To reserve or not to reserve:

A study of how individual characteristics and market conditions might explain variation in generic reservation rates among general practitioners

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Abstract

Background: When a patent of an active ingredient expires, generic companies can enter the market and offer equivalent drugs to compete against the brand version. Unless the general practitioner (GP) states otherwise in the prescription, i.e. makes a reservation, the patient will be dispensed the generic version in the pharmacy. The patient can still claim the brand version, but has to pay the additional cost himself. There are a few medically justifiable reasons for the GP to prefer the brand version, and about 7% of the prescriptions in Norway have reservations against generic substitution. However, the large variation in reservation between doctors, suggests that many reservations are based on non-medical considerations. Previous research has shown that factors such as price, age of doctor, patient population, pharmacist mark-ups and maturity of generic markets explain some of the variation.

Objectives: This thesis investigates the extents to which market conditions and general practitioners' characteristics might explain variations in the rates of generic reservation. In addition to the previously studied factors we will introduce some new explanatory variables that, to our knowledge, have not been tested before. Specifically, the effect of competition between GPs in municipalities might provide new insights.

Methods: To find links between GP-reservation and the above-mentioned characteristics, data from pharmacy sales and the Norwegian GP-registry were analysed. Both descriptive statistics and alternative models (binary, fixed effects, OLS regression, two-part models) were used to find marginal effects of the variables tested on reservation level.

Results: A major contribution of this thesis relates to the gatekeeper function of GPs: our results show that increased competition between GPs results in more generic reservation. Furthermore, older GPs use reservation more often, whilst the effects of sex and speciality are more inconclusive. Increased confidence in generics defined as frequent prescriptions, translates into lower reservation levels. Active ingredients that have recently become subject to generic competition have higher reservation levels. In general, the effects are also stronger in new generic markets as compared to older markets. The results are consistent across the alternative models used.

Acknowledgements

I wish to express my sincere gratitude to my main supervisor Tor Iversen at the institute of Health and Society at the University of Oslo. After being hesitant about a number of possible thesis subjects, it was very relieving to find a professor with a stimulating topic that also had a profound interest in the subject. This has also been the case throughout the work on the thesis, where he has always been highly supportive.

I would also like to give a special thanks to my co-supervisor Helga Festøy and the people at the section of pricing at The Norwegian Medicines Agency. Without your vital insights in the complicated regulatory framework of generics in Norway, this thesis would not have been possible. One aspect of the thesis that made it even more rewarding was being able to take part in the great working environment in the department of pharmacoeconomics.

Coming from a family with a great interest in health policy, I had hereditary disposition to choose a similar career path. I am highly grateful to my mum, Marianne, my dad Jan Abel, and my brother Nils for all the professional insights, meals, laughter and support you have given me throughout these years.

Lastly I would like to thank The Institute of Health and Society, UiO, where I have spent most of my awake time the last few years. Professionally, it has been very stimulating (I've learnt a lot!). I'm also thankful to the great student advisors, who always help out when students are too lazy to read emails in full. Lastly, it has been a great social environment, filled with a lot of fun and laughter (except for some backgammon matches).

Ole

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Acronyms

AIC: Akaike information criterion

ATC: Anatomic Therapeutic Chemical (classification)

FFS: Fee-for-service

GP: General practitioner

HELFO: The Norwegian Health Economics Administration

NIS: National insurance scheme

NMA: Norwegian Medical Association

NOMA: Norwegian Medicines Agency

OTC: Over the counter (drugs)

POM: Prescriptions only medicines

PRP: Pharmacy retail price

twopm: two-part model

VIF: Variance inflator factor

WHO: World Health Organization

Translation

Co-payment ceiling - Egenandelstak

GP-regulatory framework - Fastlegeordningen

HELFOs electronic system for settlement with pharmacies – Apotekoppgjøret

Ministry of Health and Care Services - Helse- og omsorgsdepartementet

National insurance scheme – Folketrygden

Norwegian Directorate of Health – Helsedirektoratet

Norwegian GP registry – Fastlegeregisteret

Norwegian Medical Association – Legeforeningen

Norwegian Pharmacy Association – Apotekforeningen

1 Introduction

When a patent for a drug expires, generic competitors can enter the market and compete for market shares by using the same active ingredient as was earlier patented. For many years, the choice of prescription was entirely at the discretion of the physician: if the prescription had the brand name, this is what the patient was dispensed. As of March 2001, to ensure cost savings for both the patient and the national insurance, pharmacies were allowed to substitute drugs within the same active ingredient if deemed possible by the Norwegian Medicines Agency.

The physician may still prescribe the most expensive product, but the pharmacy will offer the generic equivalent to a lower price to the customer. The national insurance scheme (NIS) will only reimburse the price of the product with the lowest price, *except* for the cases when the physician has made a reservation against generic substitution. If such a reservation is made, NIS pays the added cost of being prescribed a brand drug. Today, GPs reserve against generic substitution in about 7.5% of prescriptions.[1] In absence of a reservation note from the GP, patients are still allowed to receive the brand drug, but must pay the added cost out-of-pocket.

Although generics contain the same active ingredient, there are some medically justifiable reasons to prefer the brand drug. To a large extent however, GPs have a wide range of patients and provide care for fairly similar patient populations. You would therefore expect that reservation rates do not differ much between GPs. When they do, several explanations might exist. This master thesis seeks to investigate characteristics of physicians, and the market conditions in which they operate, that might explain variation in generic reservation rates. Previously studied factors like sex, age, geographical location and price differences will be investigated, in addition to some hitherto less explored aspects related to generic market entry and the competitive environment of GPs. Detailed datasets will be used to analyse the different effects quantitatively.

[1] https://helfo.no/Documents/Analyser_og rapporter/Kontrollrapport-Legens_reservasjon_mot likeverdig_bytte på apotek-2015.pdf

The thesis[2] will be structured as follows. Chapter 2 provides an institutional background for analysing reservation. Chapter 3 makes the theoretical foundation for the hypotheses' analysed. Chapter 4 explains how the data was obtained and aggregated in order to perform the statistical analysis in Chapter 5. The results of the different models are presented in Chapter 6, and further discussed in Chapter 7. Lastly, Chapter 8 provides the conclusion.

[2] Acknowledging that a majority of GPs in this sample are men, we will for simplicity use masculine. To keep it simple, patients will also be referred by use of masculine.

2 Institutional arrangements

2.1 The market for general practitioners (GPs)

GPs form an important part of the primary health service in Norway. Since 2001 when the organization of general practitioners was reformed, GPs are directly responsible for all patients enrolled on their list. The maximum number of patients on the list is chosen by the GP himself, but is not to exceed an upper limit of 2500 patients (Norwegian Medical Association, 2013, pp. 68-69). Some relevant statistics of the Norwegian GP-market are provided in Table 1.

Table 1: Characteristics of General Practitioners (GPs) in Norway

Patients per list (mean)	1 132	
Number of female GPs	1 768 (39%)	Average of 4 quarters in 2014
Number of male GPs	2 710 (61%)	Average of 4 quarters in 2014
Number of specialists	2 542 (53.3%)[3]	
Number of ordinary patient initiated switches[4]	261 122	Sum of 4 quarters in 2014
Total number of patient initiated switches	366 145	Sum of 4 quarters in 2014

Source: Norwegian Directorate of Health for 2014 (2015)

Whenever a patient has a medical condition, he has to consult his designated GP for an appointment, or seek the emergency care unit in cases of urgency. If a patient is unhappy with his GP, or for other reasons prefers a different GP, he can switch to a new GP with open spots on his list (Norwgian Directorate of Health, 2015)[5].

2.1.1 Remuneration

The majority of GPs in Norway are paid in a combination of fee for service (FFS) and capitation[6]. The FFS part is regulated by law, and ranges widely depending on the nature of the intervention. The capitation part is a fixed sum per patient – NOK 427 as of 1. July 2015[7]. FFS and capitation form the GPs income. Accordingly, income can be increased by attracting

[3] This number is from NMA, as HELFO has not provided statistics for specialists since 2004. http://legeforeningen.no/Emner/Andre-emner/Legestatistikk/Yrkesaktive-leger-i-Norge/Legeforeningens-fastlegestatistikk---artikkel/

[4] Switches due to patients moving or GPs reducing or ending their practice are not included.

[5] A patient can switch up to twice a year. One additional switch is given to those who change place of residence

[6] A small number of GPs are salaried, commonly those in areas with low population density.

[7] https://helfo.no/helseaktor/kommuner-og-fylkeskommuner/basistilskudd-for-fastlegeordningen-i-kommunene

more patients and thereby augmenting the capitation-based income, and/or increase the number of services for each patient already on the list.

2.1.2 Patient co-payment

With a few exceptions[8], all patients are charged with a co-payment when visiting their GP that varies depending on the services provided. If the accumulated co-payments in a calendar year reach an upper ceiling (egenandelstak 1) of NOK 2,185, the public third party payer (NIS) covers all exceeding expenses (HELFO, 2015b). The services included in "egenandelstak 1" are limited to co-payments to doctors, pharmacies, physiologists, hospitals, x-ray institutes and patient-travels (HELFO, 2015d). For drugs bought at pharmacies, the co-payment is 38%, but at a maximum of NOK 520 per delivery (HELFO, 2015c). Many patients reach the co-payment ceiling quite rapidly, especially those with chronic conditions. In 2009, 900 000 people[9] reached the ceiling within the calendar year.

2.2 The market for generics

To encourage innovation of new drugs, patents are given to new active agents. This gives the manufacturer a temporary monopoly to recuperate the costs of development, in addition to earning a profit. Once the patent expires, other manufacturers can copy the active ingredients[10] of the brand drug and make generic versions.

As defined by the WHO (2015b); *"a generic drug is a pharmaceutical product, usually intended to be interchangeable with an innovator product, that is manufactured without a licence from the innovator company and marketed after the expiry date of the patent or other exclusive rights"*.

In order to be considered interchangeable, the generic has to have the same drug preparation and be considered *bioequivalent* to the brand drug. The latter is determined through testing the bioavailability of the generic and compared its brand counterpart. Bioavailability is a

[8] Prenatal care control, patients under 16 years old, psychotherapeutic care of children under the age of 18, communicable diseases of public concern.

[9] https://www.regjeringen.no/contentassets/be20df89eefb4e10beaf237622a43fe4/no/pdfs/prp200920100020000dddpdfs.pdf p. 12

[10] The excipients may however differ.

measurement[11] of the extent to which an active ingredient is absorbed by the body (Merck , 2014). Numerous tests have concluded that generics have the same clinical effect as brand drugs when compared using studies of bioequivalence (NOMA, 2015b).

Active ingredients are classified in the anatomic classification (ATC) system[12]. The system classifies active ingredients over five levels according to their: anatomical; therapeutic; pharmacological; chemical groups, and; subgroups (WHO, 2015a). Accordingly, a generic drug and its reference drug always have the same ATC number.

There are various ways of obtaining a marketing licence for generics. An application for a licence can be acquired centrally through the European Medicines Agency (EMA) for the whole European Economic Area (EEA), or decentralized through national medicines agencies for marketing in a limited number of countries (NOMA, 2015e)

If a generic competitor is deemed substitutable with its branded counterpart, NOMA puts it on the "substitution list" (byttelisten)[13]. The list states which drugs can be substituted in the pharmacy within a "substitution group" (byttegruppe). All drugs within a substitution group contain the same active ingredient and the same drug preparation. The drugs might however differ in terms of strength and package size. The list is updated twice a month, and distributed to all pharmacies (NOMA, 2015d).

2.2.1 Maximum price

All prescription-only medicines (POMs) entering the Norwegian market are priced according to a *reference price* system, fully explained by NOMA (2015c). The reference price system states that pharmacies can claim a maximum retail price, with some exceptions[14], equal to the

[11] The bioavailability is assessed using a statistical method called plasma concentration-time relationship (AUC). Two drugs are considered bioequivalent if 90% of the confidence interval for the relationship between the average of the AUC-measurements lie within the range of 0.8 – 1.25.

[12] See Appendix A for thourough explanation of the ATC system

[13] A separate group consisting of a wide range of professionals, called "Byttegruppen" acts as an advisory body to NOMA on questions relating to the substitutability of drugs.

[14] If there is a viable risk that the producer will not find it profitable enough to market its drug on the Norwegian market. See http://www.legemiddelverket.no/Blaa_resept_og_pris/pris-paa-legemidler/maksimalpris/Documents/Retningslinjer%20for%20prisfastsettelse.pdf for a thorough explanation.

average price of the three lowest priced countries in a group of nine reference countries[15]. When a medicine's patent expires, generic competitors can file an application to NOMA for a marketing licence for that active ingredient. If granted, the generic enters into competition with the branded drug[16].

2.2.2 Stepped price

The stepped price system was introduced in 2005, and is a mechanism for ensuring reduced prices on medicines once generic competition has arisen. The stepped price is the maximum price refunded by NIS. The system entails a percentage reduction of the previously defined maximum retail price over two to three cuts: the first cut is a 35% reduction, and commences once there is generic competition; the second cut occurs after 6 months, and; the third 12 months after the second, at the earliest. The size of the last two cuts depends on the sales of the active ingredient (Norwegian Pharmacy Association, 2015, pp. 34-37). An overview is provided in below[17].

Table 2: Example of cuts in stepped price system

Sales before generic competition	1st price cut	2nd price cut	3rd price cut	
Below 100 mill NOK	35%	59%	Sales > 15 mill	69%
Above 100 mill NOK	35%	81%	Sales > 30 mill	88%
			Sales > 100 mill	90%

(NOMA, 2015f)

NOMA can use discretion with respect to setting the stepped price. This includes the option not to implement cuts if there is reason to believe that in doing so, generic competitors will find it unprofitable to stay in the market (Festøy & Ognøy, 2015, p. 21).

All pharmacies are obliged to offer at least one drug within the substitution group on stepped price. Because pharmacies commonly offer only one drug on stepped price, manufacturers compete towards wholesalers in order to become the preferred drug. In most cases, but not

[15] Sweden, Denmark, Netherland, Great Britain, Finland, Germany, Austria, Belgium and Ireland

[16] It is voluntary for the generic company sell a certain drug or package even if granted a licence.

[17] In addition to the general cuts in Table 2, the active ingredients "atorvastatin" and "simvastatin" have cuts of 94% and 96%, respectively.

always, this is a generic. Drugs not on stepped price, commonly the branded version, are priced according to the higher maximum price described above (NOMA, 2015f). NIS usually only covers the price of the stepped priced drug. If the patient for some reason prefers the more expensive brand version (patient reservation), he has to pay the difference between the maximum price and the stepped price out of pocket in addition to the co-payment. Only the co-payment, however, enters into the calculation of the co-payment ceiling (Norwegian Pharmacy Association, 2015, p. 36).

2.2.3 Reservation against generic substitution

The doctor often prescribes the brand name of the active ingredient. This does not impede the pharmacy in giving the generic version to the patient. If the doctor prefers the patient to use the brand version, even though it has entered into generic competition, he must state so in the prescription – he makes a reservation against generic substitution. In doing so, NIS pays the added cost, not the patient. The entire co-payment of the drug also enters into the calculation of the payment ceiling (NOK 2185 as of 01.01.2015). Since many patients reach the co-payment ceiling within a calendar year, this is assumed to be of less importance however[18].

In the example of the patients' expenses in Table 3 below, all cuts are based on an initial maximum price of NOK 1000. However, the price of the branded drug will in most cases be reduced by the mechanisms of the maximum price system where comparator countries reduce prices. In the example, the price of the branded drug will therefore be lowered gradually from NOK 1000. The co-payment in situations where a doctor reservation has been made will therefore be reduced as time is passed from generic entry.

[18] In any case the patient's co-payment will increase compared to choosing the drug on stepped price, due to the fact that the maximum price is higher than the stepped price (Norwegian Pharmacy Association, 2015, pp. 36-37).

Table 3: Patient expenses with and without reservation

	Maximum price	**Co-payment (38%)**	**Reimbursement by national insurance (62%)**	**Extra payment with patient reservation** (for an unchanged maximum price)	**Total patient payment: co-payment + extra payment**
	Patient reservation				
Brand drug before generic competition	1000	380	620	0	380 + 0 = 380
Stepped price with 31% price reduction	664	252	412	336	252 + 336 = 588
Stepped price with 81% price reduction	220	84	137	780	84 + 780 = 864
Stepped price with 90% price reduction	131	50	81	869	50 + 869 = 919
	Doctor reservation				
Brand drug after generic competition	1000	380	620		380 + 0 = 380

(Norwegian Pharmacy Association, 2015, p. 37)

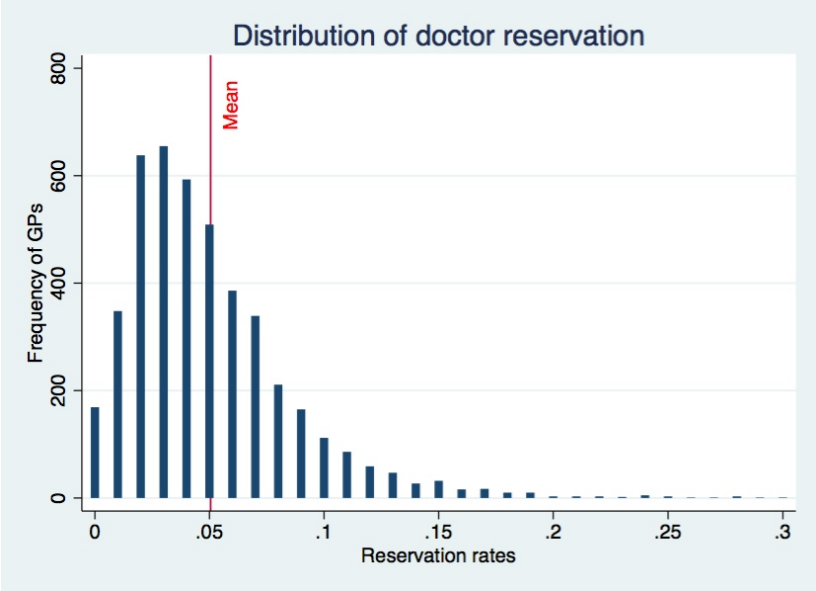
There are not many medical justifications to prefer a branded drug to a generic; NOMA (2015a) lists a few:

- The patient already uses various types of medicines, and might have trouble maintaining control of the different types.
- The patient has had an allergic reaction when using generic version before.

Several studies have shown that the above-mentioned reasons are fairly rare, but nonetheless highly valid. In an extensive literature review of all relevant publications on the subject between 2000 and 2011, Håkonsen & Toverud (2012, p. 28) found that "between 8-34% of patients reported poorer effects and/or new side effects after a change". Compliance to administered drug use has also been shown to negatively correlate with the use of generics (Håkonsen, Eilertsen, Borge, & Toverud, 2009). This underlines the importance of good information to patients, and the use of reservation against substitution by doctors in cases where substitution can lead to non-compliance.

The variation in reservation between physicians however, suggests that many reservations are not grounded in medical considerations. In our data (cf. Chapter 4), we can see from Figure 1 that most GPs have reservation rates below, or close to the mean reservation for all GPs. There is however a non-trivial amount of GPs with reservation rates well above the mean.

Figure 1: Variation in reservation between GPs



A recent report by the Norwegian Health Economics Administration (HELFO) (2015a), discovered in a micro-study large disparities between physicians; for reservations made by 15 GPs, only 34% of the reservations complied with guidelines. This suggests that there might be other reasons than medical considerations that explain variations between doctors.

2.3 Marketing

Marketing of pharmaceuticals in Norway is regulated through the Regulations of Pharmaceuticals (Ministry of Health and Care Services, 2010). Although the regulations are fairly restrictive, some leeway is given to the pharmaceutical industry in promoting their products. All marketing of prescription-only medicines (POMs) towards patients is prohibited. However, pharmaceutical companies can promote these medicines through channels where health personnel are the sole recipients of this information – e.g. health journals/periodicals, visits from pharma sales reps, sponsoring of conferences etc. NOMA audits these activities through inspections and the gathering of statistics, and has the opportunity to sanction violations of the regulations.

2.4 Pharmacies

Pharmacies are the main dispensers of drugs in Norway. As of 2014 there were 800 pharmacies of which 33 were hospital pharmacies (Norwegian Pharmacy Association, 2015, p. 4). Until a regulatory amendment in 2001, all pharmacies were individual enterprises. The

amendment opened for wholesalers to vertically integrate with pharmacies, forming pharmacy chains. Today, the pharmaceutical market in Norway is dominated by three such chains[19] (Norwegian Pharmacy Association, 2015, pp. 10-11). Wholesalers negotiate prices with the pharmaceutical companies. This often leads to different mark-ups on both generics and branded drugs between different pharmacies depending on their vertical integration.

[19] Alliance Boots, Celesio AG/McKesson Coorporation and Apotek 1 Gruppen/Phoenix

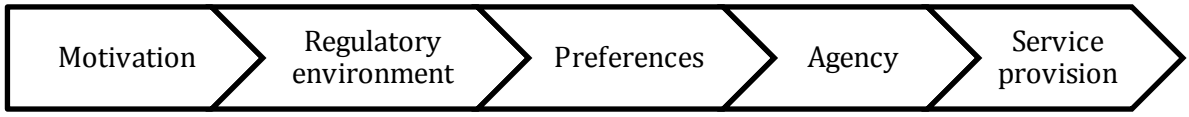
3 Theoretical framework

3.1 Literature review

What motivates physicians, and to whom do they act as agents?

In order to understand prescription behaviour amongst GPs, one must understand what motivates them and what induces them to perform certain tasks. Eisenberg (1986) argues that doctors are motivated from a wide range of sources, including financial self-interest, concern for the social good and concern for their patients. There has been extensive research on the subject (see e.g. Holte et al (2015), Lundin (2000))

Arguably, a GP's preferences towards performing a given task will be determined by his motivations, but also be subject to the regulatory environment in which he acts. These preferences turn into degrees of *agency* towards the third-part payer and the patient, which again will decide the *service provision* of the physician. In other words, motivation does not decide service provision alone, context matters.



In psychology, it is common to distinguish between *intrinsic* and *extrinsic* motivation. *Intrinsic* motivation leads to actions that are based on the rewards of *inherent satisfaction*, whilst *extrinsic* refers to behaviour that is instrumental to a separate consequence (Ryan & Deci, 2000). In economics, incentives are often viewed from an *extrinsic* perspective; a simple example would be performing a task for money. A public health planner looking to increase efficiency among physicians, might therefore introduce a regulatory environment that makes their income more dependent on the amount of services they provide. Frey & Jegen (2000) has however shown that such extrinsic motivation can crowd out intrinsic motivation, and thereby dampening the effect of the incentive. Hence, the regulatory environment, or market conditions, in which a doctor operates, will affect his preferences and in turn what he does. These regulations are put in place to serve various interests, of which the most important are those of payer, and those of the patient. In this scheme the doctor

serves as a "double agent" for both the payer and the patient, with their interests often conflicting (Lundin, 2000).

Ellis & McGuire (1990) elaborate on the agency problem mathematically, arguing that physicians maximize a utility function that is contingent on both personal income and patient welfare. At a certain point, physicians are faced with a trade-off between higher income, and increased patient welfare. The degree of agency the doctor displays towards his patients is in their model determined by how much he values his patients benefit – or by using the words of Arrow (1963); how altruistic the doctor is.

In reading the ethical guidelines of the Norwegian Medical Association (2015) the agency problem becomes more apparent. In the preamble of the guidelines it is stated that "the doctor shall help the sick regain their health", but also that "the doctor shall take societal expenses into consideration when performing his duties". The first can be argued represent agency towards the patient, and based on the intrinsic motivation of any doctor – they want to make their patients as healthy and happy as possible. This might however be in conflict to the latter guideline, where the doctor acts more as an agent for the third party payer than the patient. Taking societal expenses into consideration can be thought of as intrinsic motivation, but also extrinsic if policymakers introduce regulatory frameworks to incentivize such considerations.

Inducing doctors to do more, and more of the "right tasks", was one of the reasons for introducing *Fastlegeordningen* in 2001, a structural change in the organization of GPs. Amongst others, the reform has made GP-income more contingent on the amount of tasks they perform and the amount of patients they are responsible for. Dissatisfied patients can therefore translate into loss of income for the GP. According to Norheim & Carlsen (2003) the reform has led to increased patient pressure in referrals, thereby reducing the gatekeeper function of GPs. Arguably, the reform has contributed to reducing GP-influence, in favour of patients getting their will. Put differently; more of the physicians "agency" is directed towards the patients' interests than those of the third party payer. Moreover, studies have shown that patients' confidence in their GPs has been reduced. In studying patient perceptions over time, Godager et al (2009) found that patients were less satisfied with their relationship to their GP and less content about their GPs medical knowledge, since the introduction of the reform.

For pharmaceuticals, a shift in agency may have led to more patients getting the prescription they prefer – e.g. a doctor reservation against generic substitution. Since a non-trivial amount of a GP's income is capitation-based, every dissatisfied patient that decides to change GPs constitutes an income-loss. The GP will therefore have an incentive to give in to patient demand. However, this willingness will depend on what emphasis a given GP places on personal income, patient-welfare and societal expenses, amongst others. In terms of what motivates a GP to write a reservation note, I will depict the argument through set of equations, drawing on the framework of Ellis & McGuire (1990). They use the model with respect to the amount of tasks that a physician performs, but the arguments still holds when applying it to generic reservations. The main addition I make, is introducing income as a function of patient benefit.

3.2 The models

A GP's utility from the proportion of reservations X is given by the function $U(.)$ in equation *(i)*. Increasing the proportion of prescriptions that contain a reservation note is contingent on the patients' utility from treatment $B(.)$, the GP's income $\pi(.)$ and the societal expenses $S(.)$. All the functions are increasing in X. $S(.)$ is negative, with reference to the earlier mentioned ethical guidelines of the Norwegian Medical Association. The corresponding constants, α, l and k are positive, and refer to the emphasis a given GP puts on the different elements in his utility function.

$$\text{i)} \qquad U_i(X) = \alpha B(X) + l\pi - kS(X)$$

The income function $\pi(.)$ is given by the revenue R from capitation, which is a function of $B(.)$. We will call this function $G(X)$. This is done to capture the fact that the GP needs to keep his patients satisfied in order for them not to switch GPs. The fee-for-service part of the GP's income is ignored in this equation, since the reimbursement rate from the state does not vary across brand/generic drugs. To simplify the equations, income is thus given by.

$$\text{ii)} \qquad \pi = R(B(X)) = G(X)$$

The maximization problem for the GP is to choose the optimal proportion of generic reservation.

$$\text{iii)} \qquad U(X) = \alpha B(X) + lG(X) - kS(X)$$

$$\max U \; w.r.t. X$$

After derivation and some algebra, we get the first order condition of the GP[20]

$$\textbf{iv)} \qquad \boldsymbol{\alpha B'(X) + lG'(X) = kS'(X)}$$

Equation *(iv)* tells us that for a marginal increase in doctor reservation, the increase in patient benefit and the GP's income must be equal to the increase in societal costs. This will however depend on how much the GP values the increase in patient benefit, both from an altruistic (α) and an income (l) perspective, relative to how much he values societal expenses (k). Accordingly, we observe that the proportion of reservation is a function of the GP's preferences.

$$\text{v)} \qquad \boldsymbol{X^* = X^*(\alpha, l, k)}$$

These preferences can differ depending on context, regulatory framework, market conditions or characteristics of the GP (e.g. age, sex, specialist). To see how a change in these preferences affects the chosen proportion, we calculate the change in X for a marginal increase in either preference through first order conditions[21].

Increase in altruism $\quad \boldsymbol{\frac{\partial X}{\partial \alpha} > 0}$ $\qquad$ *Increased weighting of income* $\quad \boldsymbol{\frac{\partial X}{\partial l} > 0}$ $\qquad$ *Increased weighting of societal expenses* $\quad \boldsymbol{\frac{\partial X}{\partial k} < 0}$

These equations tell us, *ceteris paribus*, that the proportion of reservation is increasing in α and l, and decreasing in k.

The above results show what impacts the GP's choice of *proportion* of reservation for their entire patient population. Equivalently, the discrete choice a GP makes between reservation and non-reservation can be modelled for every prescription. Drawing on Green (2005, pp. 684-685) a random utility model is applied, reflecting the discrete choice of the GP. *(vi)* is the GP's utility of choosing a generic prescription, which is equal to an unobserved variation ε_G,

---

[20] ⇨ $U'(X) = (\alpha + l)B'(X) - S'(X) = 0$
We assume that $B'(X)$ is concave, $S'(X)$ is convex. The second order condition for an interior solution is fulfilled; i.e. $(\alpha + l)B''(X) - kS''(X) < 0$

[21] We assume that the second order condition for an interior solution is fulfilled. See Appendix B for derivation and proof

known only to the GP himself. *(vii)* is the GP's utility from making a reservation, and thereby choosing the brand drug. With the same notation as earlier, this is a function of *added* patient benefit, income and societal costs, in addition to the unobserved variation ε_B.

vi) $$U(G) = 0 + \varepsilon_G$$

vii) $$U(B) = \alpha B + l\pi - kS + \varepsilon_B$$

The probability of making a reservation in *(viii)* is contingent on the preferences of the GP. The necessary condition for the GP to reserve, is therefore that the utility of using a reservation is larger than for non-reservation: $U(B) > U(G)$. The solution to the reservation problem is thus given by equation *(ix)*.

viii) $$P(Y = 1|\alpha, l, k) = Prob(U(B) > U(G))$$

$$Prob(\alpha B + l\pi - kS + \varepsilon_B - \varepsilon_G > 0|\alpha, l, k)$$

ix) $$\boldsymbol{Prob(\alpha B + l\pi - kS + \varepsilon > 0|\alpha, l, k)}$$

As for the case of *proportion*, we see that the choice for the GP is a function of patient benefit, personal income and societal expenses. His corresponding preferences will determine the choice-outcome, in addition to the unobserved variation ε. This term represents factors that could make a GP more inclined to choose either prescription.

There are many other justifiable reasons and explanations for making a generic reservation that were not discussed explicitly through the equations above; e.g. personal beliefs, marketing, habits etc. Although being a simplified example, the above findings show how important doctor characteristics, or preferences are, when weighing different considerations before determining whether or not to make a reservation. These preferences, which also reflect the GP's agency, can be thought of as expressed through the different weights given to the constants, α, l and k. There are many reasons as to why they might differ between GPs, and I will now consider a few of them.

Competition

Patients who do not get the treatment or prescription they desire, have the opportunity to shop around for a more accommodating GP. This opportunity will however depend on the competitive forces in their municipality, or GP-catchment area.

In a capitation system, a patient switch translates into an income loss for the GP. The GP's ability to recuperate this income through adding new patients to the list will depend on the competitive environment. The argument goes that GPs in a competitive environment are more preoccupied with pleasing their patients because a switch is easy for the patient, and costly to the GP. With respect to our model, increased competition can take the form of a larger reduction in utility from an income-loss (large $G'(X)$)[22]. Equivalently, the doctor can become more responsive towards the patient from an income motive (large l).

Godager et al (2015) studied the effect of competition on the gatekeeping role of physicians in terms of referrals to specialist care. Amongst others, they hypothesized that increased competition would lead to an escalation in referrals out of fear of losing patients from their lists – a retention effect. In their empirical results, however, they only found weak support. They concluded that this might be due to an offsetting effect, namely from doctors limiting referrals to make up for the income loss by performing more of the services themselves. In our case of generic reservations, however, the latter effect is presumed to be irrelevant as neither form of prescription is expected to lead to more follow-up consultations than the other.

A possible opposing effect from increased competition is the GP's ability to convince the patient of the generic's equivalence. If the GP's patient list has a large deficit compared to his desired list ceiling, one could argue that he has the opportunity to spend more time on each patient. Since convincing is time-consuming, a GP with many patients in line might discount the increased societal costs from reservation relative to his income loss from treating less patients. In a literature review, Dugdale et al (1999) showed that less time per patient is associated with both a higher frequency of referrals and more use of prescription medicines. Although not explicitly discussed in their article, these findings can indicate that busy GPs are more responsive to patients' demand.

Price differences

In any third-party payer system, the effects of prices on health care are modest in curbing unwanted behaviour. This is because doctors do not face any direct costs in prescribing a

[22] If we assume that income has increasing returns on utility at a decreasing rate (concave), the utility loss will be larger for GPs with a large patient-shortage compared to those who are close to their patient ceiling.

certain medicine, and patients only pay a *share* of the costs. This may lead to overconsumption of a good since the user does not bear the full cost of treatment – a situation of *moral hazard*, as defined by Pauly (1968). If a patient is unhappy with a generic prescription, he will however need to pay the entire *added cost* (cf. subsection 2.3.3). The size of this added cost, or price difference between generics and branded drugs, might therefore affect willingness among both doctors and patients to make a reservation.

Prices can affect generic reservation levels both directions in terms of reservation. One hypothesis is that, *ceteris paribus*, for a larger price difference patients will exude more pressure on GPs to file a reservation note in order to avoid the added cost themselves. In the model, this can translate into a larger increase in patient utility from being granted a reservation from the GP (large $B'(X)$). Contrary, a large price difference might make the GP more attentive to containing societal costs, and limiting unnecessary reservation. In a comparison of UK- and Italian GPs' prescribing behaviour, Hassel et al (2003) found that societal cost containment was a significant consideration in choice of prescription to their patients. Correspondingly, our model would predict a large $S'(X)$. Depending on whether the GP places more weight on societal than patient concerns, the price-effect can therefore work both ways.

Previous studies using Norwegian data show that the effect of price difference is limited at most. Dalen et al (2011) show a negative effect of price differences on reservation levels, with the effect being fairly volatile across the years studied. In comparing older generic markets with markets that had recently received generic competition, they found the effect of price to be weaker for the latter. In studying the Swedish pharmaceutical market, Lundin (2000) finds that a higher price difference increases generic prescriptions by physicians. Since Swedish patients have to pay the added cost of a brand drug out of pocket, Lundin interprets the findings as a sign of physician agency in favour of the patient. Put differently, the physician cares more about costs incurred by the patient than those by the state ($\alpha > k$), indicating moral hazard. A way of interpreting the findings is that GPs do not care too much about prices per se, but about their patients' contentment of the services provided – both out of a wish to please their patients, and from an income perspective. If true, this would in our model translate into higher values on the constants α and l, relative to that of k.

Pharmacies also play an important role concerning generic switching. Because the differences in mark-ups on generics and brand-drugs can be substantial, pharmacies will have an incentive to push either one on the basis of maximizing income. Brekke et al (2013) found in their study of Norwegian pharmacies, that there was a strong, positive effect between market share of a generic and the difference in generic and brand margins. This led them to conclude that a pharmacist's agency towards the patient is contingent on potential added payoff. In Norway, it is commonly the case that pharmacies have higher margins on generics than brand-drugs.

Habits and confidence

GPs encounter, on average, more than 70 patients every week[23]. Since many of their patients face similar medical problems, it would not be surprising if the GP had a certain disposition to duplicate advice or prescriptions made to former patients, even if the cases differ slightly. One could say that the GP, to some extent, acts out of habit. Furthermore, in prescribing a drug more often and to a wide range of patients, a GPs confidence in therapeutic choices might be reinforced.

In terms of reservation, an example would be that GPs with a patient population that justifies a high degree of reservation (e.g. elderly), translates their prescription pattern to other patient-groups. This is discusses by Hellerstein (1998) in her article on prescription decisions among physicians. In addition to the hypothesis on patient population, she argues that older physicians might be more prone to continue prescribing the branded version: if a given physician prescribed a drug for the first time before it had gone off-patent, path dependency could lead the physician to maintain his prescription pattern after the patents expiration date and generic entry (Hellerstein, 1998, p. 123). Her data does not allow for a thorough testing of the hypotheses, but the results clearly states that doctors with older patient population use more branded drugs, although with insignificant results regarding the physician's age. On the other hand, even if GPs do not pay attention to whether or not an active ingredient has gone off patent, their patients might. If so, the patient's habit of using a certain brand, might lead him to exert pressure on his GP to make such a reservation.

[23] http://tidsskriftet.no/article/2237928: Average number of consultations per GP per year is 3400. With 5 weeks of vacation, this means 3400/47 = 72 consultations /week

The argument of habit-formation is also expected to depend on the frequency of prescriptions a doctor makes of a given active ingredient. Repetition of behaviour is likely to reinforce habit. Whether or not this repetition takes the form of increased or decreased reservation is hard to say. Since non-reservation is far more normal, we would however, be inclined to suggest that this definition of habit leads to decreased reservation. Equivalently, an increasing amount of prescriptions made for a given drug will presumably make the GP more confident in its effectiveness. From a confidence perspective, a higher frequency of prescriptions might therefore make the GP more persuasive in the eyes of the patient. If true, this may result in a smaller increase in patient benefit from receiving a brand drug (small $B'(X)$). Correspondingly, a confident doctor might have less sympathy for patients' demand for the brand version, resulting in a lower agency parameter α. From a habit perspective, path dependency can be captured in our discrete choice model *(ix)* by a small residual ε.

Coscelli (2000) used a rich dataset with both doctor- and patient-level data to study habit formation among GPs in Italy. At the time, brands were not allowed to compete through pricing. The dependent variable of his analysis was whether or not a patient was prescribed a different brand for a given molecule compared to last prescription. To show that habit-formation was indeed explaining prescription behaviour, he found that doctors who prescribed a certain brand more often also had fewer switches. Although not discussed in his article, this might also be interpreted as confidence in using a given brand. While not testing generic reservation, Coscelli's findings indicate that GPs have strong preferences in prescribing.

Marketing

It is well established that the pharmaceutical industry seeks to influence doctors in their prescription behaviour. What is also well known, is that they often succeed. In their seminal article "… There's No Such Thing as a Free Lunch", Orlowski & Wateska (1992) studied the effects of a pharma-sponsored symposium to a holiday destination, on doctors' prescription behaviour in the US. Despite that the majority of doctors attending doubted that the trip would affect their behaviour, a substantial and significant increase in prescription of the sponsor's drugs was observed in the wake of the symposium.

In Norway, the marketing of pharmaceuticals is more heavily regulated than in the above case (cf. Section 2.3). In a survey of Norwegian doctors and their relationship to the pharmaceutical industry by Aasland & Førde (2004), 70% responded that further education would suffer in absence of the industry. Additionally, 52% said that doctors were indeed influenced by marketing. Interestingly, younger doctors were also found to be more sceptical towards the industry, supporting other research that has found higher generic reservations among older GPs.

In our model, marketing towards a GP can be captured by a large residual ε. Additionally, marketing can persuade the GP that the health outcome of his patients is more tied to receiving a brand-drug, resulting in a higher agency parameter α. In other words, a GP who does not regard generics as equivalent in terms of effectiveness, will more highly value the patient's benefit from receiving a brand drug.

Perceptions about generics

Even with clear guidelines in place about which circumstances deem generic reservation necessary, there is some leeway for GPs to exude personal convictions.

In a study of US physicians by Shrank et al (2011), about half of the respondents agreed, or somewhat agreed to the statement: "I am concerned about the quality of generic medications". There are many reasons why this number should be lower in a Norwegian setting, but it clearly indicates that there is a non-trivial number of GPs who have second thoughts about the substitutability of branded drugs for generics. In the same study, it was also shown that the age groups 35-54 and 55-and-above, were respectably 2.42 and 2.68 times more likely to report negative perceptions about the efficacy of generic drugs than the younger physicians. The authors hypothesized that the findings might be due to training environment; medical students today are to a larger extent exposed to generic drugs than what was the case some years ago. Although not discussing training environment explicitly, Dalen et al (2011) also found some support for there being different attitudes towards generics across age groups. In using data from the Norwegian Prescription Database, they found that older GPs used reservation more often.

Doctors who are inclined to prefer a brand version drug will presumably need more conviction in the form of information of the generic's therapeutic equivalence for them not to

make a reservation. This gathering of information can be conceived as a time-cost to GPs. Hellerstein (1998) argues that any positive costs to the GP in learning about generics, will lead him to underinvest in this knowledge[24]. Even if the GP is convinced about generics efficacy, their patients might not be. Studies have shown that many patients perceive generics as inferior to brand drugs (i.e. Ganther & Kreling (1999) and Håkonsen & Toverud (2012)). If true, the argument of time-costs can be translated into explaining the equivalence to patients. The less convinced patients are (and the more GPs value their utility), the more costly it will be for GPs to explain the safety/efficacy of generics.

In terms of our model, characteristics of GPs (age, sex, specialty) can influence their attitudes towards generics, and accordingly their agency, α. Time costs are not explicitly present in the utility functions *(i)* and *(vi)*, but can be captured by the preference parameter, l: if you are willing to use time in explaining generic equivalence, you also care less about your income (small l). Moreover, a well-informed GP (e.g. a specialist) might also be perceived as more confident. This would in turn have similar effects as described earlier.

3.3 Research questions

As should be clear from the literature review and the model, there are several factors that can explain different reservation rates among GPs. Arguably, these factors can in broad be examined through either one of two dimensions: *personal characteristics* (of GPs) and *market conditions*. These two dimensions will also make up the foundation of the research questions investigated in this thesis. There are many research questions that can fall under these dimensions, and several have been studied in depths previously. The ones chosen in this thesis reflect what we consider to be of most interest and what our data permit to investigate. Moreover, we will also look more closely on how reservation rates among patients affect the corresponding rates of their GPs.

[24] In her article that is based on the US market, she assumes that the patient prefers the generic drug due to cost-savings. If a Norwegian patient has any preference towards the brand version, the argument would be reversed due to third-party payment.

Personal characteristics

Some personal characteristics of the GPs are easily observable to the researcher. As discussed in Chapter 3, GPs with similar characteristics are also likely to exhibit related preferences in prescription behaviour.

Research questions

- Do factors like age, sex and whether or not the GP is a specialist in family medicine affect reservation levels?
- Does habit formation and increased confidence in the use of different active ingredients help explain a decision to use reservation or not?

Market conditions

One GP's choices and professional environment is not isolated from what other GPs do, and what medical tools are available. Treatment decisions, or decisions to use reservations in our case, is therefore likely to be influenced by factors exogenous to the GP.

Research questions

- Are there differences in reservation levels depending on whether or not the generic market for that active ingredient is old or new?
- Does increased competition between GPs for patients reduce the gatekeeper function of GPs, and in our case lead to increased reservation?
- Are there geographical differences in reservation levels? A previous study by Stoinska-Scheider (2011) suggests that centrality of municipalities can serve as a proxy for both competition and marketing efforts.
- Do price differences between brand- and generic drugs affect reservation levels?

4 Data

After filing an application to the Norwegian Directorate of Health, two datasets were retrieved from the following registries; The Norwegian GP Registry (Fastlegeregisteret)[25] and HELFOs electronic system for settlement with pharmacies (hereinafter "HELFO registry"). These were merged and formed the basis of the analysis. All data management and statistical analysis was performed using the statistical software STATA 14.

In order to base the analysis on a relevant sample, a number of changes had to be made to the data from the HELFO registry. Most notably, only drugs that had *genuine generic competition* at the time of prescription were included in the analysed dataset. Genuine generic competition is here defined as a situation where a given drug package was on the substitution list at the time of prescription, and where there were actual sales of that drug[26]. To make this extraction, every drug package included in the dataset was checked against sales records from *Farmastat*[27] and the substitution list in NOMA's drug database *Athene*. Moreover, since dispensing of drugs can take place long after the prescription has been made, it is hard to make any solid assumptions about whether or not there was genuine generic competition for a given package at the time of prescription. This is especially the case for drugs with volatile sales.

Together, this meant that a non-trivial amount of drugs within each ATC-group had to be excluded from the HELFO registry (1 262 789 observations, 9.43% of total). When merging with the GP registry, another 3 367 897 observations were excluded due to unmatched observations and irregular numbers. To make sure our results were not biased by choice of sample, two separate extractions were made; one *main sample* where all drugs with sales in a given month were included, and one *limited sample* where only drugs that had sales the entire period were included. See appendix C for an explanation of the quite extensive work that had to be carried out on sample selection and merging of datasets.

[25] Some municipality-level data from GP registry were retrieved from a publically available online-version: https://helsedirektoratet.no/Sider/Statistikk-fastlege.aspx

[26] We do however recognize that even in cases where there are no generic sales, the fact that generics are on the substitution list might drive down prices of brand drugs. The choice of sample is not expected to affect our main results by much. One exception might be the relative effects of indications and ATCs, that are of less interest in this thesis.

[27] Independent database for drug statistics

4.1 Choice of active agents

Most of the active agents were chosen on the background of a previous master thesis written by Anna Stoinska-Schneider (2011) in collaboration with NOMA. Her thesis explored similar research questions as those posed here, using the ATCs within the indications related to *GERD*, *cholesterol* and *depression*. However, the data used in her thesis was retrieved from other sources, and contained less detailed information[28]. Using the same active agents will therefore allow for comparison across different datasets. Furthermore, five more ATCs within the indications *hypertension* and *migraines* were added to the dataset. This was done to allow for exploring new research questions related to recent generic market entry. Three of these ATCs will, however, not be included in the models in Chapter 6. They will only be discussed in the descriptive statistics as "control ATCs" to allow for comparison of ATCs within indications.

It is emphasised that the pharmacological effect of the active agents and the disease they treat (indication) were not considered when choosing what active agents to analyse. Based on information from the U.S. National Library of Medicine (2015), a short overview of the different indications is given below. A further overview of the ATCs, indications and corresponding data coding is provided in Table 4.

Gastroesophageal reflux disease (GERD) is a disease where backflow of stomach acids causes heartburn. The drugs Omeprazole, Pantoprazole, Lansoprazole and Ranitidine all treat the symptoms of this disease, which in most cases are chronic throughout the life course.

High cholesterol level is a lifestyle disease that can lead to heart attack and stroke. Simvastatin and Pravastatin are drugs that lower the production of cholesterol, and thereby decrease the probability of blood clots.

Depression can have many root causes. Citalopram, Paroxetine and Escitalopram are all in a class of drugs called serotonin reuptake inhibitors. These are antidepressants that help the patient maintain mental balance by increasing the serotonin level.

[28] Her raw data contained *proportions* of doctor reservations. When using a binary model, all proportions were counted as a "1", irrespective of the size of the proportion.

Hypertension, or high blood pressure, is associated with a variety of lifestyle risk-factors including smoking, alcohol and a low activity level. Amlodipine, Felodipine, Lercanidipine belong to the drug class of calcium channel blockers that relax the blood vessels and thereby relieving some strain from the heart in pumping the blood.

Migraine headaches do not have well-established causes, but is hereditary. Sumatriptan and Zolmitriptan are in a class of drugs called selective serotonin receptor agonist that give pain relief from symptoms of migraine attacks. They do this by stopping pain signals going to the head through narrowing blood vessels in the head.

Table 4: Overview of active ingredients and indications

ATC number	ATC name	Class	Main indication[29]	Generic competition[30]	Market-code[31]	ATC-code	Indication-code
	ATCs in analysis						
A02BC01	Omeprazole	Proton pump inhibitors	Peptic ulcer/GERD	Before 2004	old_drug	0	0
A02BC02	Pantoprazole	Proton pump inhibitors	Peptic ulcer/GERD	12.01.2007	old_drug	1	0
A02BC03	Lansoprazole	Proton pump inhibitors	Peptic ulcer/GERD	05.01.2005	old_drug	2	0
A02BA02	Ranitidine	H2-receptor antagonists	Peptic ulcer/GERD	Before 2004	old_drug	3	0
C10AA01	Simvastatin	HMG CoA reductase	High cholesterol level	Before 2004	old_drug	4	1
C10AA03	Pravastatin	HMG CoA reductase	High cholesterol level	10.15.2004	old_drug	5	1
N06AB04	Citalopram	Selective serotonin reuptake inhibitors	Major depression	Before 2004	old_drug	6	2
N06AB05	Paroxetine	Selective serotonin reuptake inhibitors	Major depression	05.01.2004	old_drug	7	2
N06AB10	Escitalopram	Selective serotonin reuptake inhibitors	Major depression	03.01.2010	new_drug	8	2
C08CA13	Lercanidipine	Calcium channel blocker	Hypertension	08.01.2010	new_drug	11	3
N02CC03	Zolmitriptan	Selective serotonin receptor agonist	Migraines	03.15.2012	new_drug	13	4
	Control ATCs excluded from models						
C08CA01	Amlodipine	Calcium channel blocker	Hypertension	03.15.2004		9	3
C08CA02	Felodipine	Calcium channel blocker	Hypertension	Before 2004		10	3
N02CC01	Sumatriptan	Selective serotonin receptor agonist	Migraines	06.01.2006		12	4

[29] Ref: https://www.nlm.nih.gov/medlineplus/druginformation.html

[30] Date for substitution group. For single packages of drugs, the date might come at a later time. Overview retrieved from excel document "Oversikt over virkestoff inkludert i trinnprissystemet" (NOMA, 2015f)

[31] Later in the statistical part, old and new generic markets will be analyzed separately.

5 Statistical analysis

In the statistical analysis, several different models are applied. The reasons for this are twofold;

i) The distribution of the data does not seem to fit the assumptions of any model perfectly. This is unsurprising due to the large mass of zeros in the dependant variable. Using multiple models can therefore serve as a test of significance.

ii) All the research questions cannot be tested simultaneously using one single model.

A number of models were considered, including count models (poisson, zero-truncated poisson) and other variants of time-series models (between- and random effects[32]). Different transformations of the dependant variable were also studied (log- and exponential transformation). The models used in this thesis are based on the dependent variable being analysed as either a binary, or aggregated as a proportion. The decision to use the models and variables below, was based on theoretical applicability and performance of the different models.

5.1 Variables

Many variables were tested in the models applied. Table 5 below consists of the main variables that will be used in the models.

[32] As suggested by Green (2005, p 379) Hausman tests were performed to see whether random or fixed effects models were most suitable. In every case, the test rejected the random effects models. See Appendix E for test outputs.

Table 5: Description of variables included in analysis

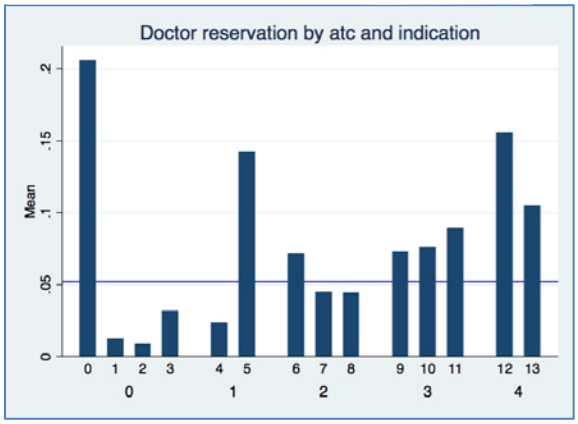
Variable name	Explanation
doctor_reservation	Proportion of prescriptions that contained a doctor reservation note. Binary variable in probit version, where every observation represents a single prescription.
patient_reservation	Proportion of prescriptions that contained a patient reservation note. Multiplied by 100 in order to make it easier to interpret. 1 unit increase = 1 percentage point change. Binary variable in probit version, (=1) if patient reservation made.
GP-characteristics	
specialist	Binary indicator variable. (=1) if doctor is a specialist in family medicine.
age_dummy	Ordinal dummy-variable for age of doctor. (=1) if age < 40, (=2) if 40 ≤ age < 55, (=3) if 55 ≤ age.
male	Binary indicator variable. (=1) if doctor is male.
ln_freq_pres_indication **ln_freq_pres_atc** **ln_freq_pres_new_drug** **ln_freq_pres_old_drug**	Number of prescriptions made for a given indication/ATC/old_drug/new_drug by one doctor in a given year. The variable is log-transformed to better fit normality assumptions of models. Also it seems more theoretically pleasing to view the change in terms of percentages than a marginal increase in prescriptions.
Market conditions	
comp_municipality	Proportion of aggregated GP-list ceiling in one municipality that is filled. A larger size of the variable is interpreted as increased competition. The variable is multiplied by 100 in order to make it easier to interpret. 1 unit increase = 1 percentage point change
price_difference **price_difference_indication** **price_difference_new_drug** **price_difference_old_drug**	Difference between average price with and without a reservation note for all drugs within one indication/ATC/new_drug/old_drug in a given year.
indication	Dummy variable for what indication the drug is treating. Indication 1 (cholesterol) is used as baseline. Dummies are listed in table 4
atc_code	Dummy variable for the active ingredient. Dummies are listed in table 4
year	Time variable. Baseline is 2011.
centrality	Categorical variable defined by Statistics Norway[33] to capture geographical effects. Municipalities are assigned to a category from 0-3 defined on the basis of population and public services provision in an area. 0 are the most central counties and 3 the least central. Baseline is 0.

33 http://stabas.ssb.no/ItemsFrames.asp?ID=5285605&Language=nb&VersionLevel=ClassLevel

5.1.1 Aggregation of dependent variable

When applying a binary model, every observation constituted a single prescription as presented in the original data. Accordingly, the data did not need much transformation. However, for the other models (twopm, linear regression and fixed effects) the dependent variable had to be aggregated into proportions for every GP. Figure 2 shows mean reservation levels by indication for all ATCs included in the raw data from the HELFO registry. In looking at the reservation levels, it should be clear that the kind of indication and ATC a drug is prescribed for, affects the level of reservation. This means that whether one uses indications or ATCs as dummy variables, will affect the results. Choosing either ATCs or indications, will accordingly also lead to different sizes of the dependent variable in the aggregated versions.

Figure 2: Aggregation by ATC



0-4 represent indications. See Table 4 for explanation

To allow for comparison with the results obtained by Stoinska-Schneider (2011), her indications were used as the basis for our overall analyses (hereinafter "overall"). This meant that an extraction of indications 0, 1 and 3 had to be made from the main sample. In order to analyse differences between matured and more recent generic markets, two separate extractions were also made on the basis of ATCs for "old" drugs (hereinafter "old") and "new" drugs (hereinafter "new")[34]. Figure 3 shows mean reservation rates for "overall", whilst Figure 4 for that of the "old" vs. "new".

[34] "Old" drugs include ATCs 0-7. "New" drugs include ATCs 8, 11 and 13. Distinction was based on start of generic competition, as defined as date of substitution group. Revisit Table 4 for an overview.

Figure 3: Mean reservation by indication (overall)

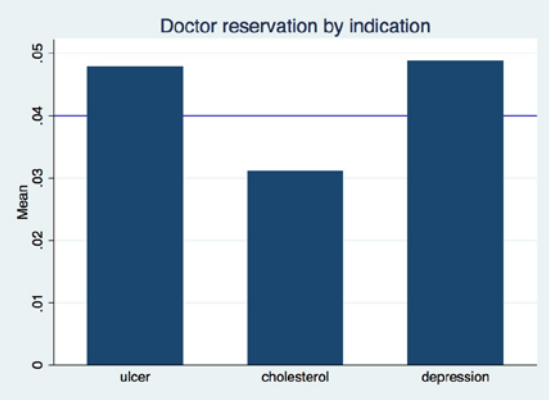
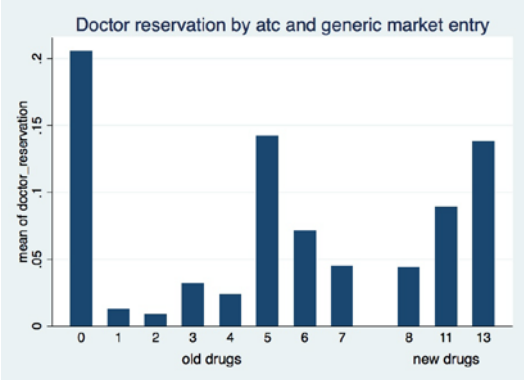


Figure 4: Mean reservation by ATCs and generic market entry



Accordingly, aggregation was made on indication for "overall", and on ATCs for "old" and "new". To allow for a seamless merge with the GP-registry, proportions were depicted separately for every year. This means that there are a maximum of five observations for every GP, every year in the aggregated version of "overall"; each observation of reservation constituting the mean level of reservation for that GP, for a given indication. Equivalently, there are respectively 8 and 3 observations for every GP each year when aggregating on ATCs for "old" and "new". The raw dataset used for the descriptive statistics contained 8 564 136 observations. However, the number of observations included in the analyses differs depending on whether we are looking at indications in "overall", or ATCs in "old" and "new". Since the original data is used in the binary models, these have fewer observations than the models that need aggregated data. This becomes clear when looking at Table 6.

Table 6: Number of observations by type of model and extract from main sample[35]

Extracts	"Overall"		"New"		"Old"	
Type of dummy used for drugs	Indications (0-2)		ATCs (8, 11, 13)		ATCs (0-7)	
Model type	Binary	Aggregated	Binary	Aggregated	Binary	Aggregated
Maximum number of obs. per GP	"Number of prescriptions made during 4 years for the 3 indications"	(3 indications) * (4 years) = 12 obs.	"Number of prescriptions made during 4 years for the 3 ATCs"	(3 ATCs) * (4 years) = 12 obs.	"Number of prescriptions made during 4 years for the 8 ATCs"	(8 ATCs) * (4 years) = 32 obs.
Total number of obs.	6 507 305	44 268	1 712 336	35 581	5 319 744	105 588

[35] For an extensive overview of the distributions of observations for the different models and samples, see Appendix D

To sum up, three different analyses will be performed using models where the dependent variable is a binary, and where it is aggregated as a proportion. Since the analyses are based on different ATCs/indications, separate extracts from the original sample were made, explaining the different number of observations.

Lastly, to analyse changes over time, differences within "old" and "new" ATC's could not be accounted for when the fixed effects model[36] was applied. This means all ATC's within "old" and "new" were treated as the same. This was done to avoid "repeated values within panels"[37]. Correspondingly, fixed effects models were also run separately for the three indications in "overall".

5.2 Theoretical background for the applied models

As noted earlier, there are several different statistical methods that will be applied in the analysis. A short introduction will be given for each model, keeping in mind that a trade-off had to be made between extensiveness of explanations and ease of reading.

5.2.1 Ordinary least squares (OLS) regression

In OLS estimation, the sum of squared residuals is minimized. The residual is the difference between the actual and the fitted value of the dependant variable we seek to explain, y (Wooldridge, 2013, p. 30). Equation *(x)* shows the linear prediction of y, with corresponding slope coefficients $\boldsymbol{\beta}$ for every variable $\boldsymbol{X}$ and the intercept β_0.

$$\text{x)} \qquad y = \beta_0 + \boldsymbol{\beta X} + u$$

The variable we seek to explain, doctor_reservation, can take on any number between 0 and 1. In an OLS estimation, however, estimates of the dependent variable are not bounded by these limits since increases in X have constant effects (Hill, Griffiths, & Lim, 2012, pp. 588-589). This might in turn lead to meaningless predictions; e.g. "GP X has a reservation rate of – 0.5". The OLS regression is based on assumptions[38] about the dependent and explanatory variables and the residuals; amongst other normally distributed error terms. Since the

[36] A discussion of the model specification follows in subsection 5.2.3
[37] A STATA error report arising from multiple observations within one time variable. E.g. having separate observations for ATCs within one year for a model.
[38] See Hill et al (2012, pp. 172-173) for list of assumptions.

majority of the observations of the dependent variable in our sample are "0", it is likely that the assumptions do not hold. This in turn can lead the model to produce biased estimates. However, the model has proven to have strong predictive power, even in cases where one or more of the assumptions are violated (Wooldridge, 2013, p. 252). The OLS model will only be applied to "overall" to limit the extensiveness of the analysis. It is in any case expected to predict similar results as that of the probit model.

5.2.2 Binary response models

The definition of a binary variable is that it only takes one of two possible values: "0" or "1". Since the dependent variable in our raw data is a binary, the advantage of modelling it accordingly seems appropriate. The aim of the binary model is to estimate the probability of y being equal to 1, given the observed parameters. As presented by Wooldridge (2013, p. 584) the general model is given by

xi) $$P(y = 1|\boldsymbol{x}) = G(\beta_0 + \boldsymbol{x\beta})$$

where *G(z)* is a function taking values z in the range $[0,1]$. *G(z)* is most commonly modelled as a *logistic function* ("Logit") or as a *standard normal cumulative distribution function* ("Probit"). According to Wooldridge (2013) the probit model is often preferred by economists due to the normality assumption of the error term. This is also the model used in this thesis. For estimating the Probit and Logit model, maximum likelihood estimation is used, thereby accounting for heteroskedasticity (Wooldridge, 2013, p. 587). Accordingly, the distributional assumptions that were stricter under OLS regression are now relaxed. Since a non-binary variable does not represent a choice in our case, the predicted value needs to be translated into a prediction of choice of reservation; "0" or "1". A general rule explained in Wooldridge (2013, p. 591), states that

xii) $$\hat{y} = \begin{cases} 1 & \hat{p} \geq 0.5 \\ 0 & \hat{p} < 0.5 \end{cases}$$

, where 0.5 is the chosen critical value. In our case where there is an overall low probability of a positive outcome (=1), the model's ability to predict generic substitution for physician i is presumed to be weak with such a critical value.

5.2.3 Two-part model

The two-part model (hereinafter "twopm") has been used for several years, in many different versions. I will consider the twopm as described by Belotti et al (2015). The idea behind the twopm is providing predictions and marginal effects based on the *combined* results of a binary and a continuous model. The binary model estimates the probability of a positive outcome, whilst the continuous model is a regression contingent on a positive value of the dependant variable. Accordingly, the model is especially fitting for data containing a large mass of zeros in the dependent variable, as this skewness now is accounted for. Using the notation of Belotti et al (2015), we see how the dependent variable y_i is predicted.

xiii) $$\widehat{y_i}|\boldsymbol{x}_i = (\widehat{p_i}|\boldsymbol{x}_i) * (\widehat{y_i}|y_i > 0, \boldsymbol{x}_i)$$

Equation *(xiv)* says that the predicted value $\widehat{y_i}$, for a given value of the covariates $\boldsymbol{x}_i$, is the product of the probability of a positive value of y_i, and the predicted $\widehat{y_i}$, given a positive value of y_i and the value of the corresponding covariates $\boldsymbol{x}_i$.

Which models one chooses to apply in the different parts of the twopm depend on the distribution of the data. The binary part consists of either a probit or a logit model, and the continuous part either an OLS regression or a generalized linear model (GLM). Based on testing different specifications, a probit and a GLM[39] will be used in this analysis.

5.2.4 Fixed effects

One problem our data might cause is that unobserved characteristics of the GP might be correlated with the independent variables. If this is the case, it might bias our results. One way of dealing with this problem is to account for constant unobservable characteristics of GPs that do not change over time. The fixed effects estimator does this by looking at change over time within individuals (Hill, Griffiths, & Lim, 2012, p. 542). The fixed effects estimator is based on "within transformation", meaning that we look at deviations from the mean of that time period for each individual. By doing this, unexplained variation that is constant over time is accounted for. The error term $\tilde{\varepsilon}_{it}$ of the time-demeaned model in

[39] With the specifications used, the GLM has similar properties as that of the OLS model.

equation *(xiii)*[40] does therefore only contain unobserved variation that changes over time t (Wooldridge, 2013, pp. 484-486).

xiv) $$\tilde{y}_{it} = \beta_2 \tilde{x}_{2it} + \beta_3 \tilde{x}_{3it} + \tilde{\varepsilon}_{it}$$

The variables in our dataset are not expected to vary much over time, but the fixed effects estimator can in any case give us an idea of how much of the unexplained variation in reservation is due to characteristics of that GP.

[40] Derivation of the time-demeaned model from within transformation:
Each GP i has the function $y_{it} = \beta_1 x_{it} + a_i + \varepsilon_{it}$ in time t. We can see that the unobserved variation is divided between those that are constant a_i and those that change over time ε_{it}
The average of the above equation, is equal to $\bar{y}_i = \beta_1 \bar{x}_i + a_i + \bar{\varepsilon}_i$. When subracting the two equations, the constant term a_i disappears and are left with the transformed time-demeaned model, as displayed in equation *(xiv)*

6 Results

6.1 Descriptive statistics

To see how reservation levels change over time and between ATC's, some key information is provided in Table 7. The three ATCs in ***bold italics*** are the control variables, listed here to allow for comparison of reservation trends for new ATCs within indications.

Table 7: Doctor reservation in main sample

		2011		2012		2013		2014		Total	
Ind.	ATC	docres	freq_pres	docres	freq_pres	docres	freq_pres	docres	freq_pres	docres	freq_pres
0	0	21.4 %	80 828	21.1 %	82 074	19.6 %	82 451	20.2 %	61 568	**20.6 %**	**306 921**
0	1	0.8 %	183 285	0.8 %	221 706	1.6 %	274 242	1.8 %	243 438	**1.3 %**	**922 671**
0	2	0.7 %	91 677	0.6 %	91 121	1.1 %	91 600	1.3 %	61 782	**0.9 %**	**336 180**
0	3	1.7 %	46 245	2.9 %	48 325	3.8 %	51 565	4.5 %	40 649	**3.2 %**	**186 784**
1	4	2.9 %	819 802	1.9 %	856 238	2.6 %	694 847	1.9 %	561 898	**2.3 %**	**2 932 785**
1	5	16.8 %	52 365	15.6 %	54 051	13.0 %	56 057	10.6 %	37 981	**14.2 %**	**200 454**
2	6	10.6 %	62 612	7.8 %	65 141	5.0 %	83 552	6.0 %	65 619	**7.2 %**	**276 924**
2	7	4.6 %	41 748	3.8 %	38 174	4.7 %	43 391	4.8 %	33 712	**4.5 %**	**157 025**
2	8	4.4 %	278 668	5.8 %	325 158	3.9 %	325 090	3.3 %	258 645	**4.4 %**	**1 187 561**
3	***9***	***13.1 %***	***164 637***	***7.8 %***	***283 596***	***5.7 %***	***369 331***	***5.6 %***	***272 372***	***7.3 %***	***1 089 936***
3	***10***	***9.6 %***	***45 447***	***8.5 %***	***43 767***	***6.2 %***	***43 743***	***5.3 %***	***30 713***	***7.6 %***	***163 670***
3	11	7.8 %	109 980	9.3 %	113 999	9.3 %	126 962	9.3 %	93 461	**8.9 %**	**444 402**
4	***12***	***18.2 %***	***63 917***	***16.5 %***	***63 788***	***15.4 %***	***70 839***	***12.7 %***	***79 906***	***15.5 %***	***278 450***
4	13	--	--	13.0 %	25 291	14.0 %	29 998	14.5 %	25 084	**10.5 %**	**80 373**
	Total	**5.9 %**	**2 041 211**	**5.3 %**	**2 312 429**	**5.1 %**	**2 343 668**	**4.7 %**	**1 866 828**	**5.2 %**	**8 564 136**

In the main sample, doctor reservation decreases steadily over time from 5.9% to 4.7%. The relative differences between ATCs are not too different in the limited sample (cf. Section 4.1). A table for the limited sample can be found in Appendix E for comparison[41].

When comparing the new drugs[42], ATC 8, 11 and 13 within their respective indications, the ATCs 11 and 13 have increasing trends as opposed to that of their counterparts: in fact, the (***bold italic***) ATCs 9, 10 and 12 seem to be decreasing. The case is not so clear for ATC 8, which follows a flatter trend not too different from its counterparts ATC 6 and 7.

[41] The trend is less pronounced in the limited sample. A noticeable difference between the two samples is that reservation levels are higher for the limited sample. This is probably due to many generic competitors being left out of the sample because of their inconsistent market shares over time.

[42] See Table 4 for definition of "new" vs "old" drugs.

The trends in doctor and patient reservations for the "new" (ATC 13) and the "old" ATC (12) within indication 4 (migraines) are illustrated separately below. The former entered into generic competition recently. The numbers 1-8 on the X-axis, represent eight half-year periods from 2011 to 2014.

Figure 5: Trend in reservation for ATC 12

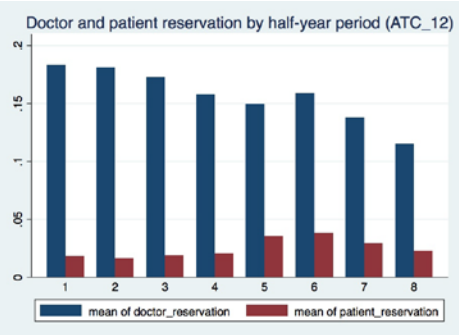
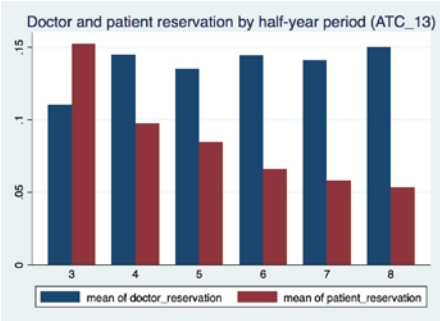


Figure 6: Trend in reservation for ATC 13



For the "old" ATC 12 in Figure 5, doctor reservation is decreasing with patient reservation being fairly constant. The "new" ATC 13 in Figure 6 entered into generic competition in March 2012, thereby explaining the lack of reservations in the first two half-year periods. This graph shows how patient and doctor reservation move distinctly in opposite directions from the start of generic competition. Doctor and patient reservation trends for indication 2 (depression) and indication 3 (hypertension) can be found in Appendix E. The trends for the latter are similar to those of indication 4, whilst the trends for depression cannot show the same associations.

Age and specialty

Age shows a strong association with reservation levels: older GPs reserve more often. The effect of being a specialist appears negligible at the aggregate level. When looking more closely within the age groups, reservation among the oldest GPs is to some extent offset if he is also a specialist. This offset is more pronounced for new, than old drugs. Lastly, the relative increase in reservation from age is larger for new than old drugs.

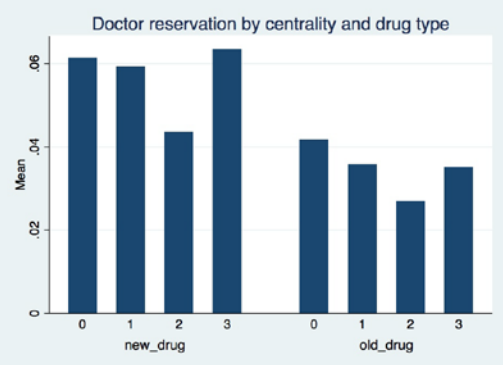
Table 8: Reservation rates depending on GPs' age and specialist status

	new drugs			old drugs		
	not specialist	specialist	total	not specialist	specialist	total
25-44 years	5.47 %	5.34 %	5.44 %	3.64 %	3.44 %	3.60 %
45-54 years	6.00 %	5.95 %	5.97 %	3.77 %	4.14 %	4.03 %
>54 years	7.40 %	6.05 %	6.30 %	4.36 %	3.83 %	3.93 %
Total	6.13 %	5.97 %	6.02 %	3.88 %	3.92 %	3.91 %

Centrality

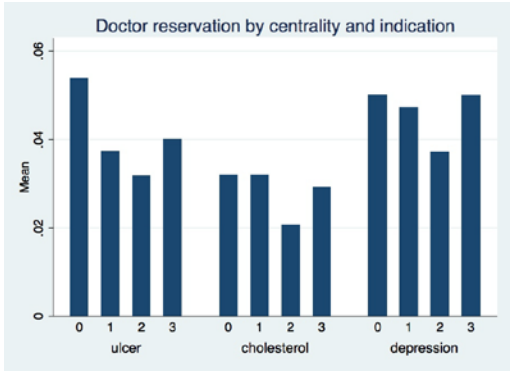
Irrespective of aggregation, doctor reservation shows similar trends over different geographical areas. In looking at figures 7 and 8 below, the trend is fairly distinct with decreasing reservation the less central the municipality becomes (moving from 0 to 3). However, there is a jump in reservation for the most peripheral municipalities conflicting with the trend, indicating that the most central and the least central municipalities have the highest reservations. Due to this last jump, we cannot find a linear relationship. Because of the consistency of the relative differences, we do however note that geographical aspects have some relevance.

Figure 7: Reservation by market entry and centrality



0-3 are degrees of centrality. See Table 5 for explanation

Figure 8: Reservation by indication and centrality



0-3 are degrees of centrality. See Table 5 for explanation

6.2 Model results

In order to avoid correlated error terms, all models were clustered on GPs. This is done to account for intragroup correlation from the fact that the prescriptions for a given GP are not independent from one another (StataCorp, 2013, p. 312). The "robust" option was also applied to all models to reduce probability of misspecification. By specifying the models in such a way, the standard errors become larger and the confidence intervals alike. This means that obtaining significant results becomes harder. However, the findings you do get are more reliable.

In order to model the effect of price differences, it was decided to include variations over time as a dummy variable (year), instead of performing separate analysis for every year[43]. Because of the extensiveness of models and extracts applied, this makes interpretation of the results more manageable. Furthermore, since the difference in price is equal within every

[43] The outputs when modelling for separate years are included in Appendix H.

indication for a given year, price difference will automatically be omitted if the analysis is performed separately for every year.

Lastly, marginal effects for the probit model were obtained by using *average partial effects*. As pointed out by Wooldridge (2013, p. 591), *partial effects at the average* is often unfitting for calculating marginal effects of a discrete outcome. The goodness of fit measures in Tables 9-11 gives an idea of the performance of the different models. We want R^2 and Pseudo R^2 to be as large as possible, whilst AIC (akaike information criterion) to be small. The latter serves best to compare models rather than as an absolute measure. In the fixed effects model, "Within" says how much of the variation in reservation for a given GP is explained by the independent variables, whilst "between" refers to the variation between GPs. "Entire model" reflects the goodness of fit for the model as a whole (StataCorp, 2013, p. 369). Explanation of the results follows in Section 6.4.

Table 9: Model results: "Overall"

	Regression		Probit			Two-part model					
						Probit		GLM		Combined	
Indep. var.	Beta	P-val.	ME[44]	Beta	P-val.	Beta	P-val.	Beta	P-val.	Beta	P-val.
ulcer	-0.0264	0.000	-0.0139	-0.1927	0.000	-0.9074	0.000	-0.0266	0.000	-0.0317	0.000
depression	0.0225	0.000	0.0297	0.2767	0.005	0.4378	0.000	0.0107	0.000	0.0168	0.000
price_difference	-0.0003	0.000	-0.0003	-0.0030	0.000	-0.0056	0.000	-0.0003	0.000	-0.0003	0.000
male	-0.0020	0.085	-0.0034	-0.0398	0.006	0.0128	0.557	-0.0012	0.422	-0.0005	0.637
age_dummy (2)	0.0036	0.006	0.0040	0.0484	0.012	0.0404	0.124	0.0048	0.005	0.0040	0.001
age_dummy (3)	0.0047	0.002	0.0034	0.0408	0.082	0.0655	0.027	0.0077	0.000	0.0065	0.000
comp_municipality	-0.0003	0.001	-0.0179	-0.2095	0.063	-0.0047	0.002	-0.0003	0.004	-0.0003	0.000
ln_freq_pres_year	0.0013	0.097	0.0058	0.0681	0.000	0.6602	0.000	-0.0283	0.000	-0.0047	0.000
specialist	-0.0003	0.792	-0.0021	-0.0247	0.269	0.0317	0.172	-0.0022	0.144	-0.0008	0.484
centrality 1	-0.0028	0.035	-0.0056	-0.0665	0.000	-0.0157	0.561	-0.0028	0.083	-0.0022	0.071
centrality 2	-0.0086	0.000	-0.0148	-0.1951	0.000	-0.1834	0.000	-0.0062	0.020	-0.0079	0.000
centrality 3	-0.0005	0.748	-0.0043	-0.0500	0.011	0.0807	0.020	-0.0057	0.005	-0.0022	0.160
2012	0.0021	0.013	-0.0007	-0.0073	0.368	0.0691	0.001	0.0016	0.160	0.0027	0.004
2013	-0.0106	0.000	-0.0112	-0.1306	0.000	-0.2334	0.000	-0.0109	0.000	-0.0123	0.000
2014	-0.0101	0.000	-0.0119	-0.1397	0.000	-0.1291	0.000	-0.0157	0.000	-0.0133	0.000
constant	0.1377	0.000		-0.9890		-0.4194	0.169	0.3164	0.000		
Goodness of fit	**R^2: 0.0222**		**Pseudo R^2: 0.0097**			**Pseudo R^2: 0.1542**		**AIC: -2.5204**			

ME: Marginal effect, Beta: coefficient (which is equal to ME under regression and GLM), P-val: p-value, giving the smallest significance level that would lead to rejection of the null hypothesis of the coefficient = 0. A common cut-off for deeming coefficients significant is a p-value below 0.05

[44] The marginal effects are calculated using "average marginal effects" (APE). APE gives separate significance levels. These are not included in the output since they generally do not differ more than +/- 0.003.

Table 10: Model results for "new" vs. "old" drugs

	NEW drugs									OLD drugs								
	Probit			TWOPM						Probit			TWOPM					
				Probit		GLM		Prediction					Probit		GLM		Prediction	
Independent variables[45]	**ME**	**Beta**	**P-val.**	**Beta**	**P-val.**	**Beta**	**P-val.**	**ME**	**P-val.**	**ME**	**Beta**	**P-val.**	**Beta**	**P-val.**	**Beta**	**P-val.**	**ME**	**P-val.**
price_difference	0.0006	0.0050	0.000	0.0052	0.000	0.0013	0.000	0.0010	0.000	0.0000	0.0001	0.079	0.0008	0.000	-0.0001	0.003	0.0000	0.006
male	0.0001	0.0013	0.942	0.0033	0.876	0.0090	0.007	0.0047	0.040	-0.0023	-0.0312	0.054	0.0370	0.032	-0.0015	0.661	0.0020	0.189
age_dummy (2)	0.0082	0.0745	0.001	0.0176	0.511	0.0122	0.006	0.0072	0.013	0.0028	0.0380	0.081	0.0522	0.013	0.0114	0.006	0.0067	0.000
age_dummy (3)	0.0110	0.0981	0.000	0.0666	0.022	0.0199	0.000	0.0148	0.000	0.0026	0.0351	0.169	0.1012	0.000	0.0147	0.001	0.0110	0.000
comp_municipality	-0.0441	-0.3785	0.007	-0.0045	0.005	-0.0001	0.628	-0.0004	0.026	-0.0147	-0.1957	0.095	-0.0041	0.001	-0.0001	0.809	-0.0003	0.006
ln_freq_pres_year	-0.0049	-0.0425	0.000	0.5579	0.000	-0.1083	0.000	-0.0113	0.000	0.0030	0.0398	0.009	0.4384	0.000	-0.1216	0.000	-0.0080	0.000
specialist	-0.0056	-0.0484	0.022	0.0365	0.113	-0.0118	0.003	-0.0031	0.237	-0.0007	-0.0099	0.658	0.0302	0.088	0.0053	0.120	0.0036	0.021
centrality 1	0.0002	0.0017	0.935	-0.0198	0.460	0.0069	0.091	0.0019	0.502	-0.0027	-0.0359	0.064	0.0040	0.843	-0.0059	0.109	-0.0015	0.376
centrality 2	-0.0136	-0.1284	0.000	-0.1470	0.001	0.0141	0.103	-0.0044	0.390	-0.0123	-0.1834	0.000	-0.1392	0.000	-0.0021	0.760	-0.0096	0.001
centrality 3	0.0020	0.0167	0.619	0.0120	0.747	0.0082	0.236	0.0050	0.267	-0.0058	-0.0796	0.001	-0.0069	0.797	-0.0181	0.000	-0.0060	0.008
2012	0.0246	0.2082	0.000	0.3978	0.000	0.0334	0.000	0.0456	0.000	-0.0078	-0.1035	0.000	-0.0415	0.000	-0.0159	0.000	-0.0075	0.000
2013	0.0119	0.1088	0.000	0.0955	0.000	0.0427	0.000	0.0260	0.000	-0.0038	-0.0477	0.000	0.0033	0.787	-0.0148	0.000	-0.0042	0.000
2014	0.0040	0.0392	0.013	0.1554	0.000	0.0159	0.000	0.0177	0.000	-0.0063	-0.0827	0.000	0.0828	0.000	-0.0336	0.000	-0.0049	0.000
constant		-3.3998	0.000	-3.9308	0.000	-0.0438	0.537				-0.7184	0.000	-0.8313	0.000	0.7118	0.000		
Goodness of fit	**R^2: 0.0328**			**Pseudo R^2: 0.1863**		**AIC: -0.9208**				**R^2: 0.1311**			**Pseudo R^2: 0.2420**		**AIC: -0.5541**			

ME: marginal effect, Beta: coefficient (which is equal to ME in GLM), P-val: p-value, giving the smallest significance level that would lead to rejection of the null hypothesis of coefficient = 0. A common cut-off for deeming coefficients significant is a p-value below 0.05

[45] ATCs have been controlled for. With a few rare exceptions, the dummies were all highly significant.

Table 11: Model results for fixed effects

		Indication 0		Indication 1		Indication 2		Old drugs		New drugs	
Indep. var.		Beta	P-val.	Beta	P-val.	Beta	P-val.	Beta	P-val.	Beta	P-val.
price_difference		-0.0001	0.023	-0.0002	0.000	0.0006	0.000	-0.0000	0.007	0.0004	0.000
comp_municipality		-0.0001	0.623	-0.0002	0.018	-0.0005	0.001	-0.0001	0.031	-0.0004	0.015
ln_freq_pres_year		-0.0025	0.269	0.0040	0.004	-0.0101	0.002	0.0024	0.148	-0.0012	0.615
patient_reservation		-0.0006	0.000	0.0002	0.558	-0.0012	0.001	-0.0003	0.176	-0.0008	0.000
constant		0.0713	0.000	0.0881	0.000	-0.0509	0.033	0.0510	0.000	-0.0122	0.623
R^2	within	0.0026		0.0145		0.0333		0.0026		0.0101	
	between	0.0308		0.0050		0.0018		0.0041		0.0005	
	entire model	0.0142		0.0067		0.0081		0.0036		0.0006	

Beta: estimated coefficient and marginal effect, P-val: p-value, giving the smallest significance level that would lead to rejection of the null hypothesis of coefficient = 0. For the reasons mentioned in subsection 5.1.1, the models run for each indication 0-3 are samples from the aggregated version of "overall". A common cut-off for deeming coefficients significant is a p-value below 0.05

6.3 Goodness of fit and specification[46]

6.3.1 Linear regression model

The regression model was assumed unfitting from the start, but was included to compare against the other models. Furthermore, its fairly simple interpretation was appealing. The R-squared tells us that 2.22 % of the variation in doctor reservations is explained by the independent variables (Hill, Griffiths, & Lim, 2012, p. 136). Whether or not this is a good result, is hard to say with the independent variables at hand.

A Breuch-Pagan test (httest) was run to test for heteroskedasticity. The test firmly rejected the null-hypothesis of no heteroskedasticity (prob > chi2 = 0,000). To account for this we used robust standard errors, clustering on GPs. Upon inspecting the corresponding plot of residuals vs. fitted values in Figure 9, it is clear that the data indeed does not fulfil the assumptions of the model. The residuals seem to be increasing with the fitted values, within a boundary. This boundary is probably due to the nature of the dependant variable (0,1). When performing a regression with a log-transformed version of the dependent variable, the residuals are less biased – as seen in Figure 10. This indicates that the large zero mass of the

[46] For ease of reading, the goodness of fit and specification tests discussed in this section are only based on the "overall" models. Output of tests for "new" and "old" are provided in Appendix F. These tests gave the same conclusions as for those of "overall".

dependent variable affects the model undesirably. Since the log-transformed version creates many missing observations, the corresponding interpretation changes. Furthermore, as the GLM part of the twopm has a similar foundation[47], it was chosen to not use the log-version for the OLS regression.

Figure 9: Residual plot for applied model

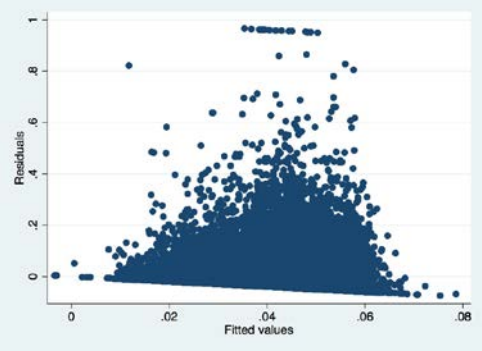
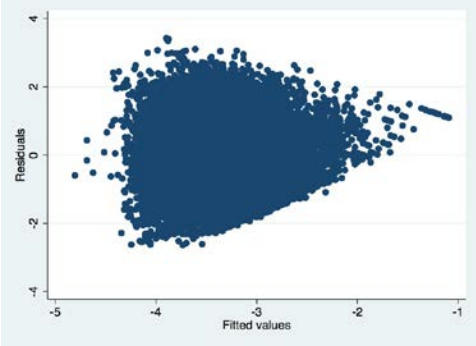


Figure 10: Residual plot for log-transformed dependent variable



The Ramsey test for omitted variables was also performed, with the null-hypothesis of no omitted variables being firmly rejected (prob > F = 0,000). To test for multicollinearity, a VIF-test was run. This stated that no multicollinearity was sufficiently present for any of the variables, except for indication 2, and price difference[48].

To conclude, it should be fairly well established that a linear regression model is somewhat unsatisfactory to employ on this dataset with the current modelling of variables. For the reasons already mentioned, the results will still be included.

6.3.2 Probit model

The (McFaddens) pseudo R-squared in the probit has a slightly different interpretation compared to the R^2 in the OLS model. Higher values of the Pseudo R^2, like in the OLS indicates better fit[49]. All others things equal, adding more independent variables increases this measure. This would therefore help explain why the Pseudo R^2 is larger for "old" than that of "overall" and "new"[50].

[47] The GLM in the twopm only predicts reservation given that reservation has taken place.
[48] See Appendix F for output and explanation.
[49] See link for a thorough discussion of R^2: http://www.ats.ucla.edu/stat/stata/output/Stata_Probit.html
[50] For capturing the effect of drug type, "main" has 3 dummies (indications), "new" 3 (ATCs) and "old" 7 (ATCs)

To see the predictive power of the model, we choose to look at the models ability to predict doctor reservations based on the independent variables at hand. If we choose a critical value of y_hat > 0,5 (like in subsection 5.2.2) as a condition for a reservation, our model predicts zero reservations[51]. The model's ability to predict the true cases of reservation, the sensitivity of the model, is therefore non-existent. The model's ability to predict cases of non-reservation, the true-negative, is however 100%. This is clear when looking at Figure 11.

Figure 11: Sensitivity vs. specificity

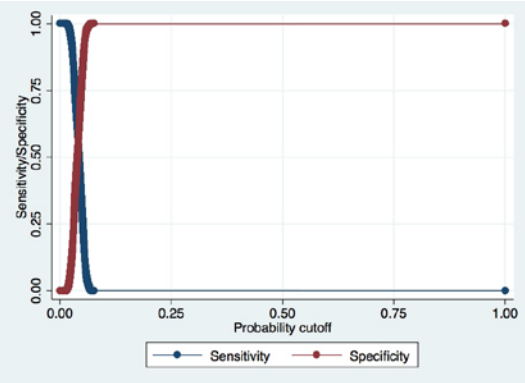
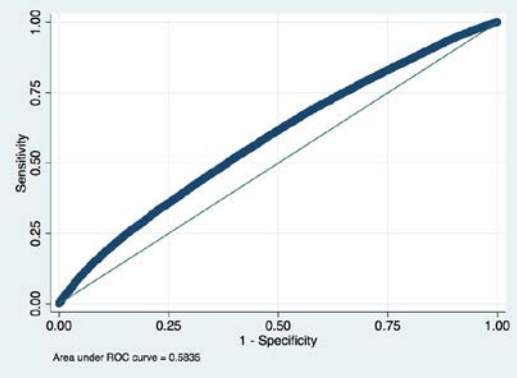


Figure 12: Predictive power- ROC



The lack of predictability is unsurprising, due to the fairly low amount of reservations all over. Additionally it is hard to determine *which* of one GPs prescriptions should contain a reservation or not, as there is no way of distinguishing these from one another. If choosing a different cut-off point however, say 0.05, we see from Figure 11 that specificity increases and sensitivity decreases. The "receiving operating characteristics" (ROC) curve in Figure 12 shows how the predictive power varies with different cut-offs. The area under the curve is a measurement of the models overall predictability (StataCorp, 2013, pp. 1119-1121). In our model, this is 0.5835: or 8.35 percentage points better than tossing a coin.

Lastly a Pearson goodness-of-fit test was applied (estat gof) to examine the observed versus the predicted number of responses of the model. The test[52] did not reject the null hypothesis (Prob > chi2 = 0.000) that the data were consistent with the applied distribution (StataCorp, 2013, pp. 494-495). Together, this leads us to conclude that the model is correctly specified, but with weak predictive power.

[51] See Appendix E for output, including with different cut-offs.
[52] See Appendix E for output

6.3.3 Two-part model

According to Belotti et al (2015, p. 18) the ability to assess the fit of the overall predictions of the twopm is limited. By looking at the predictions in Table 12 and comparing to the true proportion of doctor reservation, we can however get an idea.

Table 12: Predictions of twopm

Variable	Obs	Mean	Std. Dev.	Min	Max
y_hat_twopm	73.371	0.0663068	0.0410831	-0.0610938	0.1742107
doctor_reservation	73.371	0.0661678	0.1116615	0	1

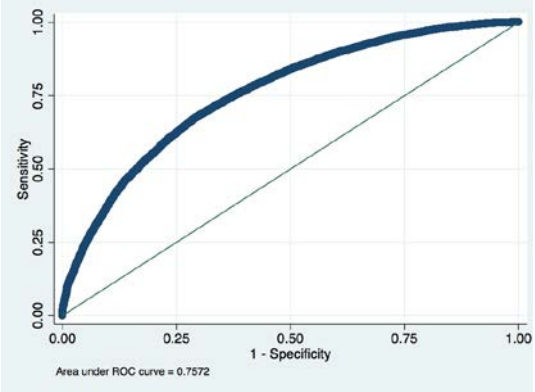
As we can see, the mean of the predictions, "y_hat_twopm" is almost identical to the true mean. Since the theoretical basis of the model chooses coefficients of the independent variables to minimize the variation between the predicated and the true reservation level, this is therefore unsurprising. The standard deviation is far smaller than the true variation however. This is due to the specification of the model in accounting for the large zero-mass in the data. Since the predictions of the twopm are not bounded, we can furthermore note that it also predicts negative values.

Although the goodness of fit is hard to test for the overall model, the separate parts of the probit and the GLM model are easier to assess.

Probit: The pseudo R-squares are higher for the probit model when specified within the twopm than what was the case when it stood alone. This is probably because the overall proportion of positive outcomes for the dependent variable is higher when it is aggregated on GPs. The relative size of the pseudo R-squares across "overall", "old" and "new" are similar to the other probit version, for the same reasons as outlined in subsection 6.3.2.

The model's ability to distinguish between reservation and non-reservation is fairly good, with an area under the ROC-curve in Figure 13 equal to 0.7572[53]. Lastly, a Pearson goodness-of-fit test was performed. The null hypothesis that the data are consistent with the applied distribution, could not be rejected (Prob > chi2 = 0.0000)[54]. Together, this suggests that the modelling is satisfactory.

Figure 13: Predictive power- ROC



GLM: Deviance residuals are the equivalent of the residuals in OLS-models, for models that use maximum likelihood. According to McCullagh & Nelder (1989), deviance residuals are approximately normally distributed if the model is correct. Furthermore, by looking at the deviance residuals vs. doctor reservation we can assess the model's goodness of fit.

Figure 14: Distribution of deviance residuals

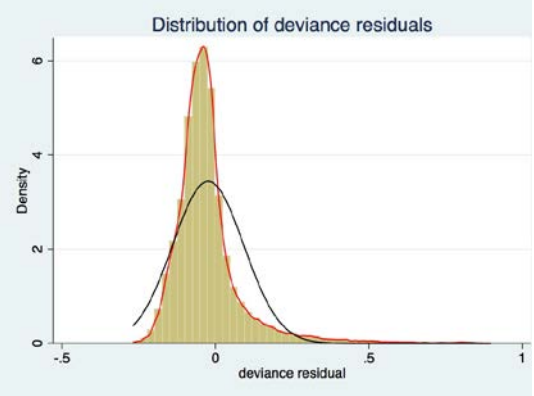
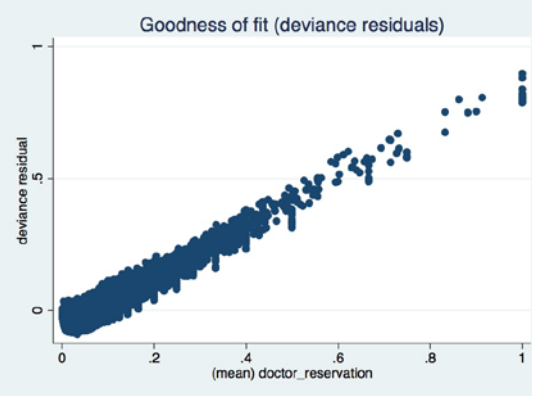


Figure 15: Goodness of fit (deviance residuals)



As we can see from Figure 15, the deviance residuals show a strong and fairly balanced correlation with doctor reservations. As with the predictions from the OLS model, deviance residuals can take on negative values contrary to that of what is observed in real life. With respect to the distribution of the deviance residuals in Figure 14, we see that the kernel density plot in red, to a large extent overlaps the normal distribution in black. The similarity is not as strong as one could hope for, but we deem it reasonable enough. Considering the

[53] The mass of zeros is greatly reduced when modelling every positive outcome as 1. This likely explains the increased fit.
[54] Output provided in Appendix F

goodness of fit separately for the models in twopm, the specification and corresponding applicability of the overall twopm seems fitting.

6.3.4 Fixed effects

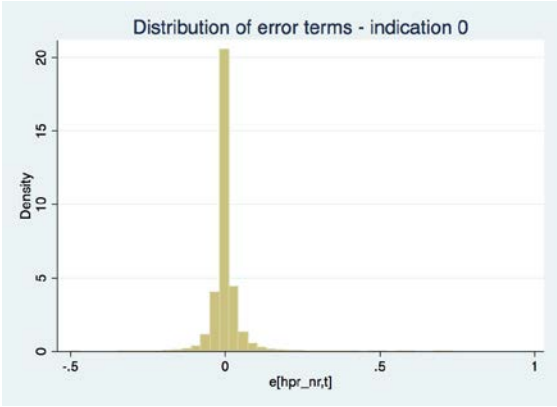
The three R-squares in the different fixed effects models in Table 12 tell us that the independent variables explain fairly little. This is especially the case if you compare the R-squares to rho, which say that differences in the unobserved characteristics of the GPs explain around 60%. When running fixed effects models, F-tests are automatically computed. These test the hypothesis that all coefficients are equal to zero. As we can see in Table 13 this can firmly be rejected for all indications. As mentioned earlier, clustering with robust standard errors was used to account for heteroskedasticity. When testing the models without such specification, heteroskedasticity was present[55].

Table 13: Results from fixed effects models

	Ulcer (0)	Cholesterol (1)	Depression (2)	Old drugs	New drugs
rho[1]	**0.6406**	**0.5942**	**0.5605**	**0.6425**	**0.5735**
Prob > F	**0.0033**	**0.0000**	**0.0000**	**0.0000**	**0.0000**

For the fixed effects model to produce linear unbiased estimators, a number of assumptions need to be fulfilled. To see whether most of the assumptions are satisfied, one can look at the distribution of the individual error terms for the GPs[56]. If they are normal, the specification is correct (Wooldridge, 2013, pp. 509-510). We can see from Figure 16 that this is the case for indication 0. The other indications show similar distributions and are included in Appendix F. This suggests that the model is fit for analysing the data at hand.

Figure 16: Distribution of error terms



[55] See Appendix F for tests.

[56] The other assumptions that cannot be verified by looking at the distribution are i) random sampling and that ii) each explanatory variable changes over time.

6.4 Interpretation

The most important insight we can draw from the models, is that they give highly consistent predictions. In the "overall" models, 10 out of 15 independent variables give significant results in all of the models. Of these 10 variables, 9 have the same sign across the different models and differ only slightly in terms of size of marginal effects. In the separate models for "new" and "old" ATCs, the predictions are equally coherent for the large majority of variables. The variables that come out as insignificant, can by and large easily be explained. Taking into account the results from "overall", "old" and "new", the predictions of the fixed effects models are also very close to what we would expect. Before looking more closely at the effects separately, some clarification is needed. Since the dependent variable is modelled differently in all models, the results have to be interpreted with caution.

The interpretation of the marginal effects varies depending on the variable and model in question. For log-transformed variables, a one *percentage* increase in the independent variable is associated with a change in the dependent variable equal to 1/100*coefficient of the independent variable[57] (Wooldridge, 2013, pp. 713-715). E.g. if the coefficient of ln_freq_pres_indication_year = 0.0167, the effect of a 1% increase in the coefficient ln_freq_pres_indication_year on doctor_reservation, would be equal to 0.000167 (=0.0167*(1/100)). The other non-transformed variables are easier to interpret: a one-unit increase in the independent variable is associated with a change in doctor reservation equal to the size of the coefficient of that independent variable. As noted earlier, the variables on competition and patient reservation are multiplied by 100 to make their interpretation more intuitive. Here, a one-unit change represents one percentage point increase. If the independent variable is a dummy variable, the change is measured relative to the defined baseline[58].

There are some further substantial differences between the models in terms of interpretation. The regression model and the probit model are fairly similar, but with the former predicting proportion of reservation for one GP, and the latter probability that a given GP will make a reservation for a given prescription. In terms of the twopm, the combined results are of most interest, but the two models that form its base also provide some valuable insight. The probit

[57] Considering the equation $y = \beta_0 + \beta_1 \log(x)$, a rule of approximation states that $\Delta y \approx \left(\frac{\beta_1}{100}\right) \%\Delta x$

[58] See table 5 for overview of variables and corresponding baselines

part of the twopm is more biased towards a GP making a reservation[59], and thereby showing larger marginal effects than what is the case for the other probit model. The GLM model predicts reservation given that it has taken place, which also explains why many coefficients differ with respect to the probit part of the twopm.

We see that the fixed effects models have fairly small R^2, and that the predicted coefficients of the independent variables have small values. Since neither of the independent variables included are expected to change much at all, the fact that we have significant, and fairly consistent results across indications, is an interesting observation in itself.

Price difference

Price difference is statistically significant in most of the models. In general the models show small negative marginal effects, which was also what Stoinska-Schneider (2011) found. When distinguishing between "old" and "new" ATCs, the effects are positive. For the fixed effects models, the findings are inconclusive. The sizes of the effects are also small. Together, this makes it difficult to make any solid predictions. The relatively weak effect from price, and the different signs across the models, might be attributable to the inclusion of indications or ATCs as dummy-variables. Since price differences vary between indications and ATCs, the dummy variables for indications might capture some of the effect that price has on reservation.

Male

The results for the male-variable are in broad insignificant. The few exceptions have low coefficients and point in different directions, which suggests that the sex of the GP does not affect reservation.

Age

Relative to other independent variables examined, age is amongst the best predictors of reservation. Both dummies have positive coefficients, and are for the most part highly significant. In the few cases where either one of the dummies is not significant, the other one is. One observation worth noting is that the two age dummies in "overall" do not differ much, whilst the dummy for the oldest age group has consistently higher coefficients when

[59] Since all positive results are counted as 1.

differentiating between “old” and “new”. Together, this suggests that GPs aged over 40 have a tendency to use reservation more often than younger GPs.

Specialist

The dummy variable specialist is with a few exceptions, insignificant. However, being a specialist is strongly correlated with age (correlation = 0.41). This was also clear in Section 6.1 when looking at the descriptive statistics. When testing the models, including “specialist” as an independent variable did not seem to affect the predictive power of the other independent variables. Nevertheless, it is more intuitive that age increases the probability of becoming a specialist than the other way around. This does not mean that there cannot be differences within age groups (cf. Section 6.1), although our models in general cannot show any meaningful association. One exception worth noticing is that for “new” ATCs, being a specialist is negatively and significantly associated with reservation levels in the GLM part of the twopm.

Competition

The variable on competition gives good results. It is highly significant in almost all models, and its negative sign indicates that increased competition leads to more reservation. Although the size of the coefficient is small, the effect is not necessarily week when considering its definition in Table 5. E.g. a 10-percentage point change in the competition proportion, leads to a 3-percentage point reduction in reservation in twopm model of “overall” in Table 9. Note that “new” ATCs has a much larger size of the coefficient than that of “old” ATCs. Together, these results suggest that increased competition lead to more reservations, and especially so in new generic markets.

Frequency of prescriptions

Frequency of prescriptions is a highly significant variable in all models in “overall”, “old” and “new”, but with altering signs. However, when considering the different interpretations of the models, this might not be surprising. When all physicians are pooled together, the probability of making a reservation increases with the amount of prescriptions you make. This becomes especially clear in the probit part of the twopm. The effect is likely due to the fact that many GPs did not make a reservation for one or more active ingredients a given year. When looking at the GLM part of the twopm, one can however see that contingent on having made a reservation; the proportion of reservations is decreasing in frequency of

prescriptions. This is the number that is of most interest, and indicating that confidence in generic equivalence, or habit formation leads to fewer reservations. The predictions of the combined parts of the twopm give the same result.

In terms of change over time, predictions in the fixed effects models are inconclusive. The results are not surprising considering that the initial frequency is not accounted for in these models, only the change. Deviations from one GPs mean level of prescriptions are expected to be less than deviations of means between physicians. This might provide some explanation for the weak effect when looking at change over time.

Indication

The indication dummies are highly significant in all the models. The general picture is that ulcer has lower, and depression has higher rates of reservation than cholesterol. It should be clear beyond any doubt, that reservation varies widely over indications.

Year

With 2011 as the baseline, we see a notable decrease in reservation over time for the year-dummies in "overall" and "old". Here, all the dummies are highly significant, with the exception of 2012 being slightly insignificant at times. In general, the decrease is also less pronounced for 2012 than for the years 2013 and 2014 that show fairly persistent reductions in reservation. For "new", the effect of year works in the opposite direction, with positive and significant coefficients.

Patient reservation

Patient reservation is significant with a negative sign in the fixed effects models, except for indication 1 (cholesterol) and "old". The results therefor imply that patient- and doctor reservation are to some extent substitutes. This effect is however much larger for "new" (-0.0008) than "old" (-0.0003). Together with the observations from the descriptive statistics, this suggests that patient and doctor reservation can be substitutes, and especially so in new generic markets.

Comparing with other model-specifications and samples

In general the results are not sensitive to using the limited sample as a base. Unsurprisingly, it has more predictive power, either in the form of lower AIC and higher R-squared and Pseudo

R-squared. The rise in predictive power is likely due to some of the uncertainty from lag in prescription and dispensing of drugs being removed. For the most part, the significant variables have the same signs as that of the main sample. The largest difference in using the limited sample is that the signs of the year dummies changes from negative to positive. This is probably due to the smaller sample, and thereby that the drugs included to a lesser extent reflect the true prescription options at hand for the GP. Frequency of prescriptions is negative and significant in the limited sample for the probit and OLS models – opposite of what we found when using our main sample. A possible explanation is that the drugs that are included in the limited sample also are the ones used most frequently by all GPs. If all GPs prescribe a drug often, habit and confidence might be more pronounced.

When running the twopm for the different years separately, the models are slightly weaker in terms of predictive power. Most notably, the competition variable is only significant for the years 2013 and 2014 when running models for "overall". When performing the analysis separately for "old" and "new" ATCs for every year, the results also proved similar to those from the main sample. The competition variable was more significant for "new" ATCs than for "old". The latter had a significant competition variable in the years when centrality did not, and vice versa. The reduced predictive power of the models might be due to fewer observations in the sample, but also that serial correlation is more properly accounted for.

7 Discussion

7.1 Strengths and weaknesses

One factor in the analysis is both the main strength and the main weakness: the extraction of the sample. Well over 250 different packages were checked separately against the two databases *athene* and *farmastat* to determine whether or not generic competition was taking place for that package at the time the prescription was made. This means that the sample, under the assumptions (cf. Section 4.1), to a large extent reflects the choice context of both the doctor and the patient with respect to reservation. The weakness of extraction is correspondingly that assumptions had to be made. Accordingly, there is without doubt a certain amount of prescriptions where generic reservation was a possibility that were not included in the sample. The limited sample, where only packages with sales the entire period were included, showed similar results as that of the main sample. This serves as a robustness check of the results. However, there will always be the possibility that other assumptions could lead to extraction of an even more relevant sample.

There are some key variables lacking that would have improved the analysis. Since the justifications for preferring a brand drug are linked to patient characteristics, such data might have helped explaining variations between GPs. For example, older GPs tend to have older patients, thereby deeming reservation more necessary. Equivalently, sex and residence of the GPs might affect the kind of patients they have on their list.

The reasoning for including competition was to examine GPs' gatekeeper function from an income-motive. Data on GPs' relative preferences towards income versus altruism would provide additional insight. This is an emerging research topic (e.g. (Godager & Wiesen, 2013)) that can prove valuable for understanding a GP's trade-offs. Furthermore, although most GPs are paid by a combination of FFS and capitation, some are salaried. Being able to control for this would also have been preferable.

7.2 Inference

The main findings of this study, is that GP characteristics are highly relevant in explaining reservation. This is underlined by the results from the fixed effects models, where around

60% of the variation was explained by constant unobserved individual characteristics of the GPs. By comparison, Hellerstein (1998, p. 125) estimated that almost 30% of the unobserved variation in her data was due to physician characteristics. A proportion of the variation in our data can be attributed to constant variables that cannot be included in fixed effects models (e.g. age, sex, specialist), but there are clearly many other unknown factors. Preferences are such unknown factors that are likely to have a large effect. With reference to the theoretical model; altruism, valuation of societal costs and personal income is likely to vary widely between individuals and translate into different rates of reservation.

Personal characteristics of the GP

Age had strong explanatory power across the different models, with highly significant coefficients. This supports previous findings by others, including Shrank et al (2011) & Dalen et al (2011), that older doctors use reservation more often. Stronger habits and lower confidence in the generic equivalent are some of the more immediate possible explanations, in addition to older patient populations. Having experienced more reforms and institutional arrangements, willingness to comply with guidelines can also be weakened with age. Keeping in mind that generic substitution was introduced in 2001, this might provide some understanding. Accordingly, relatively more weight will be given to the personal assessments of the GP, and in turn weaken preferences towards those of the state – like societal costs. A study by Van Leeuwen et al (1995) found that older doctors were less updated on professional knowledge than their peers. If dissemination of information about generics is slower amongst older GPs, this might also explain some of the variation. Specialists on the other hand, are likely to follow new medical developments more closely. The findings in Table 7 where specialists have lower reservation within the oldest age group would support this hypothesis. A similar association was also found in the twopm for "new" ATCs, where the negative coefficient might reflect that specialists are more aware of new generics entering the market. In turn, this awareness might translate into lower reservation levels. The increased confidence can also reduce patients' utility from being prescribed the brand version.

From a policy perspective, higher reservation among older GPs is not necessarily a problem in the long run. If one gives more weight to the hypothesis of schooling and attitudes towards generics, the results give reason to believe that the overall level of reservation is transitory.

Holding the patient population constant, todays younger GPs might have a different attitude towards generics in the late of their careers, compared to what is the case today.

Reservation does not differ noticeably whether the GP is a man or a woman. However, reservation in our model can be motivated from a wide range of factors, including income and altruism. Whether or not males or females have different preferences relating to these factors would be an interesting topic for further research. In terms of patient population, Lurås (2004) has shown that patients have a tendency to choose GPs that have the same sex as them. Without drawing any conclusions, an insignificant effect of being a male GP, might therefore also reflect that male and female patients have similar attitudes towards generics.

There are many ways of defining habit, and its effect on prescription behaviour. Dalen et al (2011) looked at GP-characteristics like age and sex, Coscelli (2000) at prescribing behaviour, and Hellerstein (1998) at spill-over effects from one patient group to another. Irrespective of how habits are defined, the above studies suggest that habits are indeed sticky and that they translate into fairly strong preferences in prescription decisions. As defined in our model, frequency of prescription can also be thought of a proxy for confidence in generic equivalence. The predictions in our models that are of most relevance in studying habit formation/confidence show desirable results: reservation decreases with increased prescriptions of drugs within that indication/ATC. We would be inclined to interpret this effect more as a sign of increased confidence rather than habit formation (cf. Section 3.2). In other words, a GP who prescribes a drug often is more likely to have prescribed the drug to a wide range of patients. Any uncertainty of the effect of generics is therefore believed to diminish, and the GP will be less likely to give in to patient pressure. Interestingly, this effect seems to be somewhat stronger for "new" ATCs than that of "old" ATCs. In the predictions of the twopms, the corresponding marginal effects are –0,0113 and -0,0080. This suggests that confidence plays a stronger part in newer generic markets where uncertainty is likely more widespread amongst GPs.

Market conditions

One of the main insights from this thesis is the effect of competition on reservation. All the models showed the same association: more competition increases reservation. This suggests that the gatekeeper function of physicians is weakened in markets with a high degree of competition. The main hypothesis is that GPs attempt to retain patients in their practice in

order not to lose income. The stronger effect of competition in new generic markets, suggests that patients are more susceptible to switching GPs in their first encounter with generic substitution. Equivalently, the GPs might fear that this is the case, and more easily give in to perceived patient pressure. With reference to the discussion on confidence and dissemination of information, this effect might come from the increased uncertainty. With respect to our theoretical model in Section 3.1; increased competition makes the patients' benefit more important for the GP from an income perspective, and especially so for the case of new generics.

Earlier literature has found that competition does have explanatory power in various parts of the GP-practice ((Sagdahl, 2010), (Lurås, 2004) (Godager, Iversen, & Ma, 2015) (Iversen & Lurås, 2011)). However, as is clear when reading previous research, there is no definite way of defining competition among GPs. Before deciding on the variable comp_municipality many others were considered, including patient shortage, herfindahl index, proportion of a single list filled, GP-spots per capita etc. In broad, these measures of competition did not have as significant and strong effects as comp_municipality[60]. They did however point in the same direction; namely that competition increases reservation. The herfindahl index however gave positive results, indicating that a decrease in competition (or increase in market power) leads to more reservation; contrary to what we would expect. This might however be the result of the index being based on municipality measures. Larger municipalities will in reality be represented by several smaller markets. The index might therefore act more as a proxy for population size than for competition[61]. Together this shows how analyses of competition are susceptible of the choice of variable, and accordingly to some extent weakens the predictions of our model.

Some of the variation in reservation between the different years studied is not easily explained, but is likely affected by our assumptions of genuine generic competition and our choice of indications/ATCs. As was clear when making the sample from the raw data, there are many generics that enter and exit the market within fairly short time frames. This gives a

[60] See Appendix I for output from different measures of competition.
[61] Centrality and herfindahl variable highly correlated (0,4022)

degree of disturbance with respect to lag in time from prescribing to dispensing the drug. Drug availability in pharmacies is also an issue.

NOMA has hypothesized that the introduction of an e-prescription module within GP computer systems may have affected overall reservation levels. A transition from manual to electronic prescriptions can have led to uncertainty among GPs in stating non-reservation and reservation correctly. In the recent report by HELFO (2015a) where reservation rates of 20 GPs were controlled, this was listed as one of the explanations for increased reservation. Amongst others, the GPs mentioned experiences with systems where reservation was listed as the default option. However, as we see in Table 14 e-prescription increases in our studied period.

Table 14: Trend in use of e-prescription

Percentage of prescriptions made with e-prescription			
2011	**2012**	**2013**	**2014**
2.3 %	23.1 %	60.7 %	62.1 %

In the most representative samples for the case of e-prescription, "overall" and "old" ATCs; the models show decreasing reservation rates, opposite of what we would expect given the hypothesis. One might be able to find different results in looking at all drugs on the market, but we cannot find the same support in our data.

When looking at "new" ATCs, the effect of the year dummies is reversed, with consistently higher reservation levels for 2012-14 than the baseline. Since the drugs included in "new" ATCs enter into generic competition at different points in time, the lack of a clear trend is unsurprising. In the descriptive statistics, however, the general picture is that GP-reservation increases over time, and patient reservation decreases. This is supported by the fixed effects model, where decreased patient reservation leads to increased GP reservation for "new" ATCs. One might expect the opposite effect: that GPs are reluctant to use a new generic when having prescribed the brand-version for years.

Keeping in mind that brand-name prescriptions can still be substituted as long as a reservation is not made, might give some explanation. In other words, the GP does not know that there is a generic competitor available when writing the prescription. On the basis of

discussions with NOMA, there is reason to believe that patients might be informed about generic substitution before the prescriber. If uninformed about the introduction of generic competition for a prescribed drug, a patient might be surprised with substitution in the pharmacy and choose to make a reservation. In the subsequent GP-visit, the patient confronts his GP with this information, and asks the GP for a reservation note to avoid the added cost himself. In time, the GP will gather more information about the generic's market entry, and become more confident about denying new patients the branded version. Doctor reservation will thereafter stabilize and find an equilibrium, which will decrease over time. This hypothesis is supported by the reservation trend of the other indications, which are either fairly stable or decreasing. This might suggest that the gatekeeper role of GPs is weakened in initial aftermath of generic market entry. Dalen et al (2011) studied the effect of new generic markets, and found that drugs that had recently gone off patent had higher rates of reservation. Since they looked at the aggregate number of reservation, and not the trend, their findings does not conflict with ours.

The models results in "overall" suggest that the indication in question explains much of the variation in reservation. The differences in reservation rates between indications might indicate that there are more medically justifiable reasons to use reservations for some indications than others. After discussions with NOMA, another possible explanation of differences might relate to a "placebo effect"; taking what the patient perceives to be an inferior medicine (i.e. generic), might be of less concern if the effect of the drug is not observable to the patient. The argument goes that if the effect of the drug is hidden to the patient (e.g. lower cholesterol level), the patient will, to a lower degree, have any opinion of the effect. Contrary, the symptoms of stomach ulcer and depression drugs are to a larger extent felt by the patient. The hypothesis was supported by the findings of Stoinska-Schneider (2011). In our results the coefficient of ulcer has a negative sign, opposite of what was found by Stoinska-Schneider (2011). Accordingly, we cannot provide any support to the hypothesis. A possible explanation to the opposite sign of the ulcer coefficient is the inclusion of more drugs within the different indications. Additionally, it might be the case that acceptance for generic versions within the ulcer indication has matured among both patients and GPs.

As discussed in the literature review, the effects of price differences on reservation can work both ways. The mixed predictions our models provide suggest that price differences do not

matter at the aggregate level. With reference to our theoretical model, it might be the case that preferences towards the patients' benefit and that of limiting societal expenses simply offset each other. Then again, the results can also mean that GPs simply don't care at all.

Lastly, we cannot find support for an unambiguous association between centrality of a municipality and the corresponding level of reservation. Stoinska-Schneider (2011) used centrality as a proxy for looking at the effect of marketing (in addition to competition). She found that central areas indeed had higher rates of reservation. Since both extremes of the centrality scale showed persistently higher rates of reservation in our results, the same conclusion could not be drawn. Possibly, less conclusive results might be due to the inclusion of the competition variable, although this was not the case when first including the dummy.

Because not all drugs are marketed as heavily as others, it would be interesting to dig deeper into a few chosen active ingredients. To skim the surface of the hypothesis, a look at Omeprazole gave some insight. In looking at Table 16, it has a consistently higher reservation rates than the indications as a whole, with a marked decrease over less central areas (2 and 3).

Table 15: Reservation by centrality and indication

Centrality	Ulcer	Cholesterol	Depression	Omeprazole	Total
0	.053769	.031998	.050120	.222904	.054190
1	.037312	.031969	.047306	.184265	.049634
2	.031781	.020595	.03711	.136872	.038372
3	.040056	.029229	.050010	.146012	.051363
Total	.047844	.031066	.048804	.205776	.052063

It has been suggested that the high reservation rates of this drug might be due to an effective marketing campaign towards GPs by pharma-reps. This gives some support to the hypothesis of marketing and its effect on GP preferences in prescription behaviour that is worth exploring further.

8 Conclusion

The compiled findings in this study suggest that GP-characteristics and market conditions are highly relevant for explaining different rates of reservation. In addition to verifying previous results from other studies, this thesis has given new insights on the effect of increased confidence. Furthermore, market conditions in the form of competition and maturity of generic markets proved important in explaining different reservation rates. Although not explicitly measured, the factors studied give strong reasons to believe that preferences are important, and that they are not isolated from context.

In the grand of things, however, what motivates a GP in his choice of using a reservation note might not matter that much as long as the overall reservation rate is unproblematic. This leads us to the overarching question of *what* rate of reservation is problematic? If there is such a thing as a "correct" rate of reservation, the costs of inducing GPs to make correct reservation choices might outweigh the corresponding benefits.

Acknowledging the trouble of stating a "correct" rate of reservation, it is hard to say whether or not it is problematic. The most theoretically pleasing way to define a problematic rate of reservation is large (positive) deviations from the mean. A GP with 20-percentage points higher reservation rate than his peers is at least questionable. This was also made clear by the recent report of HELFO (2015a) that deemed reservation practices of 20 GPs as both highly excessive and costly.

Reducing information imperfections in the form of increasing knowledge about generic market entry and generic equivalence might reduce the amount of outliers. Compiling the findings, however, reservation levels among the large majority of GPs are unproblematic. Nevertheless, the findings do show that in practicing their profession, GPs are far from isolated from personal convictions and market forces.

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Appendix A: ATC-explanation

A thorough explanation of the ATC classification system is given below, as described in its entirety by the WHO Collaborating Centre for Drug Statistics Methodology[62]:

"In the Anatomical Therapeutic Chemical (ATC) classification system, the active substances are divided into different groups according to the organ or system on which they act and their therapeutic, pharmacological and chemical properties.

Drugs are classified in groups at five different levels. The drugs are divided into fourteen main groups (1st level), with pharmacological/therapeutic subgroups (2nd level). The 3rd and 4th levels are chemical/pharmacological/therapeutic subgroups and the 5th level is the chemical substance. The 2nd, 3rd and 4th levels are often used to identify pharmacological subgroups when that is considered more appropriate than therapeutic or chemical subgroups. The complete classification of metformin illustrates the structure of the code:

A	*Alimentary tract and metabolism*
	(1st level, anatomical main group)
A10	*Drugs used in diabetes*
	(2nd level, therapeutic subgroup)
A10B	*Blood glucose lowering drugs, excl. insulins*
	(3rd level, pharmacological subgroup)
A10BA	*Biguanides*
	(4th level, chemical subgroup)
A10BA02	*metformin*
	(5th level, chemical substance)

Thus, in the ATC system all plain metformin preparations are given the code A10BA02."

[62] http://www.whocc.no/filearchive/publications/1_2013guidelines.pdf

Appendix B: Derivation of equations and proof

Increase in altruism:	$\frac{\partial X^*}{\partial \alpha} = \alpha B''(X)\frac{\partial X}{\partial \alpha} + B'(X) + lG''(X)\frac{\partial X}{\partial \alpha} - kS''(X)\frac{\partial X}{\partial \alpha} = 0$ $\Rightarrow \frac{\partial X}{\partial \alpha} = -\frac{B\prime(X)}{(\alpha B''(X)+lG''(X)-kS''(X))}$
	$\alpha, l, k > 0$ $B''(X)<0$, $G''(X)<0$, $S''(X)>0$ $\Rightarrow (\alpha B''(X) + lG''(X) - kS''(X)) < 0$ $B'(X) > 0$ $\Rightarrow -\frac{B\prime(X)}{(\alpha B''(X)+lG''(X)-kS''(X))} > 0$ $\Rightarrow \boldsymbol{\frac{\partial X}{\partial \alpha} > 0}$
Increased weighting of income:	$\frac{\partial X^*}{\partial l} = \alpha B''(X)\frac{\partial X}{\partial l} + lG''(X)\frac{\partial X}{\partial l} + G'(X) - kS''(X)\frac{\partial X}{\partial l} = 0$ $\Rightarrow \frac{\partial X}{\partial l} = -\frac{G\prime(X)}{(\alpha B''(X)+lG''(X)-lS''(X))}$
	$\alpha, l, k > 0$ $B''(X)<0$, $G''(X)<0$, $S''(X)>0$ $\Rightarrow (\alpha B''(X) + lG''(X) - kS''(X)) < 0$ $G'(X) >$ $\Rightarrow -\frac{G\prime(X)}{(\alpha B''(X)+lG''(X)-kS''(X))} > 0$ $\Rightarrow \boldsymbol{\frac{\partial X}{\partial l} > 0}$
Increased weighting of societal expenses:	$\frac{\partial X^*}{\partial l} = \alpha B''(X)\frac{\partial X}{\partial l} + lG''(X)\frac{\partial X}{\partial l} + G'(X) - kS''(X)\frac{\partial X}{\partial l} = 0$ $\Rightarrow \frac{\partial X^*}{\partial k} = \frac{S\prime(X)}{(\alpha B''(X)+lG''(X)-kS''(X))}$
	$\alpha, l, k > 0$ $B''(X)<0$, $G''(X)<0$, $S''(X)>0$ $\Rightarrow (\alpha B''(X) + lG''(X) - kS''(X)) < 0$ $S'(X) > 0$ $\Rightarrow \frac{S\prime(X)}{(\alpha B''(X)+lG''(X)-kS''(X))} < 0$ $\Rightarrow \boldsymbol{\frac{\partial X}{\partial k} < 0}$

Appendix C: Sample selection and merging

In the original dataset from the HELFO registry each observation constituted a unique prescription[63] made by a single GP, with the variable doctor_reservation equal to "1" if a reservation had been made. Depending on the statistical method used, the dates of prescriptions were aggregated yearly for every GP over the years the dataset covered (2011-2014). The year 2014 contained notably fewer observations than for the other years. This is likely due to the extraction of raw data: observations for each year were provided in separate files, and each of them contained a certain amount of observations from the preceding year. Since the subsequent year of 2014, 2015, was not provided, 2014 had fewer observations. According to the Directorate of Health, this was due to some drugs being dispensed from the pharmacy in the year after they were prescribed. The corresponding bias in reservation levels was considered to be limited at most.

Extraction of sample

The thesis studies possible physicians have different rates of reservation against generic substitution, with doctor reservations as the dependant variable. For this variable to be relevant, it had to be based on a sample of prescriptions where the GP had the option to make a generic reservation. Not all drugs with an off patent active ingredient are put on the substitution list, and not all drugs that are on the substitution list have generic competitors. The reason for this can be that the volume sold of a drug is too low for generic manufacturers to be interested in entering the market. It might also be the case that the brand-company has lowered its price to a level where generics are not in a position to compete. It was therefore decided to only include drugs where there was *genuine generic competition* at the time of prescription. Genuine generic competition is here defined as a situation where a given drug package was on the substitution list at the time of prescription, and where there were actual sales of that drug. We do however recognize that even in cases where there are no generic sales, the fact that generics are on the substitution list might drive down prices of brand drugs. In order to account for our assumptions, the NOMA drug-database *Athene* and the independent database of drug statistics *Farmastat* were consulted.

[63] All prescriptions were for partially refundable drugs (blåresept)

Athene has information on when a particular drug was placed on NOMAs substitution list. All prescriptions that were made before a certain drug was put on this list were eliminated from the sample. This can be the case for directly imported brand drugs that are substitutable with a parallel imported[64] brand drug.

Farmastat retrieves information from drug sales and –volume. Data on all generic drugs within the ATC-groups used in the analysis were checked. If there were no sales in a particular month, there can neither have been any genuine generic competition. For a few drugs, sales were fairly volatile; in that there might have been sales for the entire data-period, except for a few months within this time frame. This posed some methodological challenges in terms of what sample to use, especially since the actual sale of a drug can take place well after the prescription was made.

A certain amount of the drugs in the sample was not registered on the substitution list but had still recorded sales in *farmastat*. This was thoroughly investigated for every drug where this was the case. Some drugs had changed id-number during the time-period of the dataset, and was accordingly still included in the sample. Others were imported drugs for purposes of filling a temporary shortage of drugs in pharmacies that were on the substitution list. This can occur on rare occasions as wholesalers run out of drugs for a certain active ingredient. Since the demand is fairly constant, drugs with the same active ingredients that are not on the substitution list can fill this void. Consequently, neither doctor- nor patient reservations can occur for these cases. Therefore all drugs for which this was the case, was eliminated from the sample. This also explains why some years for some active ingredients in the final sample had fewer prescriptions than others[65].

Prescriptions for chronic conditions last for up to one year, but patients can only collect a stock of three months worth of medicines every time. This means that the actual sales of a medicine can take place long after the prescription was made – as was the case for the earlier mentioned data on 2014. Since no good data were available on average time passed before a prescription is expedited in a pharmacy, it is hard to make any assumptions about this either. With this in mind we decided, in consultation with NOMA, to include prescriptions from the

[64] As defined by NOMA; parallell imported drugs are brand drugs imported from other eruopean countries where the prices are lower than in Norway: http://bit.ly/1SC6per

[65] See Table 6 in the descriptive statistics (6.1) for overview.

first month of registered sales up until the last month of sales. Some drugs had minor gaps where there were no sales. In order to not make the extraction too complex and time consuming, these minor gaps were also included[66].

Furthermore, drugs that had no sales neither at the start nor at the end of the analysed period were eliminated[67]. The drugs for which this was the case, had limited sales volume and removing them from the sample was therefore believed to cause negligible changes to the results. Lastly, all drugs that were parallel imports were removed. Parallel imported drugs are by and large brand drugs. In the few cases that they are generics, they are still not classified accordingly by NOMA. Measuring reservation for these drugs is therefore irrelevant. For a full list of what drugs were included, and for what time-periods are provided in the end of this appendix.

Since the above assumptions leave a degree of uncertainty[68], including our definition of *genuine generic competition*, it was decided to make a separate extraction of data where only packages that had sales the entire period were included. This limited sample does not reflect the true market for generics, but it evades the problem of gaps and how to account for drugs being dispensed well after the prescription was made. The reservation rates and results that are based on this sample are included in the Appendix F.

After extracting the relevant sample, the data from the HELFO registry were first merged with the two original dataset from the GP registry by health personnel number (hpr_nr) and year, and thereafter the publically available GP registry on the basis of municipality (municipality_code) and year.

After inspecting the raw data from the GP registry, a certain amount of observations had to be dropped:

- Observations for 16 doctors that were registered with an age above 1000 years

[66] The drugs for which this was the case had a fewer observations, and the decision of inclusion or not was therefore expected to cause little distortion in any case.

[67] A few drugs with a high prescription rate (e.g. > 1000 per month) were included, as exclusion of these seemed to cause some bias

[68] The assumptions are not expected to be affect the independent variables notably. This is verified when looking at the results from the limited sample in Appendix G.

- Observations for 146 doctors that had GP-lists in two or more counties
- All observations where the patient list was shared between two or more GPs (approx. 175 GPs)
- 115 prescriptions that were not registered with a health personnel (hpr) number.

Furthermore, upon merging these datasets, not all observations were matched – e.g. some physicians that had made a prescription were not registered in the GP registry.

- After extracting atc's from raw data of the HELFO registry, the number of observations (prescriptions) were 11 933 033 (928 887 were dropped due to our assumptions of generic competition).
- After merging with data from the GP registry, 3 313 537 observations from the HELFO registry, and 79 from the GP registry were unmatched. These observations were deleted, and we were left with 8 603 499 observations.
- When merging with the publically available data from the GP registry, 8 948 in old dataset and 315 from the GP registry were unmatched. This left us with 8 594 551 observations.
- Lastly, upon inspecting the ATCs closely, 30 415 observations for ATC 13 had to be deleted. These were reservations that occurred before March 2012, the time generic competition started for this ATC. The final dataset consisted therefore of 8 564 136 observations

From this final dataset, separate extracts were made and aggregated depending on the indications/ATCs studied and model applied. For a distribution of the variables depending on the different with the different extracts and aggregations, see Appendix D.

The following table list gives an overview of the packages that were included in the main sample. For the limited sample, only the packages marked "whole period" were included.

ATC	Package number	Package name	Time period included in sample
Ranitidine A02BA02	1349	RANITIDIN RATIOTAB 150MG 30ENPAC	Whole period
	1371	RANITIDIN RATIOTAB 150MG 60ENPAC	Whole period
	1380	RANITIDIN RATIOTAB 150MG 90ENPAC	Whole period
	1402	RANITIDIN RATIOTAB 300MG 30ENPAC	Whole period
	1413	RANITIDIN RATIOTAB 300MG 90ENPAC	Whole period
	5225	ZANTAC BRUSETA 300MG 15ENPAC	Whole period
	37549	ZANTAC TAB 150MG 90ENPAC	Whole period
	37564	ZANTAC TAB 300MG 90ENPAC	Whole period
	437657	ZANTAC TAB 150MG 50ENDOS	Whole period
	495259	ZANTAC BRUSETA 150MG 30STK	Whole period
OMEPRAZOLE A02BC01	7635	OMEPRAZOL RATIOPHARM ENTKAPS 20MG 28STK	Jan-Apr 2011
	7644	OMEPRAZOL RATIOPHARM ENTKAPS 20MG 56STK	Jan 2011 - Apr 2012
	7655	OMEPRAZOL RATIOPHARM ENTKAPS 20MG 100STK	Jan-Feb 2011
	17982	OMEPRAZOL BMM PHARMA ENTTAB 20MG	Jan-Mar 2011
	18018	OMEPRAZOL BMM PHARMA ENTTAB 10MG	Jan-Apr 2011
	24882	OMEPRAZOL BMM PHARMA ENTTAB 10MG	January 2011
	24896	OMEPRAZOL BMM PHARMA ENTTAB 20MG	Jan-Mar 2011
	32391	LOSEC MUPS ENTTAB 10MG 2X50STK	Whole period
	33480	LOSEC MUPS ENTTAB 20MG 56STK	Whole period
	33761	LOSEC MUPS ENTTAB 20MG 2X50STK	Whole period
	33837	LOSEC MUPS ENTTAB 20MG 28STK	Whole period
	43856	OMEPRAZOL PENSA ENTKAPS 20MG 2X50ENPAC	From September 2012
	45644	OMEPRAZOL BLUEFISH ENTKAPS 20MG 28ENPAC	From April 2014
	57775	OMEPRAZOLE TEVA ENTKAPS 20MG 28STK	From June 2014
	88679	OMEPRAZOL PENSA ENTKAPS 10MG 2X50ENPAC	From September 2012
	116039	OMEPRAZOL BLUEFISH ENTKAPS 20MG 14KAPS	Jan 2011 - Feb 2014
	116050	OMEPRAZOL BLUEFISH ENTKAPS 10MG 100KAPS	Jan 2011 - Apr 2014
	116062	OMEPRAZOL BLUEFISH ENTKAPS 20MG 28KAPS	Jan 2011 - Feb 2014
	116073	OMEPRAZOL BLUEFISH ENTKAPS 20MG 56KAPS	Jan 2011 - Feb 2014
	116084	OMEPRAZOL BLUEFISH ENTKAPS 20MG 100KAPS	Jan 2011 - Aug 2014
	412873	OMEPRAZOL PENSA ENTKAPS 20MG 14ENPAC	From September 2012
	415860	OMEPRAZOL BLUEFISH ENTKAPS 10MG 100ENPAC	From April 2014
	438191	OMEPRAZOL BLUEFISH ENTKAPS 20MG 100ENPAC	From March 2014
	515290	OMEPRAZOLE TEVA ENTKAPS 20MG 2X28STK	From June 2014
	534670	OMEPRAZOL BLUEFISH ENTKAPS 20MG 56ENPAC	From April 2014
	537275	OMEPRAZOL PENSA ENTKAPS 20MG 56ENPAC	From August 2012
	548007	OMEPRAZOLE TEVA ENTKAPS 20MG 14STK	From June 2014
	555502	OMEPRAZOLE TEVA ENTKAPS 20MG 2X50STK	From June 2014
	592605	OMEPRAZOLE TEVA ENTKAPS 10MG 2X50STK	From June 2014
	593173	OMEPRAZOL PENSA ENTKAPS 20MG 28ENPAC	From September 2012
PANTOPRAZOLE A02BC02	1411	SOMAC ENTTAB 40MG 14ENPAC	Whole period
	4801	SOMAC ENTTAB 40MG 28ENPAC	Whole period

	5209	SOMAC ENT TAB 40MG 56ENPAC	Whole period
	16851	SOMAC INJ SUB 40MG 5HGL	Whole period
	70657	PANTOPRAZOL SANDOZ INJ SUB 40MG	From March 2013
	88215	SOMAC ENT TAB 20MG 100ENDOS	Whole period
	108969	SOMAC ENT TAB 40MG 100ENDOS	Whole period
	131319	PANTOPRAZOL ACTAVIS ENT TAB 20MG 100ENPAC	Whole period
	131374	PANTOPRAZOL ACTAVIS ENT TAB 40MG 100ENPAC	Whole period
	545467	SOMAC ENT TAB 20MG 14ENPAC	Whole period
	545673	SOMAC ENT TAB 20MG 56ENPAC	Whole period
LANSOPRAZOLE A02BC03	22747	LANSOPRAZOL RATIOPHA ENTKAPS 15MG 56STK	Whole period
	22785	LANSOPRAZOL RATIOPHA ENTKAPS 30MG 28STK	Whole period
	22796	LANSOPRAZOL RATIOPHA ENTKAPS 30MG 56STK	Whole period
	22807	LANSOPRAZOL RATIOPHA ENTKAPS 30MG 100STK	Whole period
	22818	LANSOPRAZOL RATIOPHA ENTKAPS 15MG 14STK	Whole period
	22840	LANSOPRAZOL RATIOPHA ENTKAPS 15MG 2X50STK	Whole period
	22846	LANSOPRAZOL RATIOPHA ENTKAPS 30MG 14STK	Whole period
	23040	LANSOPRAZOL RATIOPHA ENTKAPS 15MG 28STK	Whole period
	23949	LANSOPRAZOL KRKA ENTKAPS 15MG 98STK	From June 2014
	23993	LANSOPRAZOL KRKA ENTKAPS 30MG 98STK	From June 2014
	164573	LANSOPRAZOL KRKA ENTKAPS 30MG 14ENPAC	From June 2014
	164584	LANSOPRAZOL KRKA ENTKAPS 30MG 28ENPAC	From June 2014
	164595	LANSOPRAZOL KRKA ENTKAPS 30MG 56ENPAC	From June 2014
	164606	LANSOPRAZOL KRKA ENTKAPS 15MG 14ENPAC	From June 2014
	164617	LANSOPRAZOL KRKA ENTKAPS 15MG 28ENPAC	From June 2014
	164628	LANSOPRAZOL KRKA ENTKAPS 15MG 56ENPAC	From June 2014
AMLODIPINE C08CA01	17196	AMLODIPIN ACTAVIS TAB 5MG 30ENPAC	Whole period
	17218	AMLODIPIN ACTAVIS TAB 10MG 100ENPAC	Whole period
	17248	AMLODIPIN ACTAVIS TAB 5MG 100ENPAC	Whole period
	22269	NORVASC TAB 5MG 30ENPAC	Whole period
	22293	NORVASC TAB 5MG 100ENPAC	Whole period
	22368	NORVASC TAB 10MG 100ENPAC	Whole period
	89152	AMLODIPIN SANDOZ TAB 10MG 100STK	From May 2012
	91765	AMLODIPIN SANDOZ TAB 10MG 30ENPAC	From May 2012
	94897	AMLODIPIN BMM PHARMA TAB 5MG	Jan-Mar 2011
	101327	AMLODIPIN SANDOZ TAB 5MG 30ENPAC	From May 2012
	448413	AMLODIPIN SANDOZ TAB 5MG 100STK	From May 2012
FELODIPINE C08CA02	10936	FELODIPIN RATIOPHARM DEPOTTA 5MG 30ENPAC	Whole period
	10947	FELODIPIN RATIOPHARM DEPOTTA 5MG 100ENDOS	Whole period
	10980	FELODIPIN RATIOPHARM DEPOTTA 10MG 100ENDOS	Whole period
	11897	FELODIPIN HEXAL DEPOTTA 5MG 30ENPAC	Whole period
	12109	FELODIPIN HEXAL DEPOTTA 5MG 100ENPAC	Whole period
	12123	FELODIPIN HEXAL DEPOTTA 10MG 30ENPAC	Whole period
	12131	FELODIPIN HEXAL DEPOTTA 10MG 100ENPAC	Whole period
	30309	FELODIPIN HEXAL DEPOTTA 2.5MG 100ENPAC	Whole period
	165431	PLENDIL DEPOTTA 2.5MG 98ENPAC	Jan 2011 - Oct 2012

	165449	PLENDIL DEPOTTA 10MG 98ENPAC	Whole period
	165548	PLENDIL DEPOTTA 5MG 98ENPAC	Whole period
LERCANIDIPINE C08CA13	13233	ZANIDIP TAB 20MG 98ENPAC	Whole period
	65934	LERKANIDIPIN ACTAVIST AB 10MG 28ENPAC	Whole period
	65945	LERKANIDIPIN ACTAVIST AB 10MG 98ENPAC	Whole period
	65956	LERKANIDIPIN ACTAVIST AB 20MG 98ENPAC	Whole period
	74575	ZANIDIP TAB 10MG 28ENPAC	Whole period
	92817	ZANIDIP TAB 10MG 98ENPAC	Whole period
SIMVASTATIN C10AA01	10908	SIMVASTATIN RATIOPHA TAB 10MG 28ENPAC	Jan 2011 - Jan 2013
	10940	SIMVASTATIN RATIOPHA TAB 10MG 98ENPAC	Jan-Jul 2011
	10955	SIMVASTATIN RATIOPHA TAB 20MG 28ENPAC	Jan-May 2011
	10966	SIMVASTATIN RATIOPHA TAB 20MG 98ENPAC	Jan-May 2011
	10999	SIMVASTATIN RATIOPHA TAB 40MG 98ENPAC	Jan-Jun 2011
	20561	SIMVASTATIN HEXAL TAB 80MG 100ENPAC	From April 2014
	21133	SIMVASTATIN ACTAVIST AB 40MG 98ENPAC	Jan-May 2011
	21156	SIMVASTATIN ACTAVIST AB 20MG 98ENPAC	Jan-Feb 2011
	21159	SIMVASTATIN ACTAVIST AB 10MG 98ENPAC	Jan-Feb 2011
	21228	SIMVASTATIN ACTAVIST AB 10MG 28ENPAC	Jan-Feb 2011
	23685	SIMVASTATIN KRKA TAB 20MG 100ENDOS	Whole period
	23703	SIMVASTATIN KRKA TAB 40MG 100ENDOS	Whole period
	38494	SIMVASTATIN BLUEFISH TAB 40MG 100ENPAC	From October 2013
	56179	SIMVASTATIN PFIZER TAB 20MG 30ENPAC	Jun 2011 - Jan 2014
	56190	SIMVASTATIN PFIZER TAB 20MG 100ENPAC	Jun 2011 - Mar 2014
	56201	SIMVASTATIN PFIZER TAB 40MG 30ENPAC	Jun 2011 - Mar 2014
	56212	SIMVASTATIN PFIZER TAB 40MG 100ENPAC	Jun 2011 - Mar 2014
	58854	SIMVASTATIN AUROBIND TAB 10MG 30ENPAC	Jan 2011 - Aug 2012
	58865	SIMVASTATIN AUROBIND TAB 10MG 100ENPAC	Jan 2011 - Jul 2012
	58876	SIMVASTATIN AUROBIND TAB 20MG 30ENPAC	Jan 2011 - Mar 2012
	58888	SIMVASTATIN AUROBIND TAB 20MG 100ENPAC	Jan-Nov 2011
	58899	SIMVASTATIN AUROBIND TAB 40MG 30ENPAC	Jan 2011 - Apr 2012
	58910	SIMVASTATIN AUROBIND TAB 40MG 100ENPAC	Jan-Oct 2011
	58921	SIMVASTATIN AUROBIND TAB 80MG 100ENPAC	Jan 2011 - Feb 2012
	96360	SIMVASTATIN SANDOZ TAB 10MG 30ENPAC	From April 2014
	96369	SIMVASTATIN SANDOZ TAB 20MG 30ENPAC	From April 2014
	96387	SIMVASTATIN SANDOZ TAB 20MG 100ENPAC	From April 2014
	96397	SIMVASTATIN SANDOZ TAB 40MG 30ENPAC	From April 2014
	96415	SIMVASTATIN SANDOZ TAB 40MG 100ENPAC	From April 2014
	97864	SIMVASTATIN TEVA TAB 10MG 98ENPAC	From October 2013
	103727	SIMVASTATIN TEVA TAB 20MG 98ENPAC	From October 2013
	111651	SIMVASTATIN SANDOZ TAB 10MG 100STK	From April 2014
	144242	SIMVASTATIN BLUEFISH TAB 80MG 100ENPAC	Nov 2013 - Oct 2014
	162874	SIMVASTATIN BLUEFISH TAB 10MG 100ENPAC	Mar 2011 - Oct 2014
	162885	SIMVASTATIN BLUEFISH TAB 20MG 100ENPAC	Jan 2011 - May 2014
	162896	SIMVASTATIN BLUEFISH TAB 40MG 100ENPAC	Jan 2011 - May 2014
	162907	SIMVASTATIN BLUEFISH TAB 80MG 100ENPAC	Jan 2011 - Apr 2014
	382531	ZOCOR TAB 40MG 98ENPAC	Whole period
	431603	SIMVASTATIN TEVA TAB 80MG 98ENPAC	From September 2013

	454165	ZOCOR TAB 10MG 98ENPAC	Whole period
	454199	ZOCOR TAB 20MG 98ENPAC	Whole period
	468776	SIMVASTATIN TEVA TAB 40MG 98ENPAC	From October 2013
	470065	SIMVASTATIN TEVA TAB 10MG 28ENPAC	From October 2013
	483175	SIMVASTATIN TEVA TAB 40MG 28ENPAC	From February 2014
	501109	SIMVASTATIN TEVA TAB 20MG 28ENPAC	From October 2013
	513195	SIMVASTATIN BLUEFISH TAB 20MG 100ENPAC	From December 2013
	517334	ZOCOR TAB 80MG 98ENPAC	Whole period
	529872	SIMVASTATIN PFIZER TAB 80MG 100ENPAC	Jul 2011 - Mar 2014
	591457	SIMVASTATIN BLUEFISH TAB 20MG 30ENPAC	Apr 2011 - Jul 2014
	593321	SIMVASTATIN PFIZER TAB 10MG 100ENPAC	Jun 2011 - May 2014
PRAVASTATIN C10AA03	35133	PRAVASTATIN TEVA TAB 40MG 100ENPAC	From April 2012
	35142	PRAVASTATIN TEVA TAB 20MG 30ENPAC	From December 2011
	35151	PRAVASTATIN TEVA TAB 20MG 100ENPAC	From November 2011
	76424	PRAVASTATIN TEVA TAB 20MG 30ENPAC	Whole Period
	76433	PRAVASTATIN TEVA TAB 20MG 100ENPAC	Jan 2011 - Feb 2012
	76442	PRAVASTATIN TEVA TAB 40MG 30ENPAC	Whole period
	76451	PRAVASTATIN TEVA TAB 40MG 100ENPAC	Jan 2011 - Dec 2012
	135408	PRAVASTATIN SANDOZ TAB 20MG 30ENPAC	Whole period
	135419	PRAVASTATIN SANDOZ TAB 20MG 100ENPAC	Whole period
	135441	PRAVASTATIN SANDOZ TAB 40MG 100ENPAC	Whole period
	180646	PRAVACHOL TAB 20MG 98ENPAC	Whole period
	567719	PRAVACHOL TAB 40MG 98ENPAC	Whole period
SUMATRIPTAN N02CC01	15145	IMIGRAN RADIST AB 50MG 6ENPAC	Whole period
	15382	IMIGRAN RADIST AB 100MG 18ENPAC	Whole period
	15442	IMIGRAN RADIST AB 100MG 6ENPAC	Whole period
	15443	IMIGRAN RADIST AB 50MG 12ENPAC	Whole period
	63339	IMIGRAN TAB 100MG 6ENPAC	Whole period
	81015	SUMATRIPTAN RATIOPHA TAB 100MG 6ENPAC	Jan-Feb 2011
	81033	SUMATRIPTAN RATIOPHA TAB 100MG 18ENPAC	Jan-Feb 2011
	85466	SUMATRIPTAN SUN INJ 12MG/ML 2X0.5MLPEN	From May 2013
	92096	SUMATRIPTAN TEVA TAB 100MG 6ENPAC	Whole period
	92105	SUMATRIPTAN TEVA TAB 50MG 6ENPAC	Whole period
	93260	IMIGRAN INJ 12MG 2X0.5ML	Whole period
	95470	SUMATRIPTAN TEVA TAB 50MG 12ENPAC	Whole period
	95507	SUMATRIPTAN TEVA TAB 100MG 18ENPAC	Whole period
	122574	SUMATRIPTAN BLUEFISH TAB 100MG 6ENPAC	From March 2014
	131563	SUMATRIPTAN BLUEFISH TAB 50MG 6ENPAC	From April 2014
	172675	SUMATRIPTAN SUN INJ 12MG/ML 6X0.5MLPEN	From May 2013
	415422	IMIGRAN NESESPR 20MG/DOS 18DOSER	Jan 2011 - Feb 2014
	429506	IMIGRAN SUPP 25MG 6STK	Whole period
	441451	IMIGRAN NESESPR 20MG/DOS 6DOSER	Whole period
	451908	SUMATRIPTAN BLUEFISH TAB 100MG 18ENPAC	From November 2014
	496122	SUMATRIPTAN BLUEFISH TAB 50MG 12ENPAC	From March 2014
	524926	IMIGRAN INJ 12MG 6X0.5ML	Whole period
	574541	IMIGRAN TAB 50MG 6ENPAC	Whole period
	574582	IMIGRAN TAB 100MG 18ENPAC	Whole period

	585232	IMIGRAN TAB 50MG 12ENPAC	Whole period
ZOLMITRIPTAN N02CC03	89497	ZOLMITRIPTAN ACTAVIS TAB 2.5MG 6ENPAC	From March 2012
	89509	ZOLMITRIPTAN ACTAVIS TAB 5MG 6ENPAC	From March 2012
	89520	ZOLMITRIPTAN ACTAVIS SMELTAB 2.5MG 6ENPAC	From March 2012
	114615	ZOLMITRIPTAN SANDOZ SMELTAB 2.5MG 6ENPAC	From March 2012
	184432	ZOMIGRAPIMELT SMELTAB 2.5MG 6ENPAC	Jan 2011 - Aug 2014
	184839	ZOLMITRIPTAN ACTAVIS TAB 2.5MG 18ENPAC	From March 2012
	403219	ZOLMITRIPTAN SANDOZ TAB 2.5MG 6ENPAC	From March 2012
	404631	ZOLMITRIPTAN ACTAVIS SMELTAB 2.5MG 12ENPAC	From March 2012
	435537	ZOMIG TAB 5MG 6ENPAC	Jan 2011 - Feb 2014
	435545	ZOMIG TAB 5MG 18ENPAC	Whole period
	435594	ZOMIG TAB 2.5MG 6ENPAC	Jan 2011 -Dec 2013
	435610	ZOMIG TAB 2.5MG 18ENPAC	Whole period
	458492	ZOLMITRIPTAN SANDOZ TAB 2.5MG 18ENPAC	From March 2012
	477725	ZOLMITRIPTAN ACTAVIS TAB 5MG 18ENPAC	From March 2012
	480274	ZOLMITRIPTAN SANDOZ TAB 5MG 18ENPAC	From March 2012
	526597	ZOLMITRIPTAN SANDOZ TAB 5MG 6ENPAC	From March 2012
	551408	ZOMIGRAPIMELT SMELTAB 2.5MG 12ENPAC	Whole period
	564770	ZOLMITRIPTAN SANDOZ SMELTAB 2.5MG 12ENPAC	From March 2012
CITALOPRAM N06AB04	9053	CITALOPRAM RATIOPHAR TAB 10MG 28ENPAC	Jan - Aug 2011
	9296	CITALOPRAM RATIOPHAR TAB 20MG 28ENPAC	Jan - Mar 2011
	9307	CITALOPRAM RATIOPHAR TAB 20MG 98ENPAC	Jan - Aug 2011
	69188	CITALOPRAM TEVA TAB 10MG 100ENPAC	Jan - Jun 2011
	69197	CITALOPRAM TEVA TAB 20MG 30ENPAC	Jan 2011 - Apr 2013
	69206	CITALOPRAM TEVA TAB 20MG 100ENPAC	Jan - Jun 2011
	69215	CITALOPRAM TEVA TAB 40MG 100ENPAC	Jan - Nov 2011
	69224	CITALOPRAM TEVA TAB 10MG 100ENPAC	From June 2011
	69233	CITALOPRAM TEVA TAB 20MG 30ENPAC	From March 2013
	69242	CITALOPRAM TEVA TAB 20MG 100ENPAC	From June 2011
	69251	CITALOPRAM TEVA TAB 40MG 100ENPAC	From December 2011
	77078	CITALOPRAM TEVA TAB 10MG 30ENPAC	Whole period
	108864	CIPRAMIL TAB 20MG 56ENDOS	Jan 2011 - May 2014
	159194	CIPRAMIL TAB 20MG 98ENPAC	Whole period
	159558	CIPRAMIL TAB 10MG 28ENPAC	Whole period
	159632	CIPRAMIL TAB 20MG 28ENPAC	Jan 2011 - May 2014
	577221	CIPRAMIL TAB 20MG 250STK	Whole period
PAROXETINE N06AB05	9987	PAROXETIN HEXAL TAB 20MG 20STK	Jan 2011 - Jul 2012
	9998	PAROXETIN HEXAL TAB 20MG 60STK	Jan 2011 - Jun 2012
	10011	PAROXETIN HEXAL TAB 20MG 100STK	Jan 2011 - Sep 2012
	15817	PAROXETIN ACTAVIS TAB 20MG 20ENPAC	Whole period
	15828	PAROXETIN ACTAVIS TAB 20MG 60ENPAC	Whole period
	15839	PAROXETIN ACTAVIS TAB 20MG 100ENPAC	Whole period
	15964	SEROXAT GSK TAB 10MG 28ENPAC	Whole period
	38448	SEROXAT GSK TAB 20MG 100ENPAC	Whole period
	56078	PAROXETIN PFIZER TAB 20MG 60ENPAC	Feb 2012 - Oct 2014
	56089	PAROXETIN PFIZER TAB 20MG 100ENPAC	Sept 2011 - Dec 2013

	59047	PAROXETIN AUROBINDO TAB 20MG 60ENPAC	Jan - Oct 2011
	59058	PAROXETIN AUROBINDO TAB 20MG 100ENPAC	Jan 2011 - Jan 2012
ESCITALOPRAM N06AB10	5757	CIPRALEX TAB 5MG 28ENPAC	Whole period
	5812	CIPRALEX TAB 10MG 28ENPAC	Whole period
	5834	CIPRALEX TAB 10MG 98ENPAC	Whole period
	5944	CIPRALEX TAB 20MG 98ENPAC	Whole period
	11047	CIPRALEX TAB 10MG 200STK	Whole period
	55757	ESCITALOPRAM RATIO TAB 5MG 28ENPAC	Jan - Dec 2011
	55779	ESCITALOPRAM RATIO TAB 10MG 28ENPAC	Jan 2011 - Mar 2012
	55790	ESCITALOPRAM RATIO TAB 10MG 56ENPAC	Jan 2011 - Jan 2012
	55801	ESCITALOPRAM RATIO TAB 10MG 98ENPAC	Jan 2011 - Oct 2012
	55856	ESCITALOPRAM RATIO TAB 20MG 98ENPAC	Jan 2011 - Oct 2012
	97524	CIPRALEX TAB 10MG 56ENDOS	Whole period
	114894	ESCITALOPRAM ACTAVIST AB 10MG 98ENPAC	From August 2011
	115854	ESCITALOPRAM TEVA TAB 5MG 30ENPAC	From June 2014
	147689	ESCITALOPRAM ACTAVIST AB 10MG 28ENPAC	From August 2011
	183669	ESCITALOPRAM TEVA TAB 20MG 100ENPAC	From June 2014
	194954	ESCITALOPRAM ACTAVIST AB 10MG 56ENPAC	From August 2011
	403119	ESCITALOPRAM ACTAVIST AB 20MG 98ENPAC	From August 2011
	409840	ESCITALOPRAM TEVA TAB 10MG 30ENPAC	From June 2014
	422719	ESCITALOPRAM TEVA TAB 10MG 56ENPAC	From June 2014
	499134	ESCITALOPRAM TEVA TAB 10MG 100ENPAC	From June 2014
	499807	ESCITALOPRAM ACTAVIST AB 5MG 28ENPAC	From August 2011

Appendix D: Distribution of variables

When studying the distributions of variables in this section, it is important to keep in min that the data will be handled slightly differently in the models applied. Specifically, since clustering on GPs is used for every model, the applied distributions will to some extent differ. This is especially the case for the probit models, since the amount of observations for one GP will depend on how many prescriptions he has made. Groups of dummies that have more than two dummies, have only frequencies depicted.

The distributions of the fixed effects models are not shown here. The size of the samples will however be equal to the amount of observations for one single indication in the aggregated versions. As for the case of "new" and "old" drugs, the fixed effects sample includes all ATC's within the categories of "new" and "old", without paying attention to the differences between ATCs within these categories. As explained in subsection 5.1.1, this is done to avoid repeated values within panels.

Aggregated sample for "new" to use in twopm and regression					
	Observations	**Mean**	**St. Dev.**	**Min**	**Max**
doctor_reservation	35 581	0,081	0,170	0	1
price_diff~e	35 581	289,89	128,20	128,73	444,47
male	35 581	0,644	0,479	0	1
comp_county	35 581	0,962	0,063	0,218	1,811
ln_freq_pr~r	35 581	3,10	1,40	0	6,32
specialist	35 581	0,623	0,485	0	1
	Observations	**Proportion of observations within group of dummy**			
atc 8	14 669	41,2 %			
atc 11	12 507	35,2 %			
atc 13	8 405	23,6 %			
centrality 0	24 406	68,6 %			
centrality 1	6 283	17,7 %			
centrality 2	1 994	5,6 %			
centrality 3	2 898	8,1 %			
2011	6 558	18,4 %			
2012	9 394	26,4 %			
2013	9 697	27,3 %			
2014	9 932	27,9 %			
age 1 (age<40)	7 913	22,2 %			
age 2 (40≤age <55)	13 547	38,1 %			
age 3 (age ≥55)	14 121	39,7 %			

Sample for "new" for probit model					
	Observations	**Mean**	**St. Dev.**	**Min**	**Max**
doctor_reservation	1 712 336	0,060	0,238	0	1
price_diff~e	1 712 336	343,8382	128,1263	128,7265	444,473
male	1 712 336	0,7116209	0,4530085	0	1
comp_county	1 712 336	0,9626418	0,0538486	0,2175	1,810811
ln_freq_pr~r	1 712 336	953010	0,8996997	0	6,318968
specialist	1 712 336	0,6778938	0,4672835	0	1
	Observations	**Proportion of observations within group of dummy**			
atc 8	1 187 561	69,4 %			
atc 11	444 402	26,0 %			
atc 13	80 373	4,7 %			
centrality 0	1 233 330	72,0 %			
centrality 1	311 212	18,2 %			
centrality 2	81 294	4,7 %			
centrality 3	86 500	5,1 %			
2011	388 648	22,7 %			
2012	464 448	27,1 %			
2013	482 050	28,2 %			
2014	377 190	22,0 %			
age 1 (age<40)	300 171	17,5 %			
age 2 (40≤age <55)	645 851	37,7 %			
age 3 (age ≥55)	766 314	44,8 %			

Aggregated sample for "overall" to use in twopm and regression					
	Observations	**Mean**	**St. Dev.**	**Min**	**Max**
doctor_reservation	44 268	0,040	0,066	0	1
price_diff~d	44 268	271,73	71,72	150,84	345,55
male	44 268	0,636	0,481	0	1
comp_county	44 268	0,961	0,065	0,22	1,81
ln_freq_pr~r	44 268	4,64	0,95	0	7,72
specialist	44 268	0,606	0,489	0	1
	Observations	**Proportion of observations within group of dummy**			
indication 0	14 728	33,3 %			
indication 1	14 800	33,4 %			
indication 2	14 740	33,3 %			
centrality 0	29 602	66,9 %			
centrality 1	7 841	17,7 %			
centrality 2	2 743	6,2 %			
centrality 3	4 082	9,2 %			
2011	10 690	24,1 %			
2012	10 969	24,8 %			
2013	11 127	25,1 %			
2014	11 482	25,9 %			
age 1 (age<40)	10 249	23,2 %			
age 2 (40≤age <55)	16 795	37,9 %			
age 3 (age ≥55)	17 224	38,9 %			

Sample for "overall" for probit model					
	Observations	**Mean**	**St. Dev.**	**Min**	**Max**
doctor_reservation	6 507 305	0,040	0,196	0	1
price_diff~d	6 507 305	281,03	67,89	150,84	345,55
male	6 507 305	0,732	0,443	0,0	1
comp_county	6 507 305	0,961	0,059	0,218	1,811
ln_freq_pr~r	6 507 305	5,286	0,720	0	7,723
specialist	6 507 305	0,673	0,469	0	1
	Observations	**Proportion of observations within group of dummy**			
indication 0	1 752 556	26,9 %			
indication 1	3 133 239	48,1 %			
indication 2	1 621 510	24,9 %			
centrality 0	4 353 400	66,9 %			
centrality 1	1 282 399	19,7 %			
centrality 2	403 309	6,2 %			
centrality 3	468 197	7,2 %			
2011	1 657 230	25,5 %			
2012	1 781 988	27,4 %			
2013	1 702 795	26,2 %			
2014	1 365 292	21,0 %			
age 1 (age<40)	1 120 281	17,2 %			
age 2 (40≤age <55)	2 333 139	35,9 %			
age 3 (age ≥55)	3 053 885	46,9 %			

Aggregated sample for "old" to use in twopm and regression					
	Observations	**Mean**	**St. Dev.**	**Min**	**Max**
doctor_reservation	105 588	0,065	0,169	0	1
price_diff~e	105 588	119,66	141,39	0,76	578,17
male	105 588	0,651	0,477	0	1
comp_county	105 588	0,961	0,065	0,218	1,811
ln_freq_pr~r	105 588	2,93	1,44	0	7,68
specialist	105 588	0,619	0,486	0	1
	Observations	**Proportion of observations within group of dummy**			
atc 0	13 286	12,6 %			
atc 1	14 575	13,8 %			
atc 2	13 358	12,7 %			
atc 3	12 308	11,7 %			
atc 4	14 794	14,0 %			
atc 5	12 065	11,4 %			
atc 6	13 212	12,5 %			
atc 7	11 990	11,4 %			
centrality 0	70 368	66,6 %			
centrality 1	19 099	18,1 %			
centrality 2	6 483	6,1 %			
centrality 3	9 638	9,1 %			
2011	25 651	24,3 %			
2012	26 243	24,9 %			
2013	26 583	25,2 %			
2014	27 111	25,7 %			
age 1 (age<40)	23 580	22,3 %			
age 2 (40≤age <55)	40 071	38,0 %			
age 3 (age ≥55)	41 937	39,7 %			

Sample for "old" for probit model					
	Observations	**Mean**	**St. Dev.**	**Min**	**Max**
doctor_reservation	5 319 744	0,039	0,194	0	1
price_diff~e	5 319 744	154,404	113,307	0,757	578,168
male	5 319 744	0,740	0,439	0	1
comp_county	5 319 744	0,961	0,060	0,218	1,811
ln_freq_pr~r	5 319 744	4,792	1,180	0	7,679
specialist	5 319 744	0,674	0,469	0	1
	Observations	**Proportion of observations within group of dummy**			
atc 0	306 921	5,8 %			
atc 1	922 671	17,3 %			
atc 2	336 180	6,3 %			
atc 3	186 784	3,5 %			
atc 4	2 932 785	55,1 %			
atc 5	200 454	3,8 %			
atc 6	276 924	5,2 %			
atc 7	157 025	3,0 %			
centrality 0	3 526 062	66,3 %			
centrality 1	1 052 275	19,8 %			
centrality 2	338 176	6,4 %			
centrality 3	403 231	7,6 %			
2011	1 378 562	25,9 %			
2012	1 456 830	27,4 %			
2013	1 377 705	25,9 %			
2014	1 106 647	20,8 %			
age 1 (age<40)	904 966	17,0 %			
age 2 (40≤age <55)	1 875 450	35,3 %			
age 3 (age ≥55)	2 539 328	47,7 %			

Appendix E: Descriptive statistics

For the reasons explained in Appendix C, the limited sample had fewer observations than the main sample. An overview of GP reservation rates for the different ATCs is provided below. As before, the ATCs in bold italics are not used in the models. A noticeable differences from the main sample, is the higher reservation rates in the limited sample. This is probably due to the many generic competitors being left out of the sample because of their inconsistent market shares. We are in other words left with a sample of drugs that have relatively higher rates of generic reservation. As noted earlier however, the relative differences between ATCs are not too different from the main sample.

Reservation rates using limited sample

		2011		2012		2013		2014		Total	
Ind.	ATC	docres	freq_pres	docres	freq_pres	docres	freq_pres	docres	freq_pres	docres	freq_pres
0	0	80.5 %	20 759	76.0 %	22 297	67.8 %	23 120	72.6 %	16 765	**74.1 %**	**82 941**
0	1	0.8 %	183 505	0.8 %	222 029	1.6 %	274 665	1.8 %	243 906	**1.3 %**	**924 105**
0	2	0.7 %	91 790	0.6 %	91 298	1.1 %	91 802	1.6 %	43 675	**0.9 %**	**318 565**
0	3	1.7 %	46 298	2.9 %	48 382	3.8 %	51 639	4.4 %	40 686	**3.2 %**	**187 005**
1	4	75.7 %	24 788	78.7 %	16 168	78.4 %	17 782	81.4 %	9 959	**77.9 %**	**68 697**
1	5	29.1 %	28 189	23.6 %	34 644	22.8 %	31 326	16.5 %	23 887	**23.2 %**	**118 046**
2	6	53.8 %	9 619	48.6 %	8 518	43.8 %	8 185	46.6 %	7 992	**48.4 %**	**34 314**
2	7	8.0 %	23 689	4.3 %	32 881	5.6 %	35 421	4.8 %	33 652	**5.5 %**	**125 643**
2	8	8.9 %	134 648	36.9 %	47 001	59.0 %	20 404	57.7 %	14 021	**22.9 %**	**216 074**
3	***9***	***13.1 %***	***165 128***	***11.9 %***	***182 955***	***10.4 %***	***196 212***	***8.6 %***	***168 005***	***11.0 %***	***712 300***
3	***10***	***8.7 %***	***44 191***	***8.1 %***	***43 443***	***6.2 %***	***43 761***	***5.3 %***	***30 696***	***7.2 %***	***162 091***
3	11	7.8 %	110 274	9.3 %	114 329	9.3 %	127 341	9.3 %	93 743	**9.0 %**	**445 687**
4	***12***	***21.0 %***	***55 620***	***19.1 %***	***55 318***	***17.7 %***	***61 201***	***14.1 %***	***71 305***	***17.7 %***	***243 444***
4	13	--	--	49.0 %	5 339	67.5 %	5 113	70.2 %	4 913	**61.9 %**	**15 365**
	Total	**11.7 %**	**938 498**	**12.3 %**	**924 602**	**11.2 %**	**987 972**	**10.3 %**	**803 205**	**11.4 %**	**3 654 277**

Trend in reservation levels for "old" ATCs 6 and 7, versus that of the "new" ATC 8.

Figure 3 Trend in reservation for ATC 6 and 7

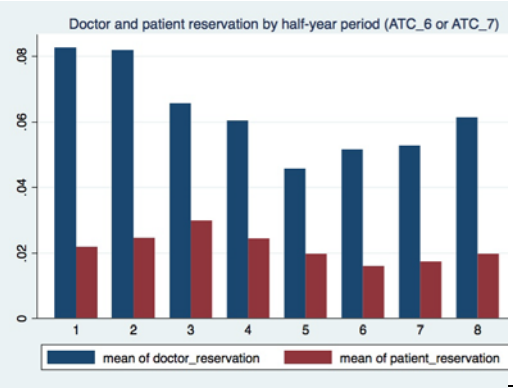


Figure 2 Trend in reservation for ATC 8

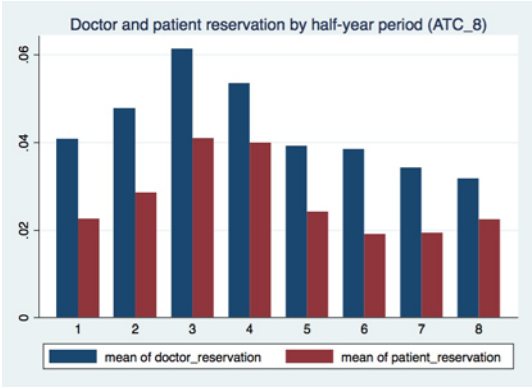


Figure 4: Trend in reservation for ATC 9 and 10

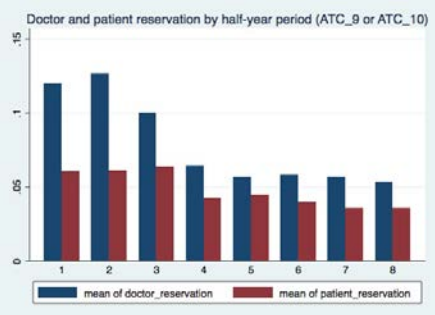
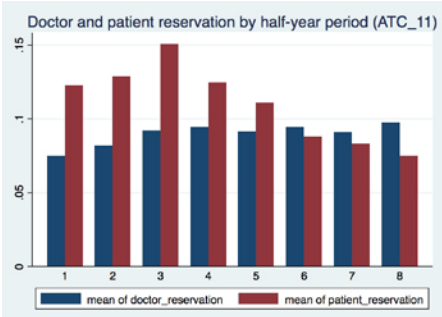


Figure 5: Trend in reservation for ATC 11



Appendix F: Tests

"Overall" models

Test of heteroskedastisity in OLS model

Hypothesis of homoscedasticity firmly rejected

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of doctor_reservation

         chi2(1)      =  1952.26
         Prob > chi2  =   0.0000
```

Test of omitted variables in OLS model

Hypothesis of no omitted variables firmly rejected

```
Ramsey RESET test using powers of the fitted values of doctor_reservation
       Ho:  model has no omitted variables
               F(3, 44249) =     15.72
                  Prob > F =      0.0000
```

Test of multicollinearity for OLS-model

Noting that determining there is no single measure of when the value of the variance inflator factor (VIF) is "too high", Wooldridge (2013, p. 98) suggests that VIFs above 10 can indicate a troublesome level of multicollinearity. In the STATA output below, we see that indication 2 and price difference are the only variables above this threshold.

Variable	VIF	1/VIF
indication		
0	93.86	0.010654
2	1.52	0.657793
price_diff~d	99.56	0.010045
male	1.11	0.899544
age_dummy		
2	2.00	0.500771
3	2.27	0.441371
comp_county	1.05	0.952832
ln_freq_pr~r	1.27	0.785831
1.specialist	1.38	0.727232
centrality		
1	1.05	0.954971
2	1.03	0.968939
3	1.07	0.930921
year		
2012	2.42	0.412628
2013	3.22	0.310858
2014	2.10	0.476865
Mean VIF	14.33	

Pearson test for goodness of fit for overall probit part of twopm

Probit model for docres, goodness-of-fit test

number of observations =	**44268**
number of covariate patterns =	**43183**
Pearson chi2(**43167**) =	**44596.52**
Prob > chi2 =	**0.0000**

Predicted probabilities: sensitivity and specificity – overall probit for twopm

Probit model for docres

Classified	True D	True ~D	Total
+	**26710**	**9164**	**35874**
–	**2829**	**5565**	**8394**
Total	**29539**	**14729**	**44268**

Classified + if predicted Pr(D) >= .5
True D defined as docres != 0

Sensitivity	Pr(+| D)	**90.42%**
Specificity	Pr(–|~D)	**37.78%**
Positive predictive value	Pr(D| +)	**74.46%**
Negative predictive value	Pr(~D| –)	**66.30%**
False + rate for true ~D	Pr(+|~D)	**62.22%**
False – rate for true D	Pr(–| D)	**9.58%**
False + rate for classified +	Pr(~D| +)	**25.54%**
False – rate for classified –	Pr(D| –)	**33.70%**
Correctly classified		**72.91%**

Probit model (main)

Predicted probabilities: sensitivity and specificity

Cut-off "0.5"

Probit model for doctor_reservation

Classified	True D	True ~D	Total
+	**0**	**0**	**0**
–	**260271**	**6247034**	**6507305**
Total	**260271**	**6247034**	**6507305**

Classified + if predicted Pr(D) >= .5
True D defined as doctor_reservation != 0

Sensitivity	Pr(+| D)	**0.00%**
Specificity	Pr(–|~D)	**100.00%**
Positive predictive value	Pr(D| +)	**.%**
Negative predictive value	Pr(~D| –)	**96.00%**
False + rate for true ~D	Pr(+|~D)	**0.00%**
False – rate for true D	Pr(–| D)	**100.00%**
False + rate for classified +	Pr(~D| +)	**.%**
False – rate for classified –	Pr(D| –)	**4.00%**
Correctly classified		**96.00%**

Cut-off "0.05"

Probit model for doctor_reservation

Classified	True D	True ~D	Total
+	**78812**	**1266843**	**1345655**
–	**181459**	**4980191**	**5161650**
Total	**260271**	**6247034**	**6507305**

Classified + if predicted Pr(D) >= .05
True D defined as doctor_reservation != 0

Sensitivity	Pr(+| D)	**30.28%**
Specificity	Pr(–|~D)	**79.72%**
Positive predictive value	Pr(D| +)	**5.86%**
Negative predictive value	Pr(~D| –)	**96.48%**
False + rate for true ~D	Pr(+|~D)	**20.28%**
False – rate for true D	Pr(–| D)	**69.72%**
False + rate for classified +	Pr(~D| +)	**94.14%**
False – rate for classified –	Pr(D| –)	**3.52%**
Correctly classified		**77.74%**

Pearson test for goodness of fit for probit model

```
Probit model for doctor_reservation, goodness-of-fit test

       number of observations =   6507305
  number of covariate patterns =     43183
          Pearson chi2(43167) =    502957.52
                  Prob > chi2 =         0.0000
```

"New" drugs

Probit

Predictive power with sensitivity and specificity, and pearson test for goodness of fit for probit model

```
Probit model for doctor_reservation

                 ———————— True ————————
Classified |         D              ~D |       Total
———————————+———————————————————————————+———————————————
     +     |     68523          758839 |      827362
     -     |     34608          850366 |      884974
———————————+———————————————————————————+———————————————
   Total   |    103131         1609205 |     1712336

Classified + if predicted Pr(D) >= .05
True D defined as doctor_reservation != 0
———————————————————————————————————————————————————————
Sensitivity                     Pr( +| D)   66.44%
Specificity                     Pr( -|~D)   52.84%
Positive predictive value       Pr( D| +)    8.28%
Negative predictive value       Pr(~D| -)   96.09%
———————————————————————————————————————————————————————
False + rate for true ~D        Pr( +|~D)   47.16%
False - rate for true D         Pr( -| D)   33.56%
False + rate for classified +   Pr(~D| +)   91.72%
False - rate for classified -   Pr( D| -)    3.91%
———————————————————————————————————————————————————————
Correctly classified                        53.66%
———————————————————————————————————————————————————————
```

```
Probit model for doctor_reservation, goodness-of-fit test

       number of observations =   1712336
  number of covariate patterns =     32957
          Pearson chi2(32941) =    215303.29
                  Prob > chi2 =         0.0000
```

Twopm

Predictive power with sensitivity and specificity, and pearson test for goodness of fit for probit part of twopm

Probit model for docres

Classified	True D	True ~D	Total
+	17361	17308	34669
–	83	829	912
Total	17444	18137	35581

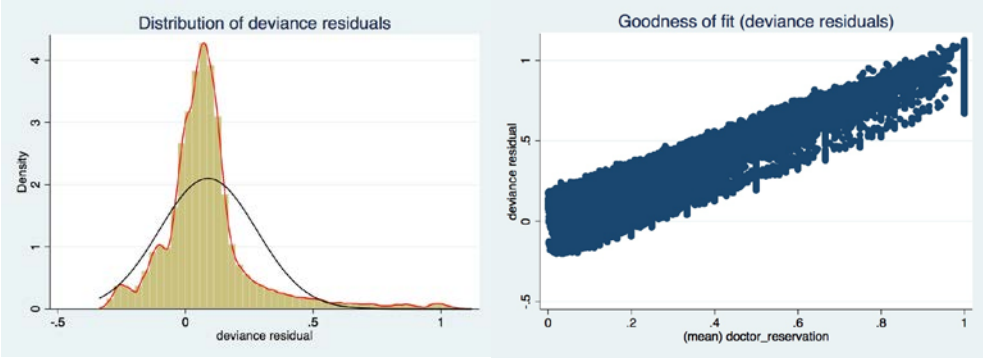
Classified + if predicted Pr(D) >= .05
True D defined as docres != 0

Sensitivity	Pr(+| D)	99.52%
Specificity	Pr(–|~D)	4.57%
Positive predictive value	Pr(D| +)	50.08%
Negative predictive value	Pr(~D| –)	90.90%
False + rate for true ~D	Pr(+|~D)	95.43%
False – rate for true D	Pr(–| D)	0.48%
False + rate for classified +	Pr(~D| +)	49.92%
False – rate for classified –	Pr(D| –)	9.10%
Correctly classified		51.12%

Probit model for docres, goodness-of-fit test

number of observations =	35581
number of covariate patterns =	32957
Pearson chi2(32941) =	33777.97
Prob > chi2 =	0.0006

Graphical representation of deviance residuals from GLM model of twopm



"Old" drugs

Probit

Predictive power with sensitivity and specificity, and pearson test for goodness of fit for probit model

Probit model for doctor_reservation

Classified	True D	True ~D	Total
+	112943	700011	812954
–	95039	4411751	4506790
Total	207982	5111762	5319744

Classified + if predicted Pr(D) >= .05
True D defined as doctor_reservation != 0

Sensitivity	Pr(+| D)	54.30%
Specificity	Pr(–|~D)	86.31%
Positive predictive value	Pr(D| +)	13.89%
Negative predictive value	Pr(~D| –)	97.89%
False + rate for true ~D	Pr(+|~D)	13.69%
False – rate for true D	Pr(–| D)	45.70%
False + rate for classified +	Pr(~D| +)	86.11%
False – rate for classified –	Pr(D| –)	2.11%
Correctly classified		85.05%

Probit model for doctor_reservation, goodness-of-fit test

number of observations = 5319744
number of covariate patterns = 96448
Pearson chi2(96427) = 767957.32
Prob > chi2 = 0.0000

Twopm

Predictive power with sensitivity and specificity, and pearson test for goodness of fit for probit part of twopm

Probit model for docres

Classified	True D	True ~D	Total
+	31427	59514	90941
–	528	14119	14647
Total	31955	73633	105588

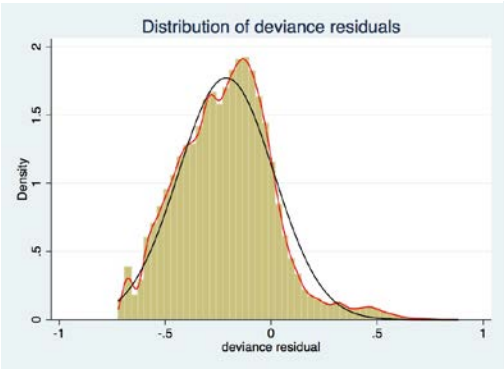
Classified + if predicted Pr(D) >= .05
True D defined as docres != 0

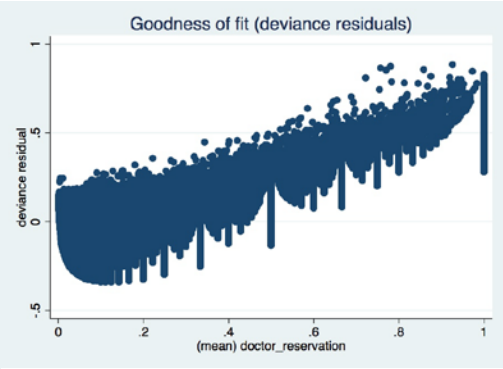
Sensitivity	Pr(+| D)	98.35%
Specificity	Pr(–|~D)	19.17%
Positive predictive value	Pr(D| +)	34.56%
Negative predictive value	Pr(~D| –)	96.40%
False + rate for true ~D	Pr(+|~D)	80.83%
False – rate for true D	Pr(–| D)	1.65%
False + rate for classified +	Pr(~D| +)	65.44%
False – rate for classified –	Pr(D| –)	3.60%
Correctly classified		43.14%

Probit model for docres, goodness-of-fit test

number of observations = 105588
number of covariate patterns = 96448
Pearson chi2(96427) = 104827.48
Prob > chi2 = 0.0000

Graphical representation of deviance residuals from GLM model of twopm





Fixed effects

Hausman test for random effects models

With reference to Green (2005, pp. 379-380), the Hausman test looks at the covariance matrix of the estimates in determining whether the errors are correlated with the independent variables. If they are, a fixed effects model is preferred. The null-hypothesis of no correlation with the regressors is rejected for every indication.

Indication 0 (ulcer)

	——— Coefficients ———			
	(b) fixed_effe~s	(B) random_eff~s	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ln_freq_pr~r	**-.002454**	**.0025416**	**-.0049957**	**.0007217**
price_diff~d	**-.0000628**	**-.0000525**	**-.0000104**	**3.94e-06**
patient_re~n	**-.059388**	**.028437**	**-.0878251**	**.0070631**
comp_county	**-.0072058**	**-.0192592**	**.0120533**	**.0082002**

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(**4**) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= **198.95**
Prob>chi2 = **0.0000**

Indication 1 (cholesterol)

	——— Coefficients ———			
	(b) fixed_effe~s	(B) random_eff~s	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ln_freq_pr~r	**.0040422**	**.0030374**	**.0010048**	**.0004647**
price_diff~d	**-.0001941**	**-.0001832**	**-.0000109**	**3.29e-06**
patient_re~n	**.0190483**	**.087429**	**-.0683806**	**.0109246**
comp_county	**-.0176375**	**-.0191597**	**.0015222**	**.0055919**

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(**4**) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= **43.09**
Prob>chi2 = **0.0000**

Indication 2 (depression)

	Coefficients			
	(b) fixed_effe~s	(B) random_eff~s	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ln_freq_pr~r	-.0101388	-.0063352	-.0038036	.0008843
price_diff~d	.0006132	.0005785	.0000347	9.58e-06
patient_re~n	-.1223165	-.0744448	-.0478717	.0070446
comp_county	-.0506654	-.0336673	-.0169982	.0103694

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 68.46
Prob>chi2 = 0.0000

Old ATCs

	Coefficients			
	(b) fixed_effe~s	(B) random_eff~s	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
ln_freq_pr~r	.0023987	.0031782	-.0007795	.000445
price_diff~D	-.0000492	-.0000437	-5.54e-06	3.48e-06
patient_re~n	-.0328872	.0614404	-.0943275	.0095554
comp_county	-.0165894	-.0189063	.0023169	.0048113

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 107.81
Prob>chi2 = 0.0000

New ATCs

	Coefficients			
	(b) fixed_effe~s	(B) random_eff~s	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
price_diff~D	.0003757	.0018225	-.0014468	.
patient_re~n	-.084009	.0320372	-.1160462	.
comp_county	-.0354577	-.2554833	.2200256	.

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= -29.99 chi2<0 ==> model fitted on these
data fails to meet the asymptotic
assumptions of the Hausman test;
see suest for a generalized test

Modified wald-test for heteroskedasticity

The null hypothesis of homoskedasticity is rejected for all models when not having specified the cluster-option.

Indication 0

```
H0: sigma(i)^2 = sigma^2 for all i

chi2 (4435)  =  1.1e+38
Prob>chi2 =      0.0000
```

Indication 1

```
H0: sigma(i)^2 = sigma^2 for all i

chi2 (4452)  =  4.2e+34
Prob>chi2 =      0.0000
```

Indication 2

```
H0: sigma(i)^2 = sigma^2 for all i

chi2 (4439)  =  7.7e+34
Prob>chi2 =      0.0000
```

"OLD" drugs

```
Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (4455)  =  2.6e+38
Prob>chi2 =      0.0000
```

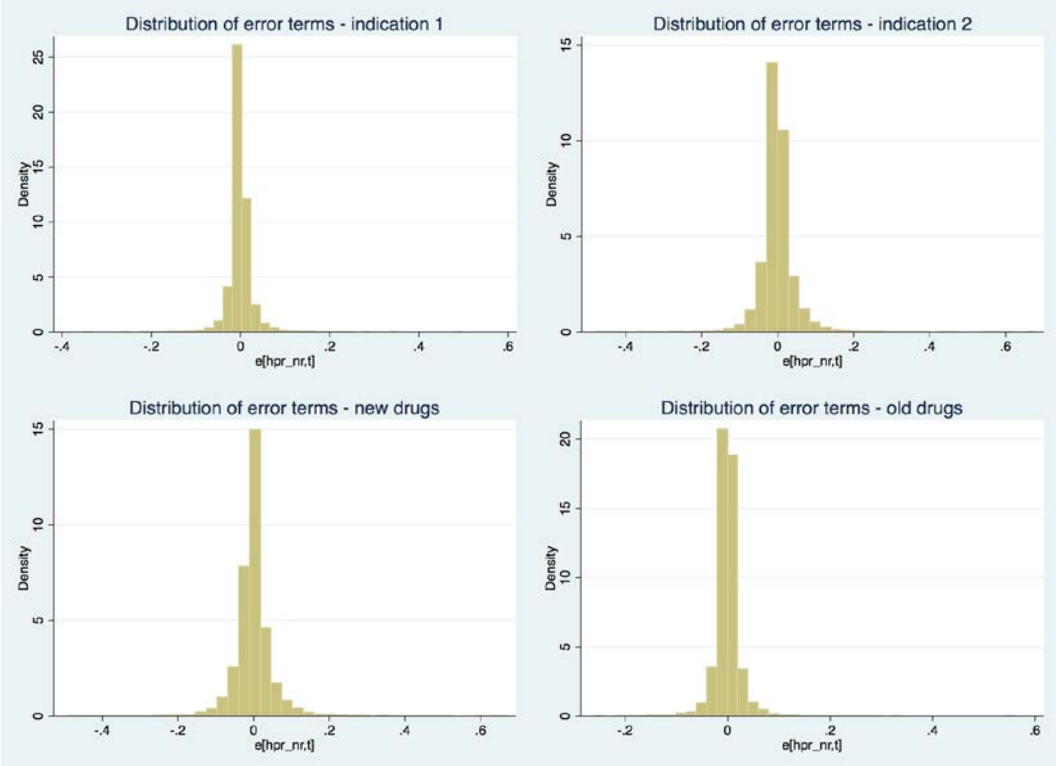
"NEW" drugs

```
Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (4429)  =  8.2e+37
Prob>chi2 =      0.0000
```

Distribution of individual error terms for indications 1 & 2, old/new



Appendix G: Model results from limited sample

Results from ”overall”

OLS REGRESSION

Linear regression — Number of obs = 41,593; F(15, 4448) = 677.48; Prob > F = 0.0000; R-squared = 0.3019; Root MSE = .25019

(Std. Err. adjusted for 4,449 clusters in doctor_dummy)

doctor_reservation	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
indication						
ulcer	-.3964827	.0080809	-49.06	0.000	-.4123252	-.3806402
depression	-.2169646	.0072635	-29.87	0.000	-.2312047	-.2027246
price_difference_ind	-.0000611	.0000865	-0.71	0.480	-.0002307	.0001085
male	-.0036146	.0041473	-0.87	0.383	-.0117453	.0045161
age_dummy						
2	.0139996	.005047	2.77	0.006	.004105	.0238943
3	.0228645	.0055826	4.10	0.000	.0119198	.0338092
comp_municipality	-.0008295	.0002876	-2.88	0.004	-.0013935	-.0002656
ln_freq_pres_indication_year	-.0048426	.0019188	-2.52	0.012	-.0086043	-.0010809
1.specialist	-.0002877	.0044017	-0.07	0.948	-.0089173	.0083419
centrality						
1	-.0139065	.0049538	-2.81	0.005	-.0236184	-.0041946
2	-.0375035	.0078023	-4.81	0.000	-.0527999	-.0222071
3	.0072438	.0071152	1.02	0.309	-.0067056	.0211932
year						
2012	.003754	.0023441	1.60	0.109	-.0008416	.0083495
2013	.0192993	.005715	3.38	0.001	.008095	.0305035
2014	.0071447	.0061108	1.17	0.242	-.0048355	.019125
_cons	.5422793	.0369845	14.66	0.000	.4697712	.6147874

PROBIT

Probit regression — Number of obs = 2,075,390; Wald chi2(15) = 5643.54; Prob > chi2 = 0.0000; Log pseudolikelihood = -628036.11; Pseudo R2 = 0.1458

(Std. Err. adjusted for 4,449 clusters in doctor_dummy)

doctor_reservation	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
ulcer	-1.484576	.0451565	-32.88	0.000	-1.573081	-1.396071
depression	-.5693165	.0245591	-23.18	0.000	-.6174514	-.5211816
price_difference_ind	-.0015394	.0003253	-4.73	0.000	-.002177	-.0009018
male	-.0247255	.0201244	-1.23	0.219	-.0641687	.0147176
age_dummy						
2	.0804563	.0286597	2.81	0.005	.0242844	.1366283
3	.0863716	.0388493	2.22	0.026	.0102284	.1625148
comp_municipality	-.0031685	.0016007	-1.98	0.048	-.0063059	-.0000311
ln_freq_pres_indication_year	-.0228602	.0220808	-1.04	0.301	-.0661377	.0204174
1.specialist	-.0379974	.0382179	-0.99	0.320	-.112903	.0369082
centrality						
1	-.1500068	.0254553	-5.89	0.000	-.1998983	-.1001153
2	-.2797236	.0363426	-7.70	0.000	-.3509539	-.2084934
3	-.1057421	.0273253	-3.87	0.000	-.1592988	-.0521855
year						
2012	.1099242	.0085661	12.83	0.000	.0931349	.1267134
2013	.0304399	.0211219	1.44	0.150	-.0109583	.0718381
2014	.0014835	.0201009	0.07	0.941	-.0379136	.0408805
_cons	.5845587	.1764716	3.31	0.001	.2386807	.9304366

TWOPM

Two-part model

Log pseudolikelihood = **-18609.726** Number of obs = **41593**

Part 1: probit

	Number of obs = **41593**
	Wald chi2(**15**) = **3832.97**
	Prob > chi2 = **0.0000**
Log pseudolikelihood = **-21939.795**	Pseudo R2 = **0.1505**

Part 2: glm

	Number of obs = **28604**
Deviance = **1326.879757**	(1/df) Deviance = **.0464139**
Pearson = **1326.879757**	(1/df) Pearson = **.0464139**
Variance function: **V(u) = 1**	[**Gaussian**]
Link function : **g(u) = u**	[**Identity**]
	AIC = **-.2317206**
Log pseudolikelihood = **3330.068575**	BIC = **-292023.2**

(Std. Err. adjusted for clustering on doctor_dummy)

doctor_reservation	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
probit						
indication						
0	**-1.862472**	**.0454237**	**-41.00**	**0.000**	**-1.951501**	**-1.773444**
2	**-.5638819**	**.033889**	**-16.64**	**0.000**	**-.6303031**	**-.4974608**
price_difference_ind	**.000349**	**.0004587**	**0.76**	**0.447**	**-.00055**	**.001248**
male	**.0284806**	**.0215916**	**1.32**	**0.187**	**-.0138382**	**.0707994**
age_dummy						
2	**.0673363**	**.026229**	**2.57**	**0.010**	**.0159284**	**.1187442**
3	**.1105563**	**.0294452**	**3.75**	**0.000**	**.0528447**	**.1682678**
comp_municipality	**-.0037022**	**.0016195**	**-2.29**	**0.022**	**-.0068763**	**-.0005281**
ln_freq_pres_indication_year	**.5261993**	**.0100647**	**52.28**	**0.000**	**.5064727**	**.5459258**
specialist						
1	**.0297289**	**.022974**	**1.29**	**0.196**	**-.0152992**	**.074757**
centrality						
1	**-.0498855**	**.0272973**	**-1.83**	**0.068**	**-.1033873**	**.0036162**
2	**-.2082921**	**.0401378**	**-5.19**	**0.000**	**-.2869607**	**-.1296234**
3	**.0522511**	**.0346052**	**1.51**	**0.131**	**-.0155737**	**.120076**
year						
2012	**.1196144**	**.0170399**	**7.02**	**0.000**	**.0862168**	**.153012**
2013	**.1204457**	**.033362**	**3.61**	**0.000**	**.0550575**	**.185834**
2014	**.1600302**	**.032667**	**4.90**	**0.000**	**.096004**	**.2240564**
_cons	**-.1416064**	**.2040202**	**-0.69**	**0.488**	**-.5414786**	**.2582658**
glm						
indication						
0	**-.2573136**	**.0089118**	**-28.87**	**0.000**	**-.2747804**	**-.2398469**
2	**-.1957354**	**.0068996**	**-28.37**	**0.000**	**-.2092584**	**-.1822124**
price_difference_ind	**-.0000376**	**.0000842**	**-0.45**	**0.655**	**-.0002026**	**.0001274**
male	**-.0053633**	**.0041463**	**-1.29**	**0.196**	**-.0134898**	**.0027632**
age_dummy						
2	**.0139028**	**.0051244**	**2.71**	**0.007**	**.0038593**	**.0239464**
3	**.0252528**	**.0055841**	**4.52**	**0.000**	**.0143082**	**.0361974**
comp_municipality	**-.0004807**	**.0003014**	**-1.60**	**0.111**	**-.0010714**	**.00011**
ln_freq_pres_indication_year	**-.1060048**	**.0022338**	**-47.45**	**0.000**	**-.110383**	**-.1016265**
specialist						
1	**-.005916**	**.0045068**	**-1.31**	**0.189**	**-.0147491**	**.0029172**
centrality						
1	**-.0081112**	**.0050206**	**-1.62**	**0.106**	**-.0179514**	**.001729**
2	**-.0265323**	**.0082323**	**-3.22**	**0.001**	**-.0426672**	**-.0103973**
3	**.0027191**	**.0067303**	**0.40**	**0.686**	**-.010472**	**.0159101**
year						
2012	**-.0073416**	**.0027445**	**-2.68**	**0.007**	**-.0127207**	**-.0019624**
2013	**.0181648**	**.0060488**	**3.00**	**0.003**	**.0063094**	**.0300203**
2014	**-.0050938**	**.0061756**	**-0.82**	**0.409**	**-.0171978**	**.0070103**
_cons	**.8771138**	**.0374883**	**23.40**	**0.000**	**.8036381**	**.9505895**

TWOPM PREDICTIONS

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
0	-.3593447	.005671	-63.37	0.000	-.3704596	-.3482298
2	-.2153942	.0063792	-33.77	0.000	-.2278972	-.2028913
price_difference_ind	8.90e-06	.0000737	0.12	0.904	-.0001356	.0001534
male	-.0008495	.0035697	-0.24	0.812	-.007846	.0061471
age_dummy						
2	.0160717	.0043166	3.72	0.000	.0076114	.0245321
3	.0282851	.0047985	5.89	0.000	.0188803	.03769
comp_municipality	-.0006991	.0002625	-2.66	0.008	-.0012135	-.0001847
ln_freq_pres_indication_year	-.0204468	.00177	-11.55	0.000	-.023916	-.0169776
1.specialist	-.0010873	.0038554	-0.28	0.778	-.0086438	.0064691
centrality						
1	-.0105279	.0043653	-2.41	0.016	-.0190838	-.001972
2	-.0383075	.0065582	-5.84	0.000	-.0511614	-.0254537
3	.0070822	.0058462	1.21	0.226	-.0043762	.0185406
year						
2012	.0069638	.0025083	2.78	0.005	.0020477	.0118799
2013	.0247032	.0053258	4.64	0.000	.0142649	.0351416
2014	.0123986	.0052923	2.34	0.019	.0020259	.0227713

Results from ”new” and ”old”

To save space, only the results from the twopm’s will be presented here.

twopm - "new" drugs

Two-part model

Log pseudolikelihood = **-14495.54** Number of obs = **2917**

Part 1: probit

Number of obs = **2917**
Wald chi2(**15**) = **4277.6**
Prob > chi2 = **0.000**
Log pseudolikelihood = **-16108.858** Pseudo R2 = **0.187**

Part 2: glm

Number of obs = **1700**
Deviance = **823.677619** (1/df) Deviance = **.048477**
Pearson = **823.677619** (1/df) Pearson = **.048477**

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

AIC = **-.187842**
Log pseudolikelihood = **1613.318224** BIC = **-164692.**

(Std. Err. adjusted for clustering on doc

doctor_reservation	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.
probit					
atc_code					
11	**-1.738146**	**.0567431**	**-30.63**	**0.000**	**-1.84936**
13	**-.5355446**	**.0460944**	**-11.62**	**0.000**	**-.6258879**
price_difference	**-.0023986**	**.000195**	**-12.30**	**0.000**	**-.0027808**
male	**.0036182**	**.0224472**	**0.16**	**0.872**	**-.0403774**
age_dummy					
2	**.0015577**	**.0284091**	**0.05**	**0.956**	**-.0541231**
3	**.0550126**	**.0306889**	**1.79**	**0.073**	**-.0051366**
comp_municipality	**-.0043405**	**.0017383**	**-2.50**	**0.013**	**-.0077476**
ln_freq_pres_atc_year	**.5498747**	**.0098141**	**56.03**	**0.000**	**.5306394**
specialist	**.0405181**	**.0240777**	**1.68**	**0.092**	**-.0066733**
centrality					
1	**-.0183384**	**.0283678**	**-0.65**	**0.518**	**-.0739383**
2	**-.2100844**	**.0471303**	**-4.46**	**0.000**	**-.3024581**
3	**.0495362**	**.0387485**	**1.28**	**0.201**	**-.0264094**
year					
2012	**.52084**	**.0224318**	**23.22**	**0.000**	**.4768744**
2013	**.6424077**	**.0256757**	**25.02**	**0.000**	**.5920842**
2014	**.7641376**	**.0275963**	**27.69**	**0.000**	**.7100498**
_cons	**.3013166**	**.1874226**	**1.61**	**0.108**	**-.0660251**
glm					
atc_code					
11	**-.3781188**	**.0146725**	**-25.77**	**0.000**	**-.4068763**
13	**.0195374**	**.0107646**	**1.81**	**0.070**	**-.0015608**
price_difference	**-.0008662**	**.0000482**	**-17.95**	**0.000**	**-.0009607**
male	**.0001404**	**.0048143**	**0.03**	**0.977**	**-.0092954**
age_dummy					
2	**.0091736**	**.0063392**	**1.45**	**0.148**	**-.003251**
3	**.0209292**	**.0067654**	**3.09**	**0.002**	**.0076694**
comp_municipality	**-.0010411**	**.0003894**	**-2.67**	**0.008**	**-.0018043**
ln_freq_pres_atc_year	**-.1164339**	**.002295**	**-50.73**	**0.000**	**-.1209321**
specialist	**-.0182005**	**.0053043**	**-3.43**	**0.001**	**-.0285968**
centrality					
1	**.012886**	**.0058894**	**2.19**	**0.029**	**.001343**
2	**.0208174**	**.0105847**	**1.97**	**0.049**	**.0000717**
3	**.0665429**	**.0089752**	**7.41**	**0.000**	**.0489519**
year					
2012	**.0304332**	**.0042302**	**7.19**	**0.000**	**.0221422**
2013	**.1195357**	**.0054662**	**21.87**	**0.000**	**.1088221**
2014	**.1072148**	**.0059247**	**18.10**	**0.000**	**.0956025**
_cons	**1.135679**	**.0421568**	**26.94**	**0.000**	**1.053054**

twopm – "old" drugs

Two-part model

Log pseudolikelihood = **-33505.496** Number of obs = **87861**

Part 1: probit

Number of obs = **87861**
Wald chi2(**20**) = **20265.19**
Prob > chi2 = **0.0000**
Log pseudolikelihood = **-34711.425** Pseudo R2 = **0.3879**

Part 2: glm

Number of obs = **30472**
Deviance = **1648.360612** (1/df) Deviance = **.0541316**
Pearson = **1648.360612** (1/df) Pearson = **.0541316**

Variance function: **V(u) = 1** [**Gaussian**]
Link function : **g(u) = u** [**Identity**]

AIC = **-.0777716**
Log pseudolikelihood = **1205.928443** BIC = **-312744.9**

(Std. Err. adjusted for clustering on doctor_dummy)

doctor_reservation	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
probit						
atc_code						
1	**-3.078163**	**.0336748**	**-91.41**	**0.000**	**-3.144164**	**-3.012161**
2	**-3.193713**	**.0370839**	**-86.12**	**0.000**	**-3.266397**	**-3.12103**
3	**-2.339293**	**.0291822**	**-80.16**	**0.000**	**-2.396489**	**-2.282097**
4	**.139642**	**.0297514**	**4.69**	**0.000**	**.0813304**	**.1979536**
5	**-2.363855**	**.0652819**	**-36.21**	**0.000**	**-2.491805**	**-2.235904**
6	**-1.239163**	**.0380719**	**-32.55**	**0.000**	**-1.313782**	**-1.164543**
7	**-2.144698**	**.0280259**	**-76.53**	**0.000**	**-2.199628**	**-2.089769**
price_difference	**.0033266**	**.0001424**	**23.36**	**0.000**	**.0030474**	**.0036057**
male	**.027521**	**.0185654**	**1.48**	**0.138**	**-.0088665**	**.0639086**
age_dummy						
2	**.0596929**	**.0227926**	**2.62**	**0.009**	**.0150203**	**.1043655**
3	**.1006006**	**.0242536**	**4.15**	**0.000**	**.0530644**	**.1481369**
comp_municipality	**-.0052722**	**.0012555**	**-4.20**	**0.000**	**-.0077329**	**-.0028115**
ln_freq_pres_atc_year	**.4740472**	**.0076159**	**62.24**	**0.000**	**.4591203**	**.488974**
specialist	**.0263808**	**.0188045**	**1.40**	**0.161**	**-.0104754**	**.0632369**
centrality						
1	**.0073825**	**.0217017**	**0.34**	**0.734**	**-.035152**	**.0499169**
2	**-.0654757**	**.0363613**	**-1.80**	**0.072**	**-.1367427**	**.0057912**
3	**.031813**	**.0286527**	**1.11**	**0.267**	**-.0243452**	**.0879713**
year						
2012	**.1608222**	**.0153667**	**10.47**	**0.000**	**.130704**	**.1909404**
2013	**.2869886**	**.0184504**	**15.55**	**0.000**	**.2508265**	**.3231507**
2014	**.4494176**	**.0196954**	**22.82**	**0.000**	**.4108153**	**.48802**
_cons	**.2043417**	**.1239317**	**1.65**	**0.099**	**-.03856**	**.4472434**
glm						
atc_code						
1	**-.4580759**	**.0081399**	**-56.28**	**0.000**	**-.4740297**	**-.4421221**
2	**-.4518787**	**.0111475**	**-40.54**	**0.000**	**-.4737274**	**-.4300299**
3	**-.4785137**	**.0075653**	**-63.25**	**0.000**	**-.4933413**	**-.463686**
4	**.0361475**	**.0059888**	**6.04**	**0.000**	**.0244098**	**.0478853**
5	**-.1373698**	**.0203862**	**-6.74**	**0.000**	**-.177326**	**-.0974137**
6	**-.0277954**	**.0105215**	**-2.64**	**0.008**	**-.0484172**	**-.0071736**
7	**-.4272583**	**.0080336**	**-53.18**	**0.000**	**-.4430038**	**-.4115128**
price_difference	**-.0002586**	**.0000455**	**-5.69**	**0.000**	**-.0003478**	**-.0001695**
male	**-.0158136**	**.00397**	**-3.98**	**0.000**	**-.0235945**	**-.0080326**
age_dummy						
2	**.0091049**	**.0051458**	**1.77**	**0.077**	**-.0009807**	**.0191905**
3	**.0077707**	**.0054975**	**1.41**	**0.158**	**-.0030043**	**.0185457**
comp_municipality	**-.0002934**	**.0002787**	**-1.05**	**0.293**	**-.0008396**	**.0002529**
ln_freq_pres_atc_year	**-.1046751**	**.0021159**	**-49.47**	**0.000**	**-.1088222**	**-.100528**
specialist	**-.0002009**	**.004185**	**-0.05**	**0.962**	**-.0084032**	**.0080015**
centrality						
1	**-.0039322**	**.0047372**	**-0.83**	**0.407**	**-.013217**	**.0053527**
2	**-.0019625**	**.008455**	**-0.23**	**0.816**	**-.0185341**	**.014609**
3	**.006639**	**.0066643**	**1.00**	**0.319**	**-.0064229**	**.0197008**
year						
2012	**-.0420529**	**.0048705**	**-8.63**	**0.000**	**-.0515988**	**-.0325069**
2013	**-.0413213**	**.0059037**	**-7.00**	**0.000**	**-.0528923**	**-.0297504**
2014	**-.0469447**	**.0058504**	**-8.02**	**0.000**	**-.0584113**	**-.0354782**
_cons	**1.072566**	**.0277111**	**38.71**	**0.000**	**1.018253**	**1.126879**

twopm predictions - "new" drugs

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
atc_code						
11	-.427102	.0090678	-47.10	0.000	-.4448745	-.4093294
13	-.0797597	.010886	-7.33	0.000	-.1010959	-.0584234
price_difference	-.0008715	.0000406	-21.48	0.000	-.000951	-.000792
male	.0006337	.0044291	0.14	0.886	-.0080472	.0093145
age_dummy						
2	.0055292	.0056228	0.98	0.325	-.0054913	.0165497
3	.0206215	.0060977	3.38	0.001	.0086703	.0325727
comp_municipality	-.0012698	.0003492	-3.64	0.000	-.0019542	-.0005853
ln_freq_pres_atc_year	.0158489	.0017534	9.04	0.000	.0124123	.0192854
specialist	-.0044502	.004799	-0.93	0.354	-.013856	.0049556
centrality						
1	.0047438	.0055394	0.86	0.392	-.0061132	.0156008
2	-.0209277	.0092887	-2.25	0.024	-.0391333	-.0027222
3	.0474952	.0084293	5.63	0.000	.0309742	.0640163
year						
2012	.0858758	.0035446	24.23	0.000	.0789286	.0928231
2013	.1585945	.0045256	35.04	0.000	.1497244	.1674646
2014	.1705364	.0048739	34.99	0.000	.1609838	.1800891

twopm predictions - "old" drugs

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
atc_code						
1	-.6308095	.0051772	-121.84	0.000	-.6409566	-.6206623
2	-.6330104	.0051878	-122.02	0.000	-.6431783	-.6228425
3	-.6057497	.0050248	-120.55	0.000	-.6155982	-.5959012
4	.0511936	.0066946	7.65	0.000	.0380724	.0643148
5	-.5344123	.0101464	-52.67	0.000	-.5542988	-.5145258
6	-.2748113	.010194	-26.96	0.000	-.2947912	-.2548314
7	-.5809213	.0052561	-110.52	0.000	-.591223	-.5706196
price_difference	.0002788	.0000222	12.54	0.000	.0002352	.0003224
male	-.0024573	.00248	-0.99	0.322	-.0073179	.0024034
age_dummy						
2	.0097161	.0030624	3.17	0.002	.003714	.0157183
3	.013802	.0032711	4.22	0.000	.0073908	.0202132
comp_municipality	-.0006869	.0001698	-4.04	0.000	-.0010197	-.0003541
ln_freq_pres_atc_year	.0161027	.0010696	15.06	0.000	.0140064	.0181991
specialist	.0028556	.0025445	1.12	0.262	-.0021315	.0078427
centrality						
1	-.0005569	.0029104	-0.19	0.848	-.0062613	.0051474
2	-.0079345	.0049285	-1.61	0.107	-.0175941	.0017251
3	.0058867	.003987	1.48	0.140	-.0019278	.0137012
year						
2012	.0048589	.0022976	2.11	0.034	.0003557	.009362
2013	.0187527	.0028055	6.68	0.000	.013254	.0242515
2014	.0339053	.0029134	11.64	0.000	.0281951	.0396154

Appendix H: Model results for separate years

For ease of reading, we have chosen to only show the results of the twopm when analysing the years separately. When limiting the models to looking at years separately, the models will accordingly be based on fewer observations.

”Overall”

TWOPM predictions 2011

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
ulcer	.0000217	.0022082	0.01	0.992	-.0043063	.0043496
depression	.0113776	.0021381	5.32	0.000	.0071871	.0155682
male	.0012536	.001765	0.71	0.478	-.0022058	.0047129
age_dummy						
2	.0057679	.0022829	2.53	0.012	.0012936	.0102422
3	.007934	.0023403	3.39	0.001	.0033472	.0125209
comp_municipality	-.0002476	.0001315	-1.88	0.060	-.0005052	.0000101
ln_freq_pres_indication_year	-.0050446	.0021954	-2.30	0.022	-.0093476	-.0007416
1.specialist	-.0024064	.0018065	-1.33	0.183	-.005947	.0011343
centrality						
1	.001395	.0020606	0.68	0.498	-.0026438	.0054338
2	-.0125973	.0026186	-4.81	0.000	-.0177296	-.007465
3	-.0050324	.0023921	-2.10	0.035	-.0097208	-.0003439

TWOPM predictions 2012

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
ulcer	.010172	.0017841	5.70	0.000	.0066752	.0136688
depression	.0286717	.0015877	18.06	0.000	.0255599	.0317835
male	-.00067	.0014453	-0.46	0.643	-.0035028	.0021627
age_dummy						
2	.0040144	.0018378	2.18	0.029	.0004124	.0076165
3	.0057729	.0019681	2.93	0.003	.0019156	.0096302
comp_municipality	-.0001299	.0001087	-1.19	0.232	-.000343	.0000832
ln_freq_pres_indication_year	-.0043605	.0018162	-2.40	0.016	-.0079201	-.0008008
1.specialist	-.0005761	.0014935	-0.39	0.700	-.0035034	.0023512
centrality						
1	-.002378	.0015282	-1.56	0.120	-.0053732	.0006172
2	-.0094583	.00261	-3.62	0.000	-.0145737	-.0043429
3	-.0027938	.0021023	-1.33	0.184	-.0069143	.0013266

TWOPM predictions 2013

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
ulcer	.0063707	.0015365	4.15	0.000	.0033592	.0093822
depression	.0052165	.001376	3.79	0.000	.0025195	.0079135
male	-.001727	.0015231	-1.13	0.257	-.0047122	.0012582
age_dummy						
2	.0015515	.001927	0.81	0.421	-.0022253	.0053284
3	.0053453	.0020855	2.56	0.010	.0012578	.0094328
comp_municipality	-.0003118	.0001215	-2.57	0.010	-.0005499	-.0000737
ln_freq_pres_indication_year	-.0048821	.0017077	-2.86	0.004	-.0082291	-.0015351
1.specialist	.000901	.001598	0.56	0.573	-.002231	.004033
centrality						
1	-.0024638	.0017429	-1.41	0.157	-.0058798	.0009523
2	-.0050284	.0028413	-1.77	0.077	-.0105973	.0005404
3	-.0045064	.0022657	-1.99	0.047	-.008947	-.0000658

TWOPM predictions 2014

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
ulcer	.0155407	.0013422	11.58	0.000	.01291	.0181714
depression	.0144289	.0011901	12.12	0.000	.0120964	.0167615
male	-.0009016	.0014124	-0.64	0.523	-.0036699	.0018666
age_dummy						
2	.0052841	.0017722	2.98	0.003	.0018107	.0087576
3	.0074219	.0018895	3.93	0.000	.0037186	.0111252
comp_municipality	-.0003941	.0000896	-4.40	0.000	-.0005696	-.0002186
ln_freq_pres_indication_year	-.0041641	.001143	-3.64	0.000	-.0064043	-.001924
1.specialist	-.0012494	.0015396	-0.81	0.417	-.0042669	.0017681
centrality						
1	-.0050449	.0013814	-3.65	0.000	-.0077523	-.0023375
2	-.005333	.0024422	-2.18	0.029	-.0101196	-.0005465
3	.0034169	.0026345	1.30	0.195	-.0017467	.0085804

"New" drugs

TWOPM predictions 2011

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
atc_code						
11	.1384531	.0207632	6.67	0.000	.097758	.1791483
13	.151664	.0111997	13.54	0.000	.129713	.173615
price_difference	.0003909	.0000656	5.96	0.000	.0002624	.0005194
male	.0056434	.0023187	2.43	0.015	.0010987	.010188
age_dummy						
2	.0085465	.0028899	2.96	0.003	.0028825	.0142105
3	.0140633	.0031669	4.44	0.000	.0078564	.0202703
comp_municipality	-.0003762	.0001747	-2.15	0.031	-.0007186	-.0000338
ln_freq_pres_atc_year	-.0057088	.0012872	-4.43	0.000	-.0082317	-.0031858
specialist	-.0045745	.0025662	-1.78	0.075	-.0096042	.0004552
centrality						
1	.0006198	.0028467	0.22	0.828	-.0049596	.0061992
2	-.0058632	.0047145	-1.24	0.214	-.0151033	.003377
3	.0024432	.004259	0.57	0.566	-.0059042	.0107906

TWOPM predictions 2012

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
atc_code						
11	.171121	.0228682	7.48	0.000	.1263001	.2159418
13	.1485936	.0111432	13.33	0.000	.1267534	.1704338
price_difference	.0003952	.0000665	5.94	0.000	.0002648	.0005256
male	.0066491	.0023352	2.85	0.004	.0020721	.0112261
age_dummy						
2	.0085833	.0029606	2.90	0.004	.0027808	.0143859
3	.0132472	.0032202	4.11	0.000	.0069358	.0195587
comp_municipality	-.0004573	.0001815	-2.52	0.012	-.000813	-.0001015
ln_freq_pres_atc_year	-.0070604	.0013027	-5.42	0.000	-.0096136	-.0045071
specialist	-.0050723	.0026355	-1.92	0.054	-.0102377	.0000931
centrality						
1	.0018518	.0028946	0.64	0.522	-.0038215	.007525
2	-.0043375	.0047895	-0.91	0.365	-.0137248	.0050498
3	.0049964	.0043479	1.15	0.250	-.0035253	.0135181

TWOPM predictions 2013

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
atc_code						
11	.1712482	.0226732	7.55	0.000	.1268094	.2156869
13	.1444851	.0111431	12.97	0.000	.1226449	.1663252
price_difference	.0003893	.0000666	5.84	0.000	.0002587	.00052
male	.0051367	.002363	2.17	0.030	.0005052	.0097681
age_dummy						
2	.0083885	.0029792	2.82	0.005	.0025493	.0142277
3	.0138369	.0032748	4.23	0.000	.0074185	.0202553
comp_municipality	-.0003	.0001816	-1.65	0.099	-.000656	.0000559
ln_freq_pres_atc_year	-.0083741	.0012824	-6.53	0.000	-.0108876	-.0058605
specialist	-.0039161	.0026478	-1.48	0.139	-.0091057	.0012736
centrality						
1	.0008099	.0029172	0.28	0.781	-.0049078	.0065276
2	-.0064883	.0047753	-1.36	0.174	-.0158477	.0028712
3	.0024553	.0045601	0.54	0.590	-.0064822	.0113928

TWOPM predictions 2014

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
atc_code						
11	.1744866	.0229123	7.62	0.000	.1295792	.2193939
13	.1382568	.0110061	12.56	0.000	.1166852	.1598283
price_difference	.000385	.0000666	5.78	0.000	.0002545	.0005154
male	.004748	.0023896	1.99	0.047	.0000644	.0094316
age_dummy						
2	.0075659	.0029847	2.53	0.011	.0017161	.0134157
3	.0128994	.0032658	3.95	0.000	.0064985	.0193003
comp_municipality	-.0004334	.0001776	-2.44	0.015	-.0007815	-.0000854
ln_freq_pres_atc_year	-.0097031	.001279	-7.59	0.000	-.0122099	-.0071963
specialist	-.0042673	.0026513	-1.61	0.108	-.0094638	.0009292
centrality						
1	.0008123	.0029458	0.28	0.783	-.0049614	.006586
2	-.0073339	.0048775	-1.50	0.133	-.0168936	.0022257
3	-.0004754	.0043508	-0.11	0.913	-.0090029	.0080521

”Old” drugs

Figure 4 TWOPM predictions 2011

	Delta-method					
	dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
atc_code						
1	-.1594124	.0042685	-37.35	0.000	-.1677785	-.1510463
2	-.1583454	.0043566	-36.35	0.000	-.1668842	-.1498066
3	-.162358	.0044478	-36.50	0.000	-.1710754	-.1536406
4	-.0838076	.0055709	-15.04	0.000	-.0947263	-.0728889
5	-.0049606	.0058673	-0.85	0.398	-.0164603	.0065392
6	-.0520852	.0057283	-9.09	0.000	-.0633125	-.0408579
7	-.1356016	.0049917	-27.17	0.000	-.1453852	-.125818
price_difference	0	(omitted)				
male	.0033455	.0022453	1.49	0.136	-.0010553	.0077463
age_dummy						
2	.0086254	.0029475	2.93	0.003	.0028485	.0144023
3	.0133574	.0030574	4.37	0.000	.007365	.0193497
comp_municipality	-.0001349	.0001635	-0.83	0.409	-.0004554	.0001855
ln_freq_pres_atc_year	-.0072469	.0010632	-6.82	0.000	-.0093308	-.005163
specialist	.0037316	.0023362	1.60	0.110	-.0008473	.0083105
centrality						
1	.0014618	.0025609	0.57	0.568	-.0035575	.006481
2	-.0138663	.0038259	-3.62	0.000	-.021365	-.0063676
3	-.0068814	.0034511	-1.99	0.046	-.0136455	-.0001174

Figure 5 TWOPM predictions 2012

	Delta-method					
	dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
atc_code						
1	-.1571814	.0042084	-37.35	0.000	-.1654296	-.1489331
2	-.1576063	.0042658	-36.95	0.000	-.1659671	-.1492455
3	-.1464028	.0045608	-32.10	0.000	-.1553417	-.1374639
4	-.1084503	.0050414	-21.51	0.000	-.1183313	-.0985692
5	-.0130459	.0057691	-2.26	0.024	-.0243532	-.0017387
6	-.0869632	.0052018	-16.72	0.000	-.0971585	-.0767678
7	-.1439351	.0050044	-28.76	0.000	-.1537435	-.1341267
price_difference	0	(omitted)				
male	.000727	.0020502	0.35	0.723	-.0032913	.0047453
age_dummy						
2	.0039527	.0027151	1.46	0.145	-.0013688	.0092743
3	.0083468	.0028297	2.95	0.003	.0028006	.0138929
comp_municipality	-.000066	.000172	-0.38	0.701	-.0004031	.0002711
ln_freq_pres_atc_year	-.0057151	.0010317	-5.54	0.000	-.0077372	-.003693
specialist	.0053936	.0021471	2.51	0.012	.0011853	.0096018
centrality						
1	-.0039815	.0022908	-1.74	0.082	-.0084713	.0005083
2	-.0166363	.0035403	-4.70	0.000	-.0235752	-.0096975
3	-.0079077	.003057	-2.59	0.010	-.0138992	-.0019161

Figure 6 TWOPM predictions 2013

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
atc_code						
1	-.139295	.0042455	-32.81	0.000	-.1476161	-.130974
2	-.1466701	.0042812	-34.26	0.000	-.1550611	-.1382791
3	-.122061	.0047809	-25.53	0.000	-.1314315	-.1126906
4	-.0783285	.0053754	-14.57	0.000	-.0888642	-.0677929
5	-.0206902	.0056976	-3.63	0.000	-.0318574	-.0095231
6	-.1076414	.0047028	-22.89	0.000	-.1168587	-.098424
7	-.1216802	.0050229	-24.22	0.000	-.1315249	-.1118354
price_difference	0	(omitted)				
male	.0025911	.0021055	1.23	0.218	-.0015356	.0067178
age_dummy						
2	.0032253	.0027443	1.18	0.240	-.0021535	.0086041
3	.0083187	.002878	2.89	0.004	.0026779	.0139594
comp_municipality	-.0003079	.0001669	-1.85	0.065	-.0006349	.0000192
ln_freq_pres_atc_year	-.0092761	.0010118	-9.17	0.000	-.0112592	-.0072931
specialist	.0052852	.0022597	2.34	0.019	.0008563	.0097142
centrality						
1	-.0004051	.0023684	-0.17	0.864	-.0050472	.0042369
2	-.0030909	.0042055	-0.73	0.462	-.0113335	.0051517
3	-.0054907	.0033014	-1.66	0.096	-.0119612	.0009799

Figure 7 TWOPM predictions 2014

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
atc_code						
1	-.1380184	.0043798	-31.51	0.000	-.1466026	-.1294342
2	-.1487898	.0043978	-33.83	0.000	-.1574093	-.1401703
3	-.1246611	.0049088	-25.40	0.000	-.1342822	-.11504
4	-.0957608	.0051384	-18.64	0.000	-.105832	-.0856896
5	-.0507142	.0057937	-8.75	0.000	-.0620697	-.0393588
6	-.0964583	.0049525	-19.48	0.000	-.1061652	-.0867515
7	-.1158622	.0052749	-21.97	0.000	-.1262007	-.1055237
price_difference	0	(omitted)				
male	.0026923	.0021753	1.24	0.216	-.0015712	.0069558
age_dummy						
2	.0115674	.0027235	4.25	0.000	.0062294	.0169055
3	.0152268	.0029033	5.24	0.000	.0095364	.0209172
comp_municipality	-.0004405	.0001356	-3.25	0.001	-.0007064	-.0001747
ln_freq_pres_atc_year	-.0098891	.0010028	-9.86	0.000	-.0118545	-.0079236
specialist	.0003434	.0023956	0.14	0.886	-.0043518	.0050386
centrality						
1	-.0034325	.0024654	-1.39	0.164	-.0082645	.0013995
2	-.005629	.0042546	-1.32	0.186	-.0139679	.0027099
3	-.0037248	.0035263	-1.06	0.291	-.0106362	.0031865

Appendix I: Competition

A number of different variables to serve as a proxy for competition were tested. The table below gives a short explanation and overview. Outputs from the twopm on all indications follow. Since the variables were not tested for all the different samples (limited sample, "old" and "new" indications etc.), some of the variables that turn out insignificant here might prove to be significant with other samples.

	Explanation	Desired sign to support hypothesis	Observed, predicted effect	p-value
comp_municipality	Proportion of aggregated list spots filled in a municipality	(-)	(-)	0,000
shortage	Dummy variable (=1) if a GP has a patient deficit of ≥ 100	(-)	(+)	0,200
herfindahl	Sum of squared proportion of market share for every GP in a municipality	(-)	(+)	0,001
competition	Proportion of list filled for a given GP	(-)	(-)	0,373
nr_open_municipalitylist	Number of lists with availability in a municipality	(-)	(-)	0,000
freq_practices	Number of practices in a municipality	(-)	(-)	0,000

“comp_municipality” – predictions twopm

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
ulcer	-.0316517	.004066	-7.78	0.000	-.0396209	-.0236825
depression	.0167676	.0011585	14.47	0.000	.0144971	.0190382
price_difference_ind	-.0003165	.0000358	-8.85	0.000	-.0003866	-.0002464
male	-.0005153	.0010914	-0.47	0.637	-.0026544	.0016237
age_dummy						
2	.0040177	.0012563	3.20	0.001	.0015553	.0064801
3	.0065159	.0014078	4.63	0.000	.0037565	.0092752
comp_municipality	-.0002928	.000074	-3.95	0.000	-.0004379	-.0001477
ln_freq_pres_indication_year	-.0046516	.0010418	-4.47	0.000	-.0066935	-.0026098
1.specialist	-.0007925	.0011314	-0.70	0.484	-.0030099	.001425
centrality						
1	-.0021808	.0012085	-1.80	0.071	-.0045495	.0001879
2	-.0079146	.0018629	-4.25	0.000	-.0115658	-.0042634
3	-.0021737	.001546	-1.41	0.160	-.0052038	.0008565
year						
2012	.0027341	.0009378	2.92	0.004	.000896	.0045722
2013	-.0122653	.0010674	-11.49	0.000	-.0143574	-.0101733
2014	-.0132928	.0009763	-13.62	0.000	-.0152063	-.0113794

“shortage” – predictions twopm

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
ulcer	-.0315588	.0040644	-7.76	0.000	-.039525	-.0235927
depression	.016769	.0011639	14.41	0.000	.0144878	.0190502
price_differ~d	-.0003158	.0000357	-8.83	0.000	-.0003858	-.0002457
male	-.0006945	.0011042	-0.63	0.529	-.0028587	.0014697
age_dummy						
2	.0042333	.0012591	3.36	0.001	.0017656	.006701
3	.0068128	.0014071	4.84	0.000	.0040549	.0095706
ln_freq_pres~r	-.0046174	.0010533	-4.38	0.000	-.0066818	-.002553
1.specialist	-.0008423	.0011305	-0.75	0.456	-.0030581	.0013734
centrality						
1	-.0020588	.0012072	-1.71	0.088	-.0044248	.0003072
2	-.0076311	.0018666	-4.09	0.000	-.0112896	-.0039727
3	-.0013045	.0015482	-0.84	0.399	-.0043389	.0017299
year						
2012	.002676	.0009379	2.85	0.004	.0008378	.0045142
2013	-.012272	.0010677	-11.49	0.000	-.0143646	-.0101794
2014	-.0138465	.0009602	-14.42	0.000	-.0157285	-.0119644
shortage	.0017875	.0013939	1.28	0.200	-.0009446	.0045195

“herfindahl” – predictions twopm

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
ulcer	-.0316329	.0040613	-7.79	0.000	-.039593	-.0236728
depression	.0167517	.0011577	14.47	0.000	.0144827	.0190208
price_differ~d	-.0003162	.0000357	-8.85	0.000	-.0003862	-.0002461
male	-.0005447	.0010919	-0.50	0.618	-.0026848	.0015953
age_dummy						
2	.0042573	.0012577	3.39	0.001	.0017923	.0067222
3	.006904	.0014066	4.91	0.000	.0041471	.009661
ln_freq_pres~r	-.0046752	.0010414	-4.49	0.000	-.0067163	-.0026341
1.specialist	-.0008093	.0011364	-0.71	0.476	-.0030366	.001418
centrality						
1	-.0026617	.0012245	-2.17	0.030	-.0050617	-.0002616
2	-.0085639	.0018925	-4.53	0.000	-.0122731	-.0048547
3	-.0037186	.0017249	-2.16	0.031	-.0070993	-.0003379
year						
2012	.0027082	.0009377	2.89	0.004	.0008704	.004546
2013	-.0122719	.0010688	-11.48	0.000	-.0143667	-.0101771
2014	-.013873	.0009592	-14.46	0.000	-.015753	-.0119931
herfindahl	.0117851	.0036463	3.23	0.001	.0046384	.0189317

“competition” - predictions twopm

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
ulcer	-.0315764	.0040632	-7.77	0.000	-.0395402	-.0236126
depression	.0167619	.0011616	14.43	0.000	.0144852	.0190387
price_differ~d	-.0003159	.0000357	-8.84	0.000	-.0003859	-.0002458
male	-.0006208	.0010975	-0.57	0.572	-.0027719	.0015303
age_dummy						
2	.0042655	.0012611	3.38	0.001	.0017938	.0067373
3	.0068904	.0014114	4.88	0.000	.004124	.0096568
ln_freq_pres~r	-.0046229	.0010524	-4.39	0.000	-.0066855	-.0025602
1.specialist	-.0009196	.0011354	-0.81	0.418	-.0031448	.0013057
centrality						
1	-.0020709	.0012077	-1.71	0.086	-.004438	.0002962
2	-.00761	.0018677	-4.07	0.000	-.0112706	-.0039495
3	-.0012847	.0015475	-0.83	0.406	-.0043178	.0017484
year						
2012	.0026728	.0009384	2.85	0.004	.0008336	.004512
2013	-.0122915	.0010692	-11.50	0.000	-.014387	-.010196
2014	-.0138708	.0009614	-14.43	0.000	-.0157552	-.0119865
competition	-.003627	.0040718	-0.89	0.373	-.0116075	.0043536

“nr_open_municipalitylist” - predictions twopm

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
ulcer	-.0327563	.0040281	-8.13	0.000	-.0406513	-.0248614
depression	.0163026	.0011562	14.10	0.000	.0140365	.0185687
price_differ~d	-.0003219	.0000357	-9.03	0.000	-.0003919	-.000252
male	-.0006791	.0010816	-0.63	0.530	-.002799	.0014408
age_dummy						
2	.0049492	.0012436	3.98	0.000	.0025118	.0073867
3	.0083523	.0014063	5.94	0.000	.0055961	.0111086
ln_freq_pres~r	-.0055783	.0010438	-5.34	0.000	-.0076241	-.0035326
1.specialist	-.0007557	.00112	-0.67	0.500	-.0029508	.0014395
centrality						
1	-.0056284	.0012459	-4.52	0.000	-.0080703	-.0031865
2	-.0112326	.0018594	-6.04	0.000	-.014877	-.0075883
3	-.0052422	.0015856	-3.31	0.001	-.0083499	-.0021345
year						
2012	.0023464	.0009357	2.51	0.012	.0005126	.0041803
2013	-.0128167	.0010686	-11.99	0.000	-.0149112	-.0107222
2014	-.0144305	.0009608	-15.02	0.000	-.0163136	-.0125475
nr_open_coun~t	-.0000818	7.52e-06	-10.88	0.000	-.0000966	-.0000671

"freq_practices" - predictions twopm

	Delta-method dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
indication						
ulcer	-.0327829	.0040266	-8.14	0.000	-.040675	-.0248908
depression	.0162271	.0011555	14.04	0.000	.0139624	.0184918
price_differ~d	-.0003216	.0000357	-9.02	0.000	-.0003915	-.0002517
male	-.0006896	.0010802	-0.64	0.523	-.0028067	.0014274
age_dummy						
2	.0049706	.0012409	4.01	0.000	.0025385	.0074027
3	.0084511	.0014034	6.02	0.000	.0057005	.0112017
ln_freq_pres~r	-.005711	.0010441	-5.47	0.000	-.0077575	-.0036645
1.specialist	-.0006408	.001118	-0.57	0.567	-.002832	.0015503
centrality						
1	-.006246	.0012522	-4.99	0.000	-.0087003	-.0037917
2	-.0119538	.0018543	-6.45	0.000	-.0155881	-.0083195
3	-.0061394	.001595	-3.85	0.000	-.0092655	-.0030133
year						
2012	.0029037	.0009352	3.10	0.002	.0010708	.0047367
2013	-.0122668	.0010642	-11.53	0.000	-.0143525	-.0101811
2014	-.0139334	.0009555	-14.58	0.000	-.015806	-.0120607
freq_practices	-.0000402	3.44e-06	-11.68	0.000	-.0000469	-.0000334