Opp.
Med	-0.0472***	-0.0473***	-0.0233***	-0.0230***	-0.00775*	-0.00745*
	(0.00186)	(0.00189)	(0.000638)	(0.000640)	(0.00370)	(0.00369)
Original	0.0907***	0.0978***	0.411***	0.406***		
	(0.00668)	(0.00668)	(0.00126)	(0.00126)		
Generic	-0.138***	-0.139***	0.0291***	0.0282***	0.0898***	0.0900***
	(0.00666)	(0.00667)	(0.000988)	(0.000986)	(0.00207)	(0.00207)
Log(Inc)	0.0000717	-0.000120	0.000530***	0.000470***	-0.0000564	-0.0000841
	(0.0000933)	(0.0000922)	(0.0000343)	(0.0000342)	(0.000129)	(0.000129)
Constant	0.236***	0.262***	-0.00102	0.0243***	-0.0584***	-0.0559***
	(0.00676)	(0.00678)	(0.00106)	(0.00108)	(0.00260)	(0.00282)
Education	Yes	Yes	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	Yes	No	Yes
Observations	32,923,856	32,923,856	12,326,138	12,326,138	500,363	500,363
R^2	0.294	0.298	0.201	0.203	0.073	0.074
Fixed Effects	'Sub*Time'	'Sub*Time'	'Sub*Time'	'Sub*Time'	'Sub*Time'	'Sub*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of painkillers, antibiotics and antiepileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. Med is a dummy that takes the value a if an individual has a medical education as a physician. $Log(Income)$ is the logarithm of income. $Education$ indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group or substitution $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 21: Regression Results, Physician Opposes Substitution

	Painkillers		Antibiotics		Antiepileptics	
	(1)	(2)	(3)	(4)	(5)	(6)
	Opp.	Opp.	Opp.	Opp.	Opp.	Opp.
Med	0.0210***	0.0211***	0.00718***	0.00724***	0.00349	0.00364
	(0.00153)	(0.00153)	(0.000462)	(0.000461)	(0.00752)	(0.00750)
Original	-0.0619***	-0.0594***	0.0191***	0.0185***		
	(0.00823)	(0.00825)	(0.000463)	(0.000464)		
Generic	-0.0926***	-0.0932***	0.00158***	0.00149***	0.0334***	0.0332***
	(0.00824)	(0.00825)	(0.000323)	(0.000323)	(0.00185)	(0.00184)
Log(Inc)	-0.000104	-0.000153*	0.0000368**	0.0000286*	0.000258	0.000227
	(0.0000677)	(0.0000675)	(0.0000137)	(0.0000137)	(0.000187)	(0.000188)
Constant	0.101***	0.109***	0.000604	0.00385***	-0.0216***	-0.0217***
	(0.00828)	(0.00830)	(0.000369)	(0.000382)		
	(0.00319)	(0.00372)				
Education	Yes	Yes	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	Yes	No	Yes
Observations	32,923,856	32,923,856	12,326,138	12,326,138	500,363	500,363
R^2	0.036	0.037	0.008	0.008	0.012	0.015
Fixed Effects	'Sub*Time'	'Sub*Time'	'Sub*Time'	'Sub*Time'	'Sub*Time'	'Sub*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of painkillers, antibiotics and antiepileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if a physician has opposed substitution. Med is a dummy that takes the value 1 if an individual has a medical education as a physician. Log(Income) is the logarithm of income. Education indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects. Fixed Effects indicates if the model controls for substitution group or substitution × month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Extended Regressions

In the following I show complete regression results for the previous models. The first three tables (Tables 22 to 24) show results for *painkillers*, Table 25 to Table 28 concern *antibiotics*, and Tables 29 to 31 describe results of *antiepileptics*.

Table 22: Painkillers: Regression Results, Substitution to Cheapest Product

	(1)	(2)	(3)	(4)	(5)
	Cheap	Cheap	Cheap	Cheap	Cheap
Med	0.0762***	0.0433***	0.0271***	0.0241***	0.0240***
	(0.00282)	(0.00299)	(0.00276)	(0.00231)	(0.00234)
Original	0.0918***	0.0990***	0.132***	0.113***	0.101***
	(0.00926)	(0.00929)	(0.00920)	(0.00885)	(0.00888)
Generic	0.274***	0.298***	0.369***	0.400***	0.402***
	(0.00926)	(0.00928)	(0.00918)	(0.00884)	(0.00887)
Log(Inc)		-0.000106	0.000619***	0.000403***	0.000663***
		(0.000132)	(0.000124)	(0.000106)	(0.000104)
Constant	0.448***	0.374***	0.368***	0.366***	0.326***
	(0.00925)	(0.00946)	(0.00931)	(0.00893)	(0.00897)
Education	No	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	No	Yes
Observations	35,595,027	32,923,856	32,923,856	32,923,856	32,923,856
R^2	0.034	0.043	0.124	0.442	0.446
Fixed Effects	'No'	'No'	'Subgroup'	'Subgroup*Time'	'Subgroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of painkillers. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if a patient consumes the cheapest available option in a substitution group. Med is a dummy that takes the value 1 if an individual has a medical education. Log(Income) is the logarithm of income. Education indicates if the model controls for the level of education according to the grades on a six-step grid. Geographical indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group or substitution × month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 23: Painkillers: Regression Results, Opposed Substitution

	(1)	(2)	(3)	(4)	(5)
	Opp.	Opp.	Opp.	Opp.	Opp.
Med	-0.0179***	-0.0356***	-0.0509***	-0.0472***	-0.0473***
	(0.00198)	(0.00213)	(0.00189)	(0.00186)	(0.00189)
Original	0.114***	0.142***	0.0693***	0.0907***	0.0978***
	(0.00650)	(0.00650)	(0.00631)	(0.00668)	(0.00668)
Generic	-0.0574***	-0.0403***	-0.123***	-0.138***	-0.139***
	(0.00648)	(0.00649)	(0.00630)	(0.00666)	(0.00667)
Log(Inc)		-0.00148***	0.000368***	0.0000717	-0.000120
		(0.000115)	(0.000100)	(0.0000933)	(0.0000922)
Constant	0.178***	0.155***	0.228***	0.236***	0.262***
	(0.00648)	(0.00667)	(0.00642)	(0.00676)	(0.00678)
Education	No	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	No	Yes
Observations	35,595,027	32,923,856	32,923,856	32,923,856	32,923,856
R^2	0.045	0.055	0.159	0.294	0.298
Fixed Effects	'No'	'No'	'SubGroup'	'SubGroup*Time'	'SubGroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of painkillers. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if a patient opposes substitution and does not consume the cheapest product in a substitution group. Med is a dummy that takes the value 1 if an individual has a medical education. $Log(Income)$ is the logarithm of income. Education indicates if the model controls for the level of education according to the grades on a six-step grid. Geographical indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group or substitution $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 24: Painkillers: Regression Results, Physician opposes Substitution

	(1) DocOpp.	(2) DocOpp.	(3) DocOpp.	(4) DocOpp.	(5) DocOpp.
Med	0.0236***	0.0224***	0.0208***	0.0210***	0.0211***
	(0.00152)	(0.00158)	(0.00154)	(0.00153)	(0.00153)
Original	-0.0767***	-0.0728***	-0.0136	-0.0619***	-0.0594***
	(0.00736)	(0.00741)	(0.00734)	(0.00823)	(0.00825)
Generic	-0.0920***	-0.0898***	-0.0411***	-0.0926***	-0.0932***
	(0.00737)	(0.00741)	(0.00734)	(0.00824)	(0.00825)
Log(Inc)		-0.000271***	-0.0000903	-0.000104	-0.000153*
		(0.0000713)	(0.0000684)	(0.0000677)	(0.0000675)
Constant	0.107***	0.105***	0.0506***	0.101***	0.109***
	(0.00737)	(0.00746)	(0.00738)	(0.00828)	(0.00830)
Education	No	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	No	Yes
Observations	35,595,027	32,923,856	32,923,856	32,923,856	32,923,856
R^2	0.003	0.005	0.030	0.036	0.037
Fixed Effects	'No'	'No'	'Subgroup'	'Subgroup*Time'	'Subgroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of painkillers. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if the primary health care provider (physician) opposes substitution and therefore the patient does not consume the cheapest product in a substitution group. Med is a dummy that takes the value 1 if an individual has a medical education. $Log(Income)$ is the logarithm of income. $Education$ indicates if the model controls for the level of education according to the grades on a six-step grid. Geographical indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group or substitution $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 25: Antibiotics: Regression Results, Substitution to Cheapest Product

	(1) Cheap	(2) Cheap	(3) Cheap	(4) Cheap	(5) Cheap
Med	0.00407***	0.0164***	0.0156***	0.0147***	0.0142***
	(0.000939)	(0.00100)	(0.000967)	(0.000873)	(0.000868)
Original	-0.237***	-0.239***	-0.304***	-0.583***	-0.578***
	(0.000894)	(0.000910)	(0.000972)	(0.00140)	(0.00140)
Generic	0.0402***	0.0411***	0.0447***	-0.0250***	-0.0240***
	(0.000776)	(0.000789)	(0.000736)	(0.00116)	(0.00116)
Log(Inc)		-0.00113***	-0.00178***	-0.000657***	-0.000568***
		(0.0000464)	(0.0000445)	(0.0000393)	(0.0000392)
Constant	0.867***	0.849***	0.893***	0.974***	0.947***
	(0.000766)	(0.00110)	(0.000968)	(0.00126)	(0.00128)
Education	No	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	No	Yes
Observations	12,857,251	12,326,138	12,326,138	12,326,138	12,326,138
R^2	0.080	0.086	0.125	0.281	0.282
Fixed Effects	'No'	'No'	'Subgroup'	'Subgroup*Time'	'Subgroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of antibiotics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if a patient consumes the cheapest available option in a substitution group. Med is a dummy that takes the value 1 if an individual has a medical education. Log(Income) is the logarithm of income. Education indicates if the model controls for the level of education according to the grades on a six-step grid. Geographical indicates if the model controls for county-level fixed effects. Fixed Effects indicates if the model controls for substitution group or substitution × month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 26: Antibiotics: Regression Results, Opposed Substitution

	(1) Opp.	(2) Opp.	(3) Opp.	(4) Opp.	(5) Opp.
Med	-0.0135***	-0.0262***	-0.0235***	-0.0233***	-0.0230***
	(0.000626)	(0.000685)	(0.000669)	(0.000638)	(0.000640)
Original	0.169***	0.171***	0.218***	0.411***	0.406***
	(0.000660)	(0.000671)	(0.000752)	(0.00126)	(0.00126)
Generic	-0.0122***	-0.0124***	-0.0206***	0.0291***	0.0282***
	(0.000533)	(0.000540)	(0.000535)	(0.000988)	(0.000986)
Log(Inc)		0.000650***	0.00134***	0.000530***	0.000470***
		(0.0000388)	(0.0000376)	(0.0000343)	(0.0000342)
Constant	0.0753***	0.0864***	0.0556***	-0.00102	0.0243***
	(0.000528)	(0.000779)	(0.000725)	(0.00106)	(0.00108)
Education	No	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	No	Yes
Observations	12,857,251	12,326,138	12,326,138	12,326,138	12,326,138
R^2	0.049	0.055	0.083	0.201	0.203
Fixed Effects	'No'	'No'	'Subgroup'	'Subgroup*Time'	'Subgroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of antibiotics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if a patient opposes substitution and does not consume the cheapest product in a substitution group. Med is a dummy that takes the value 1 if an individual has a medical education. $Log(Income)$ is the logarithm of income. Education indicates if the model controls for the level of education according to the grades on a six-step grid. Geographical indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group or substitution $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 27: Antibiotics: Regression Results, Physician opposes Substitution

Table 28: Prob. that physician opposes

	(1)	(2)	(3)	(4)	(5)
	DocOpp.	DocOpp.	DocOpp.	DocOpp.	DocOpp.
Med	0.00884***	0.00827***	0.00715***	0.00718***	0.00724***
	(0.000454)	(0.000469)	(0.000465)	(0.000462)	(0.000461)
Original	0.00440***	0.00420***	0.0120***	0.0191***	0.0185***
	(0.000277)	(0.000284)	(0.000325)	(0.000463)	(0.000464)
Generic	-0.00175***	-0.00181***	-0.0000352	0.00158***	0.00149***
	(0.000241)	(0.000247)	(0.000227)	(0.000323)	(0.000323)
Log(Inc)		0.0000395**	0.0000492***	0.0000368**	0.0000286*
		(0.0000138)	(0.0000137)	(0.0000137)	(0.0000137)
Constant	0.00568***	0.00844***	0.00276***	0.000604	0.00385***
	(0.000240)	(0.000329)	(0.000291)	(0.000369)	(0.000382)
Education	No	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	No	Yes
Observations	12857251	12326138	12326138	12326138	12326138
R^2	0.001	0.002	0.004	0.008	0.008
Fixed Effects	'No'	'No'	'Subgroup'	'Subgroup*Time'	'Subgroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of antibiotics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if the primary health care provider (physician) opposes substitution and therefore the patient does not consume the cheapest product in a substitution group. Med is a dummy that takes the value 1 if an individual has a medical education. $Log(Income)$ is the logarithm of income. Education indicates if the model controls for the level of education according to the grades on a six-step grid. Geographical indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group or substitution $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 29: Antiepileptics: Regression Results, Substitution to Cheapest Product

	(1) Cheap	(2) Cheap	(3) Cheap	(4) Cheap	(5) 'Opp.'
Med	-0.0235*	0.00133	0.00828	0.00488	0.00408
	(0.00949)	(0.00986)	(0.00909)	(0.00935)	(0.00932)
Original	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
Generic	-0.0429***	-0.0501***	-0.0737***	-0.182***	-0.182***
	(0.00150)	(0.00158)	(0.00224)	(0.00380)	(0.00380)
Log(Inc)		0.000367	-0.000330	0.0000270	0.000113
		(0.000310)	(0.000272)	(0.000266)	(0.000268)
Constant	0.962***	0.992***	1.005***	1.100***	1.096***
	(0.00107)	(0.00571)	(0.00453)	(0.00515)	(0.00577)
Education	No	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	No	Yes
Observations	543,738	500,363	500,363	500,363	500,363
R^2	0.003	0.009	0.052	0.155	0.157
Fixed Effects	'No'	'No'	'Subgroup'	'Subgroup*Time'	'Subgroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of antiepileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if a patient consumes the cheapest available option in a substitution group. Med is a dummy that takes the value 1 if an individual has a medical education. Log(Income) is the logarithm of income. Education indicates if the model controls for the level of education according to the grades on a six-step grid. Geographical indicates if the model controls for county-level fixed effects. Fixed Effects indicates if the model controls for substitution group or substitution × month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 30: Antiepileptics: Regression Results, Opposed Substitution

	(1)	(2)	(3)	(4)	(5)
	Opp.	Opp.	Opp.	Opp.	Opp.
Med	0.00598	-0.00388	-0.00862*	-0.00775*	-0.00745*
	(0.00365)	(0.00385)	(0.00356)	(0.00370)	(0.00369)
Original	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
Generic	0.0205***	0.0237***	0.0380***	0.0898***	0.0900***
	(0.000583)	(0.000635)	(0.000999)	(0.00207)	(0.00207)
Log(Inc)		-0.000314*	0.0000670	-0.0000564	-0.0000841
		(0.000144)	(0.000129)	(0.000129)	(0.000129)
Constant	0.00804***	-0.00442	-0.0127***	-0.0584***	-0.0559***
	(0.000413)	(0.00246)	(0.00205)	(0.00260)	(0.00282)
Education	No	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	No	Yes
Observations	543,738	500,363	500,363	500,363	500,363
R^2	0.002	0.005	0.028	0.073	0.074
Fixed Effects	'No'	'No'	'SubGroup'	'SubGroup*Time'	'SubGroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of antiepileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if a patient opposes substitution and does not consume the cheapest product in a substitution group. Med is a dummy that takes the value 1 if an individual has a medical education. $Log(Income)$ is the logarithm of income. $Education$ indicates if the model controls for the level of education according to the grades on a six-step grid. $Geographical$ indicates if the model controls for county-level fixed effects. $Fixed\ Effects$ indicates if the model controls for substitution group or substitution $\times$ month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

Table 31: Antiepileptics: Regression Results, Physician opposes Substitution

	(1) DocOpp.	(2) DocOpp.	(3) DocOpp.	(4) DocOpp.	(5) DocOpp.
Med	0.00890	0.00417	0.00316	0.00349	0.00364
	(0.00740)	(0.00766)	(0.00763)	(0.00752)	(0.00750)
Original	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
Generic	0.0145***	0.0159***	0.0241***	0.0334***	0.0332***
	(0.000892)	(0.000939)	(0.00142)	(0.00185)	(0.00184)
Log(Inc)		0.000253	0.000298	0.000258	0.000227
		(0.000188)	(0.000187)	(0.000187)	(0.000188)
Constant	0.00463***	-0.00874*	-0.0135***	-0.0216***	-0.0217***
	(0.000489)	(0.00357)	(0.00302)	(0.00319)	(0.00372)
Education	No	Yes	Yes	Yes	Yes
Geographical	No	Yes	No	No	Yes
Observations	543,738	500,363	500,363	500,363	500,363
R^2	0.001	0.006	0.007	0.012	0.015
Fixed Effects	'No'	'No'	'SubGroup'	'SubGroup*Time'	'SubGroup*Time'

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of antiepileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if the primary health care provider (physician) opposes substitution and therefore the patient does not consume the cheapest product in a substitution group. Med is a dummy that takes the value 1 if an individual has a medical education. Log(Income) is the logarithm of income. Education indicates if the model controls for the level of education according to the grades on a six-step grid. Geographical indicates if the model controls for county-level fixed effects. Fixed Effects indicates if the model controls for substitution group or substitution × month fixed effects. Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are reported in parentheses.

F Advertisement

In comparison to the US and other major economies marking is highly regulated. For example, advertisement of prescription drugs is not permitted in Sweden. Within this section I explore the possibility that advertisement for non-prescription (OTC) pharmaceuticals has spillover effects on the brand recognition related to perceived quality differences. I try to explore if the advertisement expenditures of OTC drugs is correlated with the perceived quality differences.

Figure 18 shows important characteristics for available non-prescriptions brands in the therapeutic group of pharmaceuticals. For each brand that spends any resources in advertisement on non-prescription drugs between 2010 and 2016 and offers at least one prescription painkiller, I show two key indicators. The market cap for advertising non-prescription drugs between 2010 and 2016 was approximately 3.6 billion SEK (around 410 million USD). First, I show the share of advertisement costs of the entire market for the specific brands. Second, I show the market share considering all painkillers for the six years conditional on being not the cheapest. One firm is responsible for nearly half of the advertisement costs of all non-prescription drugs. This company also has a high market share among those purchases of products that are not the cheapest (almost 30% of all painkillers). However, beyond the highest spending company, correlation between advertisement share of OTC drugs and the share of perceived quality differences is not observable.

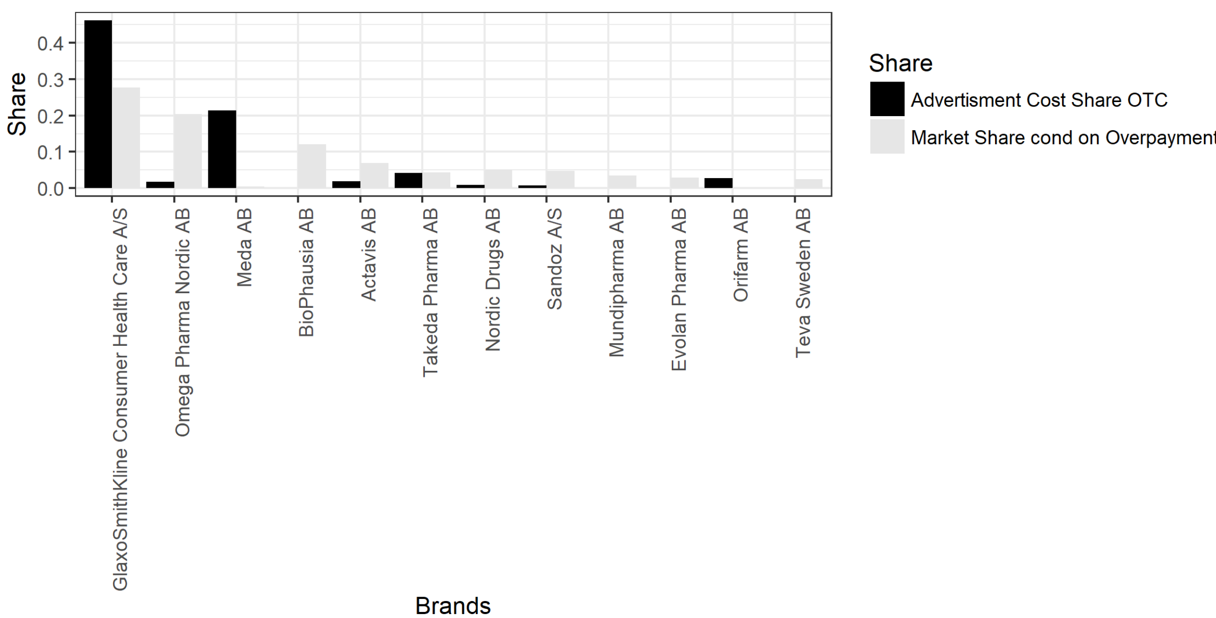
Results are similar for antibiotics but here even a the top spending company does not receives a particular market share of those patients who overpay.[5] For antiepileptics results are different. Only two brands who offer antiepileptics are also in the market for non-prescription drugs. A large market share of antiepileptics is due to these companies not offering OTC drugs.[6] Further, the two brands that are present in the market of OTC drugs spend very little on advertisement but hold a substantial market share within the antiepileptics segment.

The results do not exclude the possibility that there are spillover effects from OTC on brand recognition which itself has an effect on perceived quality differences. However, the correlation is not strong such that I suspect other channels for perceived quality differences beyond brand recognition or advertisement.

[5]See Figure 19.

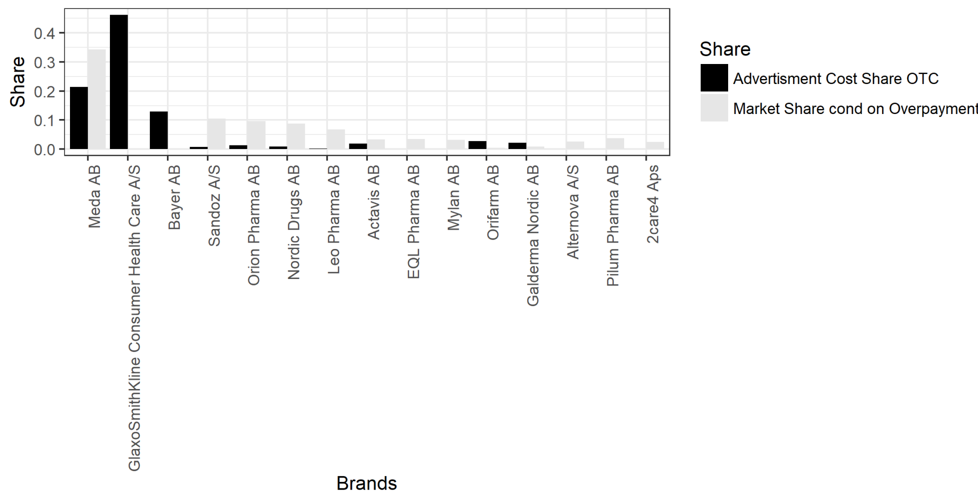
[6]See Figure 20

Figure 18: Painkillers: Advertisement Expenditure and Market Shares for Prescription Drugs



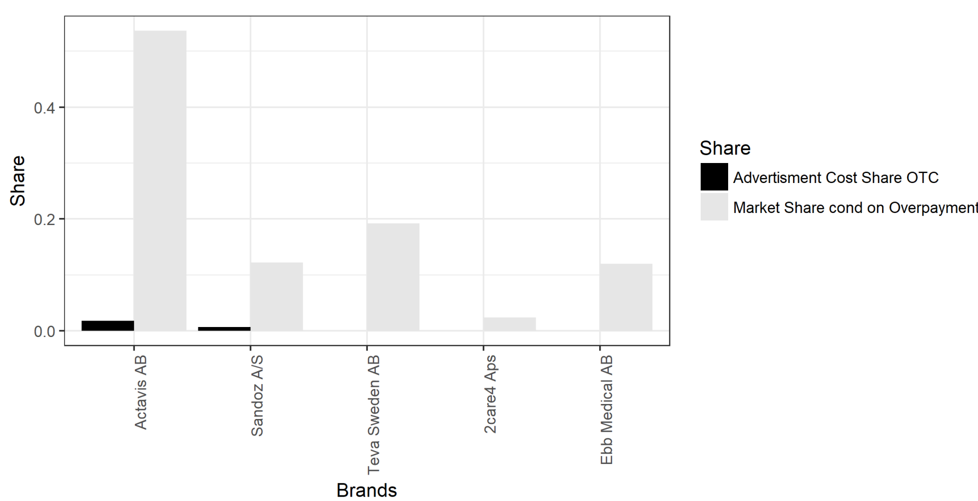
Relation between advertisement expenditure for OTC drugs, the market shares for prescription painkillers and the share of brands conditional on opposed substitution by patients. There are two bars for each brand that had advertisement expenditure between 2010 and 2016 and at least one prescription painkiller. The advertisement cost share corresponds to the share of advertisement expenditure of the entire expenditure for OTC drugs (total market cap of approx. 410 million USD). Market share describes the market share of a brand given all prescription drugs conditional on being not the cheapest one.

Figure 19: Antibiotics: Advertisement Expenditure, Market Shares



Relation between advertisement expenditures for OTC drugs, the market shares for prescription antibiotics and the share of brands conditional on opposed substitution by patients. There are two bars for each brand that had advertisement expenditure between 2010 and 2016 and at least one prescription painkiller. The advertisement cost share corresponds to the share of advertisement expenditure of the entire expenditure for OTC drugs (total market cap of approx. 410 million USD). Market share describes the market share of a brand given all prescription drugs conditional on being not the cheapest one.

Figure 20: Antiepileptics: Advertisement Expenditure, Market Shares



Relation between advertisement expenditures for OTC drugs, the market shares for prescription antiepileptics and the share of brands conditional on opposed substitution by patients. There are two bars for each brand that had advertisement expenditure between 2010 and 2016 and at least one prescription painkiller. The advertisement cost share corresponds to the share of advertisement expenditure of the entire expenditure for OTC drugs (total market cap of approx. 410 million USD). Market share describes the market share of a brand given all prescription drugs conditional on being not the cheapest one.

G Demand Model

G.1 Technical Details

Using the choice set I estimate the following structural equation.

$$u_{ijst} = \gamma_{ijs} + \rho_{is} y_{ijs,t-1} + \alpha_{is} p_{jst} + \mu_{is} y_{ijs,FIRST} + \lambda \kappa_{jst} + \varepsilon_{ijst}, \tag{2}$$

where ε_{ijst} is independent and identically distributed extreme value type two error. Given the assumption about the error term, one can separate the utility in a deterministic and unobservable part, that is, $U_{ijst} = V_{ijst} + \varepsilon_{ijst}$. The choice probability is then given by[7]

$$P_{ijst} = \frac{e^{V_{ijst}}}{\sum_{k=1}^{K} V_{ijst}}.$$

Note that $K = K_{it}$ denotes the choice set and varies for each consumer i with the choice set at time period t. The deterministic part of the utility relates to the coefficients and variables presented in the structural Equation 2. Let θ be the vector of parameters that is to be estimated and β be some individual specific random effects. The unconditional probability of a particular sequence of choices from an individual is then defined as

$$P_i(\theta) = \int \prod_{t=1}^{T} \prod_{j=1}^{K} [P_{ijst}]^{\mathscr{I}_{ijst}} f(\beta|\theta) \mathrm{d}\beta.$$

The unconditional probability takes into account that an individual makes several choices. $\mathscr{I}_{ijst}$ is an indicator that takes the value 1 if the patient chooses j in t from choice set K_{it}. $f(\beta|\theta)$ is the density function of β and is assumed to be normally distributed. Estimation follows by maximizing the log-likelihood function $LL(\theta) = \sum_i ln(P_i(\theta))$, the sum of the choice probabilities across individuals. The likelihood has to be simulated as it is not a closed form. The log likelihood is simulated by 'Halton-draws', meaning that for each parameter estimate θ, one draws values of β. As suggested by use 50 draws and take the average of

[7] Train (2009) provides a summary of all necessary derivations.

Table 32: Elasticity of Demand

	Orig	Brand Gen I	Brand Gen II	Gen I	Gen II	Gen III	Gen IV
Original	-2.811	.606	2.644	1.780	2.985	3.385	1.542
Brand Generic I	.827	-1.294	.224	1.397	1.859	1.449	1.281
Brand Generic II	1.182	.060	-2.722				
Generic I	.242	.146		-3.358	.019		.627
Generic II	.580	.314		.046	-4.595	1.487	.236
Generic III	.046	.016			.089	-5.572	
Generic IV	.121	.085		.372	.060		-3.402

This table shows the average own-price elasticities and average cross-price elasticieties of different Paracetamol, 1 gr., 100 Tablet products. Each cell is elasticity of column demand with respect to row price. Blank cells denote product combinations that have not been available at the same time.

the likelihood function. The final likelihood that is maximized takes the following form

$$SLL(\theta) = \sum_i ln \left\{ \frac{1}{100} \sum_{r=1}^{100} \prod_{t=1}^{T} \prod_{j=1}^{K} [P_{ijst}^{[r]}]^{\mathscr{I}_{ijst}} \right\}$$

$P_{ijst}^{[r]}$ is the probability of the r-th draw for patient i. Given the estimates of the structural equation, one can compute individual-choice probabilities and market shares.

G.2 Elasticity of Demand

In the following I show own-price as well ass cross-price elasticities of demand implied by the demand estimation in the main specification. Table 32 shows results for all patients, while I restrict the sample to those patients with a medical education in Table 33. The major results are the following: The own price elasticity of demand are high (between -1.3 to -5.6 for the whole sample). The cross price elasticities are positive and demand of products is especially sensitive to prices of originals and branded generic. Comparing elasticties from experts to non-experts, all elasticties of demand are higher for the sample of patients with medical education.

G.3 Robustness Check: Full Sample, Less Flexible Model, Initial Condition Problem

In the main specification of the structural model I estimate the demand using a highly flexible model with random coefficients. Estimation of the mixed-logit specification requires simulation of the the likelihood

Table 33: Elasticity of Demand, Sample with medical Education

	Orig	Brand Gen I	Brand Gen II	Gen I	Gen II	Gen III	Gen IV
Original	-3.327	1.013	3.370	2.026	3.321	2.929	1.966
Brand Generic I	1.088	-2.019	.234	1.628	2.615	2.144	1.572
Brand Generic II	1.352	.070	-3.448				
Generic I	.258	.174		-4.145	.027		.742
Generic II	.686	.527		.089	-5.543	1.525	.295
Generic III	.064	.024			.100	-6.050	
Generic IV	.171	.132		.801	.076		-4.3256

This table shows the average own-price elasticities and average cross-price elasticieties of different Paracetamol, 1 gr., 100 Tablet products for the sample of medical experts. Each cell is elasticity of column demand with respect to row price. Blank cells denote product combinations that have not been available at the same time.

function as described in section G.1. Due to the computational limitation I use a random sample of patients within my main specification. Within this robustness check I show that estimates of switching costs and perceived quality differences are robust to using the full sample in a less flexible demand estimation. Furthermore I extend the approach of controlling for the initial condition problem. In detail, consider the following utility function:

$$u_{ijst} = \gamma_{js} \times p_{jst} + \rho_s y_{ijs,t-1} + \alpha_s p_{jst} + \mu_s y_{ijs,FIRST} + C_i + \lambda \kappa_{jst} + \varepsilon_{ijst},$$

where ε_{ijst} is independent and identically distributed extreme value type two error. In comparison to the main specification I exclude the random coefficients of prices and previous choices. However, I include interactions with non-random price intercepts and prices to allow for heterogeneous elasticities. In the mixed logit approach of the main specification I control for initial choices. The approach follows the approach of Wooldridge (2005). However, I assume that the initial choice is as good as random which is unlikely as I do not observe the entire medical history of a patient and my first observed choice may already be endogenous. Wooldridge (2005) recommends to condition the unobserved household effects on the initial values as well as exogenous variables. Rabe-Hesketh and Skrondal (2013) describe an adjustment by using the within means of time varying variables as well as including the initial periods values. The authors argue that the inclusion of the initial condition of time varying covariates as well as the within means may reduces the bias. In the main specification I do not observe sufficient time variant covariates. Excluding the random coefficient allows to follow the approach of Rabe-Hesketh and Skrondal (2013) and include within means of individual specific time-variant variable (as income) $\bar{X}_i$ and initial observed values X_{i0}, such that $C_i = \beta_1 \bar{X}_i + \beta_2 X_{i0}$.

First you find the first stage of the control function in Table 34 (t-statistics of 2309). The results of the full sample are almost identical to the ones from the random sample. In Table 35 I present the result of the less flexible logit model considering the full sample. Compared to the main specification (random sample and random coefficient) main results are the same. The full sample as well as the sample of medical experts experience switching costs (state dependent coefficients in Mod.2 and Mod.2-Med are significant and 1.959 and 1.538 respectively). Also, medical experts are less likely to pay brand premia due to switching costs (similar to the main specification the brand intercepts of the branded Generic I are smaller among experts).

Table 34: First Stage of Control Function, Full Sample

	(1)
	Price
Price of Other Painkillers	0.237***
	(0.00037)
Constant	53.715***
	(0.020)
N	8,362,460

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results of the first stage estimation. One observation is the price of a product in the substitution group paracetamol, 1 g., 30 tablets. The regressor is the average price of other products of the same manufacturer in the Swedish market for painkillers. Standard errors in parentheses.

G.4 Robustness Check: Robustness Missing Instruments

Within this section I perform a robustness check of the control function presented in Section 6. Table **??** shows that the integration of the control function where I instrument prices of products with prices of the same competitor in other substitution groups leads to a reduced sample size. The reason for this effect is that some products in my sample do not have instruments because the same manufacturer does not produce pharmaceuticals in other substitution groups. In the first approach I excluded those observation. In this section I instrument the prices with the own prices (of the respective firm) to avoid any reduction in the sample size. I present the results in Table 36. Note that the only changes take place in Model 2 and Model 2-Med as I include the control function. Compared to the results in the main section (Table **??**), changes are small and the main intuition does not change.

Table 35: Regression Results Demand Model, Robustness Check: Full Sample, Less Flexible Model

	Mod.l	Mod.1-Med	Mod.2	Mod.2-Med
Branded Generic I	1.185***	.374***	1.425***	.780***
	(.004)	(.049)	(.005)	(.054)
Branded Generic I × Price	-.004***	-.002***	-.003***	-.001**
	(.00004)	(.0005)	(.00005)	(.0005)
Branded Generic II	.618***	.260***	-.096***	-.045
	(.009)	(.074)	(.007)	(.081)
Branded Generic II × Price	-.003***	-.002**	-.005***	.004***
	(.00006)	(.0007)	(.00006)	(.0008)
Generic I	-.504**	-.076	.039***	.558***
	(.007)	(.076)	(.010)	(.101)
Generic I × Price	-.003***	-.004***	-.005***	-.004**
	(.00008)	(.0008)	(.0001)	(.001)
Generic II	-1.104***	-.739***	-.572***	-.131
	(.007)	(.070)	(.007)	(.074)
Generic II × Price	-.003***	-.003**	-.002***	-.002**
	(.00007)	(.0007)	(.00007)	(.0008)
Generic III	-1.799***	-1.549***	-.958***	-.394
	(.012)	(.154)	(.022)	(.241)
Generic III × Price	-.005***	-.008***	-.001***	-.003
	(.0001)	(.002)	(.0002)	(.003)
Generic IV	-.774***	-.184	-.148***	.541***
	(.011)	(.111)	(.011)	(.114)
Generic IV × Price	-.004***	.004**	-.008***	-.005***
	(.0001)	(.001)	(.0001)	(.001)
Price Mean	.002***	.001***	.009***	.005***
	(.00003)	(.0003)	(.00005)	(.0006)
State Dependence Mean	1.999***	1.497***	1.959***	1.548***
	(.004)	(.053)	(.004)	(.059)
Constant	-.575***	-.3430***	-1.946***	-1.587***
	(.005)	(.068)	(.006)	(.084)
Control Function	no	no	yes	yes
Unobserved Heterogeneity	no	no	yes	yes
Income Control	yes	yes	yes	yes
Log-Likelihood	-5,084,273.9	-40,283.4	-4,222,533	-33,887.3
N	8,943,879	63,571	8,041,387	57,322

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results from the logit estimation. One observation is a patient choice in the substitution group of paracetamol 1 g., 30 tablets. The outcome variable is a dummy that indicates if an individual has chosen a product. Mod.1 and Mod.2 consider the whole sample whereas Mod.1-Doc, Mod.2-Doc solely consider patients with a medical education. The upper part of the table shows product-specific intercepts, dependent on branded generics and generics, the default value is an original. Each coefficient is intereacted with the price. The lower part of the table shows coefficient state dependence. Control Function indicates if the control function approach for endogenous prices has been used. Unobserved Heterogeneity indicates if the model controls for problems due to unobserved heterogeneity, i.e. including within means and initial values of income as well as the initial choice dummy. Standard errors are reportet in parentheses

Table 36: Regression Results Demand Model, Robustness Check: Missing Instruments

	Mod.l	Mod.1-Med	Mod.2	Mod.2-Med
Branded Generic I	.609***	.280**	0.753***	.518***
	(.007)	(.086)	(.014)	(.153)
Branded Generic II	.245***	.122	-.607***	-.766**
	(.009)	(.110)	(.023)	(.210)
Generic I	-.792**	-.632***	.117***	-.129
	(.015)	(.164)	(.018)	(.207)
Generic II	-1.164***	-631 ***	-.615***	-.758***
	(.013)	(.139)	(.016)	(.172)
Generic III	-1.894***	-1.731***	-1.378***	-1.130***
	(.020)	(.213)	(.023)	(.257)
Generic IV	-1.180***	-.856**	-.521***	-.401
	(.024)	(.271)	(.029)	(.337)
Random Brand Intercepts	No	No	Yes	Yes
Price Mean	-.097***	-.167***	-.116***	-.127***
	(.003)	(.028)	(.002)	(.024)
σ	.396***	.285***	.191***	.267***
	(.004)	(.041)	(.003)	(.038)
State Dependence Mean	2.02***	1.70***	.865***	1.016*
	(.022)	(.353)	(.018)	(.395)
σ	.756***	.038	.029***	.146
	(.034)	(.764)	(.029)	(.558)
Control Function	no	no	yes	yes
Unobserved Heterogeneity	no	no	yes	yes
WTP State Dependence (USD)	2.08	1.02	0.745	0.80
Log-Likelihood	-170,687	-1,197	-126,327.82	-1,005.02
N	655,228	3,873	655,228	3,873

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results from the mixed logit estimation. One observation is a patient choice in the substitution group of paracetamol 1 g., 30 tablets. The outcome variable is a dummy that indicates if an individual has chosen a product. Mod.1 and Mod.2 consider the whole sample whereas Mod.1-Doc, Mod.2-Doc solely consider patients with a medical education. The upper part of the table shows product-specific intercepts, dependent on branded generics and generics, the default value is an original. The lower part of the table shows the random coefficients for price and the state dependence. Note that I also report the standard deviation or the random coefficients. Control Function indicates if the control function approach for endogenous prices has been used. Unobserved Heterogeneity indicates if the model controls for problems due to unobserved heterogeneity. WTP State Dependence shows the point estimates of the average willingness to pay for state dependence, i.e. how much an average patient is willing to pay in order to receive the same product as in the last period.

G.5 Robustness Check: Co-payment adjusted Prices

Within this section I describe the results of the demand estimation using individual specific prices p_{ijst} that incorporate the differences in co-payment between consumers. The demand estimation involves a control function approach, results of the new first stage are reported in Table 37. The correlation between other painkillers and the products of interest is less strong than in the main specification as the prices are now also dependent on the co-payment of an individual. In Table 38 I show results for the full sample as well as the sample of medical experts. Model 2 and Model 2.Med include the control function approach. The results are in line with the ones presented in the main analysis.

Table 37: First Stage of IV Regression, Copayment adjusted prices

	(1) Price
Price of Other Painkillers	.0624***
	(.0004)
Constant	31.989***
	(0.0853)
N	623,017

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results of the first stage estimation. One observation is the co-payment adjusted price of a product in the substitution group paracetamol, 1 g., 30 tablets. The regressor is the average price of other products of the same manufacturer in the Swedish market for painkillers. Standard errors in parentheses.

G.6 Robustness Check: Forward Looking/ Myopic Patients

My demand estimation assumes that consumers are myopic and not forward looking. First of all the modeling decision is based on the fact that patients receive quantity invariant prescriptions and cannot stockpile prescription drugs. Secondly, it is unlikely that consumers know about future price developments. Third, the savings of stockpiling are not high (see section B.2). Within this section I show the lack of correlation between the quantity and price of a purchase. In case that patients are forward looking we expect that low prices or sales are at least correlated with higher quantities.[8] In the following linear regression I show that patients are not more likely to increase their quantity during an individual purchase occasion when prices

[8] Following Hendel and Nevo (2006) the negative correlation between prices and quantity is expected both from consumer stockpiling as well as from the negative slope of the demand curve. As negative correlation is necessary but not sufficient the authors develop further conditions to show that consumers are forward looking and not myopic. In case that there is no correlation between quantity and price, forward looking patients are unlikely for positive valued goods.

Table 38: Regression Evidence, Demand Model, Co-payment adjusted prices

	Mod.l	Mod.1-Med	Mod.2	Mod.2-Med
Branded Generic I	.695***	.327**	0.934***	.719***
	(.008)	(.093)	(.015)	(.159)
Branded Generic II	.251***	.123	-.883***	-1.241**
	(.009)	(.110)	(.025)	(.252)
Generic I	-1.648**	-1.437***	-.349***	-.682*
	(.020)	(.228)	(.023)	(.286)
Generic II	-1.488***	-1.436***	-.606***	-.851***
	(.015)	(.159)	(.017)	(.186)
Generic III	-2.095***	-1.999***	-.876***	-.955
	(.022)	(.242)	(.048)	(.587)
Generic IV	-1.926***	-2.104**	-1.276***	-2.01***
	(.031)	(.389)	(.036)	(.469)
Random Brand Intercepts	No	No	Yes	Yes
Price Mean	-.501***	-.720***	-.214***	-.376***
	(.008)	(.105)	(.003)	(.067)
σ	1.12***	.791***	.350***	.500***
	(.014)	(.117)	(.005)	(.066)
State Dependence Mean	2.112***	1.916***	1.038***	1.719**
	(.025)	(.422)	(.021)	(.594)
σ	.698***	.192	.069	.882
	(.040)	(1.138)	(.036)	(.931)
Control Function	no	no	yes	yes
Unobserved Heterogeneity	no	no	yes	yes
Log-Likelihood	-155,619.02	-1,082.05	-104,616.01	-787.04
N	655,228	3,873	555,685	3,267

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results from the mixed logit estimation with Co-payment adjusted prices. One observation is a patient choice in the substitution group of paracetamol 1 gr., 30 tablets. The outcome variable is a dummy that indicates if an individual has chosen a product. Mod.1 and Mod.2 considers the random sample (1/6th of the full sample, random selection) whereas Mod.1-Med and Mod.2-Med solely consider patients with a medical education within the random sample. The upper part of the table shows product-specific intercepts, dependent on branded generics and generics, the default value is the original. Note that the coefficients are partly random and estimates of standard deviations are excluded. The lower part of the table shows the random coefficients for price and the state dependence. Note that I also report the standard deviation or the random coefficients. Control Function indicates if the control function approach for endogenous prices has been used. Unobserved Heterogeneity indicates if the model controls for problems due to unobserved heterogeneity.

decrease. I argue that the non-relation is in line with the argumentation that modeling consumer myopic is adequate.

Consider consumer i purchasing product j at t for price p_{ijt}. Consumer j get dispensed quantity q_{ijt}. I show regression evidence for the following model:

$$q_{ijt} = \alpha_j + \beta p_{ijt} + \varepsilon_{ijt},$$

where α_j are brand intercepts. I present the results for the substiution group of Paracetamol 1 g, 100 tablets in Table 39. A higher price is only very low (a 10 USD dollar increase is associated with 0.02 more products during a purchase) and positive correlated with the quantity a patient purchases (p-value: 5%). The result shows that patients are either not able to increase purchases in times of higher prices (as prescriptions are connected to a fixed quantity) or they are not forward looking. The results support the modeling decisions of myopic consumers.

Table 39: Regression Evidence, Myopic Consumers

	Quantity
Price	0.000227*
	(0.000114)
Brand Intercepts	Yes
Observations	3949673
R^2	0.005

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression results for the segment of Paracetamol 1 g, 100 tablets. One observation corresponds to an individual purchase. The outcome variable is the price. Price is the price of a product. Standard errors are reported in parentheses.

G.7 Robustness Check: Advertisement and Exclusion Restriction

In section F I show a lack of strong correlation between advertisement (in the OTC drug market) and brand premia due to perceived quality differences (in the prescription drug market). However advertisement may still be a problem for the exclusion restriction in the control function approach. I instrument prices of paracetamol with prices of different painkillers of the same manufacturer in the same month. The exclusion restriction says that correlation between prices is due to cost side factors and not induces by demand. While prescriptions for substitution groups restrict substitution between products of a manufacturers in different substitution groups, it is possible that sporadic advertisement expenditure effects a manufacturers demand in all substitution groups. Further, it is likely that the demand shock due to advertisement would correlated with price changes in all substitution groups. The exclusion restriction would be violated.

Note first, that advertisement for pharmaceutical products in Sweden is highly regulated. Only marketing activity for OTC drugs is allowed and effects would be dependent on spillover effects from the OTC drug market on the prescription drug market. In section F I show that there is no strong correlation between brand premia and advertisement, in the following I show one does not observe correlation between advertisement expenditures of manufacturers and prices. As prices and advertisement are uncorrelated I do not expect violation of the exclusion restriction due to advertisement. Consider manufacturer j that spends advertisement resources Adv_{jt} and sets price for his paracetamol product of p_{jt}. In the following I show the result of a linear regression of prices of prescription paracetamol products on advertisement expenditure of OTC drugs for the same manufacturer, $p_{jt} = \alpha + \beta Adv_{jt} + \varepsilon_{jt}$. Further, I explore if lagged advertisement expenditures are correlated with prices.

Table 40 shows that neither the advertisement expenditure nor the lagged advertisement expenditure of OTC drugs is correlated with prices of prescription pharmaceuticals. The result supports that advertisement of OTC drugs do not violate the exclusion restrictions of prices.

Table 40: Regression Evidence, Advertisement and Prices

	Price			
	(1)	(2)	(3)	(4)
Adv	0.00002 (0.00002)			
Adv_{t-1}		0.00003 (0.00002)		
Adv_{t-2}			0.00004^{*} (0.00002)	
Adv_{t-3}				0.00004 (0.00002)
Constant	72.043^{***} (0.304)	71.982^{***} (0.306)	71.852^{***} (0.305)	71.853^{***} (0.306)
N	176	175	174	173

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

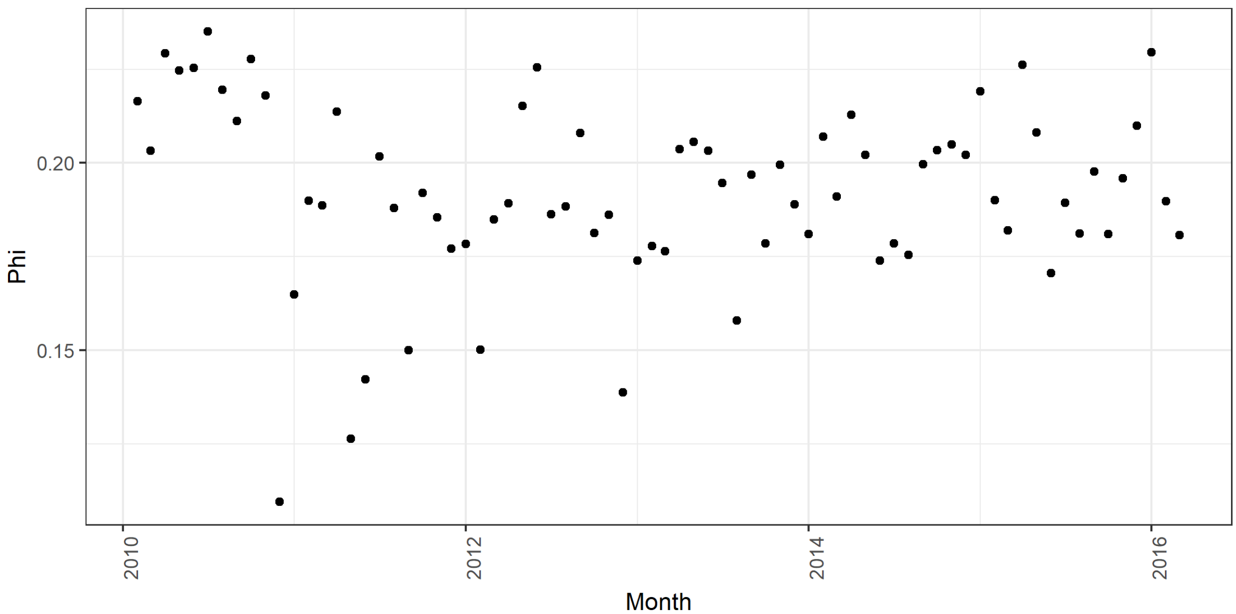
Linear least square regression results for the segment of paracetamol. One observation corresponds to one manufacturer/brand. The outcome variable is the price. Adv is the advertisement expenditure of a manufacturer for OTC drugs. Adv_{t-1} *to* Adv_{t-3} *are lagged advertisement expenditures. Standard errors are reported in parentheses.*

H Supply Model

H.1 Aggregate Transition Probabilities

Figure 21 shows the fraction of consumers that stay in a market at t to $t+1$.

Figure 21: Share of Staying Patients, ϕ



Monthly ϕ_t, the fraction of consumers that stay in a market at t to $t+1$, where one period corresponds to a calendar month. If a patient purchases the same product at least once in two subsequent months, he or she is considered as staying in the market.

H.2 Marginal Cost Estimates

Month and firm-specific marginal cost estimates:

H.3 Correlation between Markups and Marginal Costs

In Table 42 I show estimates of markups that directly follow from observable prices and the time- and firm specific marginal costs. The markups are positive on average for all but one product. Further the variability of markups is comparable to those of the marginal costs.

To test if the price variability is captured by changes in marginal costs I run a reduced form regression of prices on marginal costs. In detail consider the following model where j corresponds to a firm and t to a

Table 41: Marginal Cost Estimates, Time and Product Specific

Time Period	Original		Brand.Generic I		Brand.Generic II		Generic I		Generic II		Generic III		Generic IV	
1	3.17	(1.12)			9.04	(1.12)								
2	4.67	(1.21)			10.65	(0.4)								
3	3.59	(1.42)			9.85	(0.27)								
4	3.04	(1.14)			9.13	(1.45)								
5	3.74	(1.4)			10.77	(0.56)								
6	2.32	(0.93)			10.41	(1.24)								
7	1.14	(0.3)			9.73	(1.4)								
8	3.66	(1.33)			9.95	(0.47)								
9	2.28	(0.37)			10.01	(1.12)								
10	2.56	(0.68)			11.18	(0.6)								
11	4.27	(1.25)			11.32	(1.08)								
12	18.35	(0.3)	20.59	(0.11)	15.28	(0.2)								
13	14.01	(0.16)	17.02	(0.09)	15.13	(0.39)								
14	12.95	(0.25)	15.55	(0.13)	14.23	(0.23)								
15	14.22	(0.16)	16.59	(0.14)	15.23	(0.25)								
16	13.65	(0.12)	14.93	(0.14)	14.09	(0.37)								
17	11.71	(0.53)	6.28	(0.85)							11.18	(0.2)		
18	10.96	(1.06)	13.81	(0.13)							11.86	(1.52)		
19	11.22	(1)	13.45	(0.17)							10.07	(0.27)		
20	11.53	(0.49)	9.24	(0.56)							10.99	(0.2)		
21	12.87	(0.38)	13.74	(0.26)							12.38	(0.22)		
22	12.76	(0.26)	13.69	(0.18)							11.98	(0.28)		
23	14.77	(0.22)	16.48	(0.16)					12.68	(0.18)	12.05	(0.15)		
24	15.41	(0.32)	9.88	(0.2)					13.07	(0.15)	11.93	(0.3)		
25	16.95	(0.17)	11.64	(0.15)					12.95	(0.21)	14.54	(0.35)		
26	14.94	(0.27)	10.43	(0.34)					12.83	(0.44)	12.67	(0.19)		
27	18.95	(0.07)	16.04	(0.14)					14.69	(0.32)	17.95	(1.57)		
28	17.65	(0.15)	11.06	(0.08)					15.28	(0.23)	12.23	(0.2)		
29	19.33	(0.1)	13.57	(0.22)					19.69	(1.93)	15.76	(0.21)		
30	19.07	(0.17)	13.13	(0.18)					15.68	(0.16)	15.62	(0.37)		
31	18.32	(0.26)	13.66	(0.14)					13.33	(0.2)	15.43	(0.49)		
32	18.84	(0.15)	10.73	(0.04)					13.36	(0.17)	15.20	(0.32)		
33	18.68	(0.15)	10.56	(0.08)					13.36	(0.06)	15.34	(0.29)		
34	20.19	(0.24)	14.54	(0.13)					15.20	(0.29)	16.06	(0.09)		
35	19.70	(0.18)	14.35	(0.05)					14.40	(0.27)	16.01	(0.35)		
36	16.22	(0.13)	13.80	(0.11)					13.95	(0.21)	11.70	(0.43)		
37	19.24	(0.08)	15.97	(0.11)					14.69	(0.21)	15.76	(0.15)		
38	18.65	(0.11)	13.89	(0.09)					13.69	(0.25)	15.62	(0.42)		
39	15.99	(0.08)	14.74	(0.09)					13.64	(0.11)	14.41	(0.49)		
40	17.06	(0.09)	16.04	(0.12)					17.23	(1.6)	15.20	(0.19)		
41	18.60	(0.12)	14.17	(0.12)					14.12	(0.44)	16.20	(0.44)		
42	18.11	(0.19)	13.47	(0.14)					14.87	(0.07)	12.55	(0.27)		
43	16.78	(0.1)	15.36	(0.06)					15.66	(0.34)	15.69	(0.28)		
44	18.17	(0.14)	11.56	(0.07)					15.46	(0.21)	15.97	(1.68)		
45	19.07	(0.15)	11.90	(0.19)					16.21	(0.21)	15.84	(0.31)		
46	17.94	(0.12)	13.27	(0.08)					13.66	(0.33)	14.05	(0.19)		
47	18.74	(0.13)	13.05	(0.13)					13.63	(0.26)	15.50	(0.17)		
48	18.28	(0.14)	15.37	(0.12)			16.56	(0.32)	14.31	(0.21)	14.57	(0.36)		
49	19.35	(0.37)	16.13	(0.05)			17.76	(0.21)	15.88	(0.13)	14.53	(0.38)		
50	17.54	(0.17)	13.68	(0.1)			20.09	(1.47)	15.20	(0.31)			12.62	(0.34)
51	18.02	(0.24)	14.80	(0.05)			16.09	(0.3)	13.88	(0.29)			14.03	(0.22)
52	18.23	(0.21)	13.65	(0.08)			23.44	(1.21)	13.10	(0.31)			17.21	(1.27)
53	18.08	(0.19)	15.09	(0.06)			15.54	(0.18)	14.95	(0.19)			14.06	(0.4)
54	15.27	(0.25)	12.94	(0.11)			17.70	(1.13)	15.11	(0.31)			15.02	(0.15)
55	18.05	(0.26)	15.24	(0.08)			15.95	(0.17)	14.71	(0.43)			14.79	(0.19)
56	18.44	(0.17)	14.97	(0.07)			15.58	(0.37)	14.89	(0.57)			14.35	(0.25)
57	18.09	(0.17)	13.31	(0.1)			16.11	(0.4)	15.33	(0.19)			12.31	(0.31)
58	18.41	(0.19)	14.20	(0.12)			19.77	(1.72)	12.79	(0.35)			17.46	(1.23)
59	17.92	(0.18)	13.84	(0.07)			17.55	(1.19)	15.47	(0.25)			12.40	(0.31)
60	17.16	(0.19)	14.61	(0.07)			15.14	(0.32)	13.78	(0.15)			13.69	(0.36)
61	18.12	(0.17)	14.12	(0.16)			20.70	(1.65)	16.04	(0.32)			11.35	(0.36)
62	14.37	(0.23)	14.45	(0.1)			18.35	(1.72)	14.58	(0.34)			14.27	(0.29)
63	18.31	(0.22)	16.07	(0.06)			16.35	(0.2)	15.24	(0.24)			14.63	(0.28)
64	18.16	(0.16)	15.64	(0.11)			15.56	(0.12)	14.50	(0.2)			13.53	(0.37)
65	17.86	(0.19)	13.44	(0.11)			15.69	(0.32)	15.64	(0.44)			11.59	(0.39)
66	18.34	(1.01)	12.32	(0.13)			21.52	(1.62)					17.21	(1.34)
67	12.55	(0.27)	13.10	(0.1)			13.78	(0.16)					9.62	(0.16)
68	17.43	(0.59)	13.82	(0.14)			14.33	(0.28)					13.54	(0.28)
69	15.77	(0.26)	13.82	(0.1)			17.46	(1.14)					12.14	(0.23)
70	15.30	(0.32)	14.58	(0.21)			15.34	(0.41)						
71	15.56	(0.23)	14.43	(0.19)			14.37	(0.14)						
72	13.98	(0.35)	12.70	(0.1)			15.17	(0.14)						
73	15.64	(0.25)	14.20	(0.15)			14.55	(0.4)						
74	15.83	(0.14)	14.15	(0.1)			15.24	(0.23)						

Marginal costs estimates (in SEK) for each brand in the time between 2010 and 2016. Periods are monthly and sequentially numbered from 1 to 74. The monthly periods represent the time between 2010 and 2016. Within each period for each competitor marginal costs are estimated. Note that the standard errors are obtained by bootstrapping and reported in parentheses.

Table 42: Markup Estimates

Firm	Mean Markups	Standard Deviation
Original	10.82	7.08
Branded Generic I	11.1	4.10
Branded Generic II	16.02	2.86
Generic I	5.96	3.91
Generic II	10.27	3.26
Generic III	12.38	3.64
Generic IV	7.80	3.68

Summary of markup estimates (in SEK, 10 SEK approximately 1 USD) for different firms in the market of paracetamol, 1 g. 30 tablets. The markups are calculated directly from prices (whole say prices as a linear function of retail prices) and estimates of marginal costs. Note that the mark ups are mean markups estimated for each period a product has been present. Standard deviations are reported in the second column.

month.

$$MarginalCosts_{jt} = \alpha + Price_{jt} \times Firm_j + \varepsilon_{jt},$$

where $Firm_j$ are firm identifiers/dummies. In case that the marginal costs do indeed drive prices we expect a positive correlation between prices and marginal costs. Such a positive correlation could be interpreted of misspecified marginal costs as dynamic pricing does not drive price changes. Table 43 shows the results of the regression. Model (1) uses firm specific intercepts, Model (2) interacts the firm dummies with the prices. The results show that the correlation between prices and marginal costs is not significantly different from zero. I conclude that there is no evidence that marginal cost estimates explain price variation. Therefore price variation is possibly due to other incentive such as dynamic pricing.

I Counterfactual Analysis

I.1 Reduction of State Space

For computational feasibility I reduce the state space of firms. I reduce the state space by using a machine learning method.

First, I get back to the first stage of the previous approach of Bajari et al. (2007). I re-estimate the policy function that has been used to recover marginal costs. However, I use the LASSO that selects state variables

Table 43: Correlation Prices and Marginal Costs

	Price	
	(1)	(2)
Marginal Costs	-0.160^{*}	-0.252
	(0.063)	(0.210)
MC×Generic I		-0.707^{*}
		(0.298)
MC×Generic II		0.320
		(0.479)
MC×Generic III		-0.105
		(0.352)
MC×BrandGeneric II		0.252
		(0.378)
MC×Generic IV		0.100
		(0.482)
MC×Original		0.026
		(0.223)
Firm Specifc Intercepts	Yes	Yes
N	276	276

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Linear least square regression of prices on marginal costs. One observation corresponds to a firm's marginal costs and prices. Model 1 is a regression on firm specific intercepts and marginal costs while Model two interacts firm specific intercepts with marginal costs.

by shrinking coefficients within the policy function to zero. Econometrically the LASSO methods uses a standard least squares function with a penalty term on the coefficients. Due to the penaly some coefficients are exactly zero such that only the most important variables are non-zero. The method is related to the solution concept presented by Thiel (2019) who uses the two stage model by Bajari et al. (2007) with a lasso estimation in the first stage. Thiel (2019) further builds on the assumption that firms play a Sparse Markov Perfect Equilibrium, such that the second stage is build on the policy function estimated by the LASSO. In comparison, I use all state variables to recover marginal costs. However, I use a LASSO to reduce the state space in order to make the computation of a new Markov Perfect Equilibrium feasible. Consider the the same policy function as in the first stage of the two-stage estimation.

$$p_{jt} = \alpha + \beta m_{jt-1} + \eta |N_{t-1}| + \rho Q_t + \gamma PoM_{jt-1} + \varepsilon_{jt}. \tag{3}$$

I estimate equation 3 using a LASSO with a unit ($\lambda = 1$) strength of regularization. Table 44 shows three models. Model (1) is a regular OLS regression, model (2) shows coefficients of the LASSO, and model (3) an OLS regression using solely regressors with non-zero coefficients of the LASSO. The results show that the lagged product of the month status as well as the quantity are having non-zero coefficients in the LASSO estimation. Considering that my counterfactual analysis assumes that firms approximate the future market environment such as market size from current market conditions, the lagged product of the month status incorporates the important inter temporal association from past to current periods. In my counterfactual analysis I compute Markov Perfect Equilibria considering the previous PoM status as the state space.

I.2 Technical Details of Counterfactuals

Within this section I explain the technical details of the counterfactual derivation. Given the supply-side estimation I have firm- and period-specific marginal costs estimates. Knowing the market structure and not allowing for entry and exit, I reduce the state space significantly. In detail, I assume that firms condition their pricing solely on the knowledge of which firm was the PoM (has offered the cheapest product) in the last period. In the following I explain the details of deriving a Markov perfect equilibrium. Note that I the following steps of computation are performed in each period each period; I drop time subscripts for convenience.

There are $N = \{1, ..., n\}$ in the market. Each firm $j \in N$ sets a price $p_j \in P$. For the computation I use

Table 44: Policy Estimation, LASSO Regression

	Price		
	OLS	LASSO	Restricted OLS
	(1)	(2)	(3)
Share (t-1)	1.589^{*}	0	
	(0.797)		
$I(NoComp.(t-1)=3)$	0.062	0	
	(0.350)		
$I(NoComp.(t-1)=4)$	-0.286	0	
	(0.478)		
$I(NoComp.(t-1)=5)$	-0.286	0	
	(0.683)		
PoM(t-1)	1.752^{***}	0.128	2.047^{***}
	(0.474)		(0.399)
Quantity	0.0001^{***}	0.00005	0.0002^{***}
	(0.00003)		
Constant	61.182^{***}	68.669	59.28^{***}
	(2.203)		(1.784)
N	269	269	269
R^2	0.262		0.2344
Notes:	$^{***}p<0.001$, $^{**}p<0.001$, $^{*}p<0.05$		

Regression results for the estimation of the policy function. One observation corresponds to the monthly price of a product in the substitution group of paracetamol 1 g., 30 tablets. The outcome variable is the price of a product in period t. All regressors are potential state variables of the supply side: Share$(t-1)$ is the market share in the preceding period. $I(NoComp.(t-1)=3)$, $I(NoComp.(t-1)=4)$, and $I(NoComp.(t-1)=5)$ are dummies that take the value 1 if in the preceding period the number of firms was equal to 3, 4 or 5. PoM$(t-1)$ is a dummy that takes the value 1 if the firm was the cheapest product in the previous month. Model (1) is a linear least square regression. Model (2) is a LASSO regression with $\lambda=1$. Model (3) is a OLS regression using only the regressors with non-zero coefficients of the LASSO specification. Standard errors are reported in parentheses.

discrete values for the price, namely $P = \{12.71, 12.96, ..., 27.46, 27.71\}$. Note that the supply prices are directly linearly translated into retail prices for patients: $P^R = \{56.50, 56.80, ..., 74.20, 74.50\}$. Given the linear translation into retail prices I do not have to consider problems of double marginalization. Note also that the highest possible price is equal to the price ceiling. When estimating marginal costs I have considered a wide state space on which firms N condition their pricing strategy on past market shares, the number of competitors, the quantity of products and the past PoM status. To reduce the intense computational burden in the counterfactual analysis I reduce the state space remarkably to solely the PoM status, such that $\mathscr{S} = PoM$.[9] The state variable takes the value one if a firm has been PoM in the past period and zero otherwise, $PoM = \{1, 0\}$. Intuitively, firms based their strategy if they have been PoM in the previous period. I allow that strategies differ across different firms and within each periods.

Prices as well as the state variable determine supply-side determinants for demand $\hat{D}$. The demand is divided in two parts. A first part of the demand was already part of the market in the last period. A second part consists of new consumers. The share of the initial part is given by ϕ, a direct share from the data. Further, for the first part the state variable matters, as the demand estimates of state dependence is important. In practice I calculate $\hat{D}$ by considering both demand parts, incorporating the respective state variable. Finally, I simplify demand estimation in a similar fashion as done for the marginal cost estimation as in the previous sections. So for both demand fractions I consider the demand estimates and use the average consumer when evaluating random coefficients. In difference to the estimation of marginal costs I do not adjust choice sets as I assume that firms do not know about the identity of the previous firm which indeed would directly increase the probability of being in the choice set. In practice I assume that all products are in a choice set of the representative consumer. Therefore the previous PoM status does solely increase market shares through the state dependence parameter and not through the choice set. The second computational simplification on the demand side is that I do not keep track about potential correlation between the past choices of the average consumer and their initial choices. It is likely that initial choices are correlated with past choices such that the inter-temporal effects are higher. I therefore do not integrate the initial choices and reduce the effect of state dependence.[10] Overall the procedure of estimating equilibira requires three deviations from the marginal cost estimation: (1) A reduction of state space, however, (2) allowing for firm specific strategies. (3) An adjustment of choice sets.

[9] See Section I.1 for a motivation.

[10] Note that both simplifications decrease the computational burden immensely when forward simulating profits and therefore the demand. I access the fit when estimating the benchmark model where equilibrium prices are comparable to the actual data.

Static one-period profits are $\pi_j = \hat{D}_j(p_j - \hat{mc}_j)$ where $\hat{mc}_j$ are estimates of the marginal costs.

The structural model incorporates the dynamic feature of prices and demand. As in the estimation of marginal costs I assume that firms in a given period are forward looking. To decrease the computational burden, I have assumed that firms estimate that the consumers do not change. Also in the counterfactuals I consider the same demand for the next period, while still incorporating the effect of being the PoM for the next period. Formally the prices of a period $(p_j)_{j \in N}$ affect the transition of the state variables. Denoting the state variable of the forthcoming period with PoM', the transition can be formally described by

$$PoM' = j \quad \text{if } p_j < p_{-j}$$

So the strictly cheapest product gets the PoM status.[11] Having specified the transition function, I can write the dynamic continuation payoff for firm j as

$$V_j(p_j, p_{-j}|PoM) = \hat{D}_j(p_j - \hat{mc}_j) + \delta V_j(p'_j, p'_{-j}|T(PoM, P^n))$$

Note that δ is a discount factor. The first term is the static profit $\pi(P^n, PoM)$; the second term is the continuation payoff given the static prices.

I am searching for a Markov perfect equilibrium. In line with (Maskin and Tirole, 2001), a Markov perfect equilibrium restricts subgame perfect equilibria only to the pay-off relevant strategies of a subgame. Each firm conditions its strategy $\sigma_j \in S_j$ to the state variable, i.e. $S_j : PoM \to \Delta(P)$. A strategy $\sigma_j^* \in S_j$ forms a Markov perfect equilibrium if and only if for all $\sigma_j \in S_j$ and $PoM \in \mathscr{S}$ it holds that $V_j(\sigma_j^*, \sigma_{-j}^*|PoM) \geq V_j(\sigma_j, \sigma_{-j}^*|PoM)$. Note that I allow strategies to differ across the firms. This is important as firms have different demand parameters that affect their strategies.

To estimate the equilibrium strategies $(\sigma_j^*)_{\forall j}$ I use a value function iteration. While the dynamic programming approach is easy to implement, the difficulty arises as the computation also involves a computation of a game theoretic equilibrium. I use an algorithm in the fashion of Pakes and McGuire (1992). The general value function algorithm is defined by the following three steps that take time in each period separately (In each period different marginal costs from the marginal cost estimates are used):

Step 0: I create an educated initial guess of the value function, i.e. V^n for each possible state variable

[11] The result is robust to several adjustments. For example one could build a tie breaker rule such that in case several products have the same price and one of those products is an original, the original or the PoM from the previous month gets the PoM status.

and for each firm the value function is defined. Set n=0.

Step 1: For each possible state variable PoM (zero or one), I compute a the best reply in terms of prices P given the continuation payoff V^0 and the prices of opponents. In other words, I search for each player for the best prices given the transition function, the defined continuation value as well as the prices of opponent firms. For each firm the new valuation function is given by $V^{n+1} = \pi(\sigma^*, PoM) + V^n(\sigma^*, PoM)$.

Step 2: I test if $|V^{n+1} - V^n| < Toler$ as well as prices $|P^{n+1} - P^n| < Toler$ where $Toler$ is a tolerance level. If the value function and strategies (prices) have not converged, go back to *Step 1*.

After convergence I have found equilibrium strategies as well as valuation functions for each firm. During each iteration n increases by one.

The main concerns of the equilibrium estimation are the following: First, the algorithm does not select equilibria. Indeed I only search for pure strategy equilibria. In only three periods I do not converge to a pure equilibrium. Another concern is that there exists multiple equilibria and the algorithm just uses one. The second concern is that the lack of equilibrium selection impacts the valuation function iteration. If there are multiple equilibria and the algorithm in one iteration gives me one equilibrium and in the next iteration another one, the valuation function may not converge. I recognize the potential problems of the algorithm and try to test several robustness checks: First, I start with different initial guesses. The equilibrium outcome for different initial guesses does not change. Second, I consider if a 'bang-bang' behavior between different equilibria during the iteration is a problem. Indeed, the convergence mostly seems smooth and I do not observe any jumps between equilibria between iterations.

A very similar problem arises through wrong inference by equilibrium selection. In comparison to the actual equilibria in the data it may be possible that the counterfactuals select a different equilibrium solely because of the algorithm or starting values. I tackle the concern via the benchmark model. Within the benchmark model I evaluate the market without making changes. Further, I do all computations for the benchmark model as well as the counterfactuals parallel with the same starting values.

After having establised an equilibrium in each period, for each firm, and in all states I continue to simulate prices. I simulated prices over all monthly (or yearly) periods one thousand times to avoid mistaken inference from a specific equilibrium past. In each simulation I start with a random state. Between time periods, the states evolves in the following manner. If a firm has the strictly lowest price in t, it has state

Table 45: Results of Counterfactuals

	Benchmark Model	CF $SD = 0$
Average Prices:		
Mean Price	69.56	71.37
	(2.49)	(2.53)
Mean Min Price	68.22	71.61
	(1.68)	(1.78)
Average Expenditures:		
Price for Avg. Consumer	69.25	72.36
Compared to Benchmark		3.41%

Comparison between Benchmark Model and the counterfactual scenario of no switching costs. The upper part of the table reports prices in SEK. The counterfactual of a decrease in switching costs. The Mean Minimum Price is the average of the minimum prices across the six years. The middle part of the table shows the average shares of all products across all periods. The lower part considers measures of consumer costs and total revenue. The Price for Avg. Consumer shows the price a average consuemer would pay. The following row shows the percentage change to the benchmark model. Standard deviations in parentheses.

dependent consumers in the next period. However, if two firms set the same price, I randomize the state in the forthcoming periods. The average of the prices across the thousand simulations of the sequential time periods are used for inference.

I.3 Reduction of Switching Costs

Within this section I evaluate a counterfactual in which patient's switching costs are set to zero. The motivation of the counterfactual exercise is to analyze if results of the increased contract length match those of a decreased switching costs. In comparison to the counterfactual of an increased procurement contract length I change the preference parameter of consumers directly. I set the coefficient of previous choices (the coefficient of state dependence in the discrete choice model) equal to zero such that past choices do not effect consumers' current utility. Besides the change of the demand calculation I estimate the prices as in the benchmark model.

Table 45 shows the results of the counterfactual with no switching costs. Different price measure show that teh reduction of switching cost increase prices. Therefore the results confirm the counterfactual with an increase procurement length that intends to mimics lower importance of switching costs.

References

Patrick Bajari, C Lanier Benkard, and Jonathan Levin. Estimating dynamic models of imperfect competition. *Econometrica*, 75(5):1331–1370, 2007.

Igal Hendel and Aviv Nevo. Sales and consumer inventory. *The RAND Journal of Economics*, 37(3): 543–561, 2006.

Eric Maskin and Jean Tirole. Markov perfect equilibrium: I. observable actions. *Journal of Economic Theory*, 100(2):191–219, 2001.

Ariel Pakes and Paul McGuire. Computing markov perfect nash equilibria: Numerical implications of a dynamic differentiated product model, 1992.

Sophia Rabe-Hesketh and Anders Skrondal. Avoiding biased versions of wooldridge's simple solution to the initial conditions problem. *Economics Letters*, 120(2):346–349, 2013.

Sveriges Riksdag. Lag (2002:160) om läkemedelsförmåner m.m., 2002.

Jurre Thiel. Price discrimination, switching costs and welfare: Evidence from the dutch mortgage market. *Unpublished*, 2019.

TLV. Apotekens marginaler. http://www.tlv.se/apotek/Apotekens-marginaler/, 2016. Accessed: 2017-02-23.

Kenneth E Train. *Discrete choice methods with simulation*. Cambridge university press, 2009.

Jeffrey M Wooldridge. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics*, 20(1):39–54, 2005.