Physician altruism and moral hazard:

(no) evidence from Finnish national prescriptions data

Giovanni Crea[a], Matteo M. Galizzi[b,c*], Ismo Linnosmaa[d,e], Marisa Miraldo[f]

(Accepted for publication in *Journal of Health Economics*)

a: University of Pavia, Department of Economics and Management. Email: giovanni.crea@unipv.it.
b: London School of Economics, Department of Psychological and Behavioural Science, LSE Global Health Initiative, and LSE Behavioural Science Hub, Room 3.16, Queens House, 55/56 Lincoln's Inn Fields, WC2A 3LJ London, UK. Email: m.m.galizzi@lse.ac.uk.
c: Paris School of Economics - École d'Économie de Paris, Hospinnomics; Hôtel-Dieu, 1, Parvis de Notre-Dame, Bâtiment B1, 5° étage, 75004 Paris, France.
d: National Institute for Health and Welfare, Centre for Health and Social Economics, Mannerheimintie 166, 00271 Helsinki, Finland. Email: ismo.linnosmaa@thl.fi.
e: University of Eastern Finland, Department of Social and Health Management, Yliopistonranta 1E, Snellmania Building, 70211 Kuopio, Finland.
f: Imperial College Business School, Department of Management & Centre for Health Economics & Policy Innovation (CHEPI), South Kensington Campus, SW7 2AZ London, UK. Email: m.miraldo@imperial.ac.uk.
*Corresponding author: Matteo M Galizzi, London School of Economics, Department of Psychological and Behavioural Science, LSE Health, and LSE Behavioural Science Hub, Room 3.16, Queens House, 55/56 Lincoln's Inn Fields, WC2A 3LJ London, UK. Email: m.m.galizzi@lse.ac.uk.

Statement of contributions: Authorship is in alphabetical order. GC contributed to data cleaning, data coding, and running the empirical analyses. MMG contributed to conceptually designing the study, securing the data, developing the empirical strategy, and drafting and revising the paper. IL contributed to conceptually designing the study, securing the data, and developing the theoretical model. MM contributed to conceptually designing the study, securing the data, developing the empirical strategy, data cleaning, data coding, running the empirical analyses, and drafting and revising the paper. MMG, IL and MM gratefully acknowledge financial support from the Academy of Finland (grant number 138723) and are grateful to KELA for sharing the data.

Physician altruism and moral hazard:

(no) evidence from Finnish national prescriptions data

Abstract

We test the physicians' altruism and moral hazard hypotheses using a national panel register containing all 2003-2010 statins prescriptions in Finland. We estimate the likelihood that physicians prescribe generic versus branded versions of statins as a function of the shares of the difference between what patients have to pay out of their pocket and what is covered by the insurance, controlling for patient, physician, and drug characteristics. We find that the estimated coefficients and the average marginal effects associated with moral hazard and altruism are nearly zero, and are orders of magnitude smaller than the ones associated with other explanatory factors such as the prescriptions' year and the physician specialization. When the analysis distinctly accounts for both the patient and the insurer shares of expenditure, the estimated coefficients directly reject the altruism and moral hazard hypotheses. Instead, we find strong and robust evidence of habits persistence in prescribing branded drugs.

Keywords: pharmaceuticals; moral hazard; physician altruism; habits persistence.

JEL codes: C55, D64, I11, I13.

1. Introduction

In this article we empirically test the hypotheses of physicians' altruism and moral hazard using, for the first time, data from a national register with all statins prescriptions records in Finland between 2003 and 2010 (n=4,502,107). We develop a random utility model of physician behavior and, using a range of different panel models, we estimate the likelihood of a physician prescribing a generic versus a branded version of a drug, controlling for a broad set of physician, patient, and drug characteristics. We find no evidence in support of the hypotheses of physicians' altruism and moral hazard. We find, however, strong and robust evidence that the physicians' decisions to prescribe branded versions of statins are habit-dependent.

Whereas most of the literature discusses moral hazard from the perspective of patient behaviour, the two hypotheses of physicians' altruism and moral hazard have been addressed by economists from different perspectives. The role of physicians in healthcare insurance markets has been of interest to economists since the seminal contribution of Arrow (1963). Pioneering the economic analysis of physician behaviour, Arrow (1963) notices that physicians may have motives and objectives that differentiate them from purely profit-maximizing agents.

Together with Arrow (1963), Pauly (1968) develops the original "ex-post moral hazard" hypothesis, predicting that health insurance increases the consumption of healthcare and leads to excessive consumption of services in a competitive healthcare market. Ex-post moral hazard (henceforth simply labeled as moral hazard) has since then been the focus of numerous economic analyses (e.g. Feldstein, 1973; Manning, Newhouse, Duan, Keeler, Leibowitz, and Marquis, 1987; Dranove, 1989; Ma, 1994; Zweifel and Manning, 2000; Ma and Riordan, 2002).

Building on this literature, some studies have specifically focused on physicians' moral hazard. Blomqvist (1991), for example, models the physician as a "double agent", who acts simultaneously on behalf of the patient but also of the insurer (McGuire, 2000; Chone and Ma, 2011).

The double agency hypothesis has then been further developed by a strand of literature that presents physicians as being "altruist" agents who incorporate patients' utility in their decisions (Woodward and Warren-Boulton, 1984; Ellis and McGuire, 1986; Farley, 1986; Chalkey and Malcomson, 1998; Jack, 2005). More recently, a series of recent laboratory experiments have empirically tested the hypothesis of physician altruism with convenience samples of medical students, and have found heterogeneity in medical students' altruistic motivation towards the patients' health benefis (Hennig-Schmidt, Selten, and Wiesen, 2011; Godager and Wiesen, 2013; Hennig-Schmidt and Wiesen, 2014; Brosig-Koch, Hennig-Schmidt, Kairies-Schwarz,

and Wiesen, 2017). There is also evidence of stronger altruistic motivation in physicians than in students (Brosig-Koch, Hennig-Schmidt, Kairies-Schwarz, and Wiesen, 2016).[1]

In the more specific context of prescription drugs, Hellerstein (1998) models the physicians' moral hazard hypothesis by looking at a physician facing a choice between prescribing a branded or a generic version of a drug to her patient. Hellerstein (1998) assumes that both the (indirect) utility of the patient and the insurance expenditures enter the utility function of the physician. The physician internalises a share of the patient's utility in her own utility function, but also a share of the drug costs covered by the insurer. In line with observational evidence, Hellerstein (1998) assumes that the branded version of the drug is more expensive than the generic version. The model shows that, if the physician places a higher weight on the patient's utility than on insurance expenditures, an increase in the insurance coverage decreases (increases) the likelihood of the generic (branded) prescription. An increase in the insurance coverage, in fact, increases insurance expenditures and decreases patient's expenditures, *ceteris paribus*. As both these variables have a similar effect on the physician's utility, higher insurance coverage leads to a lower probability of generic prescribing when the physician values the utility of the patient more than the insurance expenditure.

A few studies have tested empirically the hypotheses of physicians' moral hazard and altruism in the context of pharmaceutical prescriptions by looking at the physicians' actual choices of prescribing either a generic or a branded version of the drug (Hellerstein, 1998; Lundin, 2000; Mott and Cline, 2002; Granlund, 2009; and Liu, Yang, and Hsie, 2009). However, the evidence to date in this area is mixed and not conclusive (see Section 2 for further detail on the literature). Additionally, physician objectives are modeled differently across the different studies, that often use the terms moral hazard and altruism quite interchangeably.

Our research builds on these previous contributions in that we test both the altruism and the moral hazard hypotheses in drug prescription behaviour using a national panel register of administrative data from Finland capturing physicians prescription decisions.

We first illustrate a simple theoretical model on physician decision-making based on Hellerstein (1998) which predicts that the higher is the patient's insurance coverage for pharmaceutical expenditures, the more likely it is that physicians prescribe an expensive branded version of a drug. We use the model to explicitly define the research hypotheses on altruism and moral hazard to be empirically tested. This is important because, as mentioned,

[1] See Galizzi, Godager, Linnosmaa, Tammi and Wiesen (2015) for a recent review of the literature.

the previous literature has used different operational definitions of altruism and moral hazard, and the two terms have often been used interchangeably.

We then use a national panel dataset with *all* statins prescriptions in Finland between 2003 and 2010 to empirically test the physicians' altruism and moral hazard hypotheses, while controlling for a broad range of physician, patient, and drug characteristics.

Our work innovatively contributes to the previous literature in five respects. First, by using a national register, we consider the entire "universe" of the statins prescriptions in Finland. Hellerstein (1998), Lundin (2000), Mott and Cline (2002), Granlund (2009), and Liu, Yang, and Hsie (2009) all consider specific samples of prescriptions in the US, Sweden, and Taiwan. Lundin (2000), for example, only considers data for seven drugs dispensed in two pharmacies. Considering the universe of prescriptions allows us to characterise the full set of drugs competing in the market and the whole choice set of alternatives available to physicians. Moreover, considering the universe of prescriptions allows us to draw conclusions at a level that is representative of the population, alike Leibowitz, Manning and Newhouse (1985) (and, in a different context, Coscelli, 2000).

Second, we focus on one therapeutic class of drugs that requires repeated prescriptions to target a chronic condition. Hellerstein (1998), Lundin (2000) and Mott and Cline (2002) all include very diverse types of drugs in their analyses, considering both drugs that require repeated prescriptions together with one-off drugs. For example Lundin (2000) and Hellerstein (2008) consider antidepressants and cardiovascular diseases drugs that are of repeated use together with antibiotics and laxatives that tend to be prescribed for acute episodes. Focusing on one therapeutic class of drugs that requires repeated prescriptions to target a chronic condition is important for two reasons. The first reason is that - alike Liu, Yang, and Hsie (2009) (and Coscelli, 2000) - it allows us to assess patterns of prescription over time for the same patient, and to measure how physicians' inertia in switching to generics is affected by their prescribing habits. This effect might be diluted when considering drugs that target both acute and chronic conditions and when considering data covering short periods of time (e.g. two weeks in Hellerstein, 2008; two years in Lundin, 2000). The second reason is that chronic conditions are of key policy interest given that they are major determinants of disease burden in OECD countries, and that the costs associated with their therapeutic management are a major driver of healthcare expenditure. In particular we focus on statins that target cardiovascular diseases, which are the first cause of death globally (WHO, 2004).

Third, we directly control for a broad range of physician, patient, and drug characteristics. This is an important innovation because neither Hellerstein (1998) nor Lundin (2000) have

information on income and other patient characteristics, while Mott and Cline (2002) and Iizuka (2012) find that preferences and tastes of prescribers and patients are significantly associated with drugs prescriptions and generics substitution (a point also made by Coscelli, 2000). We also have direct information on prices for all branded and generic versions of the statins in Finland, whereas Hellerstein (1998), for example, has no information on drug prices. The characterization of the cost associated with each drug prescribed, as well as its market alternatives, is key for the assessment of moral hazard.

Fourth, taking advantage of the panel structure of our national administrative register, we directly observe the repeated prescriptions of statins by physicians over time - to the same patient as well as to the whole population of patients of the same physician. Hence, by directly observing repeated prescriptions for all physician-patient pairs over time we can explicitly model habit-dependent prescriptions in our panel estimations. This is important as Hellerstein (1998), Mott and Cline (2002), and Iizuka (2012) (as well as Coscelli, 2000) find that prescribers' habits are significantly associated with prescriptions and generics substitution, even controlling for physician and insurer characteristics. Hellerstein (1998), however, lacks information on patients' prescription histories since her dataset only covers a two-week period. Neither Hellerstein (1998) nor Lundin (2000) data allow capturing physician specific habit, as they do not observe all the patients of a specific physician over time. The possibility of habits persistence in pharmaceutical consumption is also acknowledged by Granlund (2009) as an important aspect to be explicitly modelled. Modelling habits persistence is particularly crucial in the context of statins and chronic diseases where physicians file multiple prescriptions over years or even decades.

Finally, our data is unique in that it contains linked information on both dispensed and prescribed drugs. This allows us to disentangle whether the generic substitution occurred by the initiative of the physician or the pharmacist. For a variety of reasons (such as pharmacy incentives, lack of stock, generic substitution policies, among others) dispensed drugs might not correspond to prescribed drugs. Therefore, using dispensing data only (as Liu, Yang, and Hsie, 2009, for example) would not allow assessing physician prescription behaviour. On the other hand, using prescription data only, and thus not observing the amount paid when the drugs are dispensed at the pharmacy (as Hellerstein, 1998), would not allow observing the costs associated with a prescription including the amount borne by the patient and by the insurer, which are both of key importance in order to test the altruism and moral hazard hypotheses associated with generic substitution by the physician.

To the best of our knowledge, ours is the first national panel register to date in which the hypotheses of moral hazard and altruism are explicitly tested in regard to drugs prescription behavior.

Our main findings are the following. We find no evidence in support of the hypotheses of physicians' altruism and moral hazard: although, due to the large number of observations, the estimated coefficients associated with moral hazard and altruism are statistically significant, their size is very close to zero, and their effects would not be considered economically meaningful from a policy or business perspective. When the analysis distinctly accounts for the shares of statins expenditure borne by the patient and the insurer, and controls for a broad range of physician, patient, and drug characteristics, the estimated coefficients directly reject the hypotheses of physician altruism and moral hazard. Moreover, the average marginal effects of moral hazard and altruism are negligible and orders of magnitude smaller than the average marginal effects associated with other key explanatory factors, such as the class of the prescribed statins, the year of prescription, and the physician specialization.

We find, however, strong and robust evidence that the physicians' decisions to prescribe branded versions of statins in Finland are habit-dependent: physicians who have prescribed more branded drugs in the past are significantly less likely to switch to generic versions, and the effect is prominent and economically large.

The rest of the article is organized as follows: Section 2 contains a brief literature review discussing the main existing studies in the area to date, and how our study relates to this literature. Section 3 is a self-contained description of the institutional background in Finland, in particular on the pricing and reimbursement of pharmaceuticals. Section 4 presents a simple theoretical framework based on Hellerstein (1998) that generates the hypotheses to be tested empirically. Section 5 presents the data and Section 6 the econometric model. Results and conclusions are discussed in Sections 7 and 8, respectively.

2. Background literature

In a pioneering study, Leibowitz, Manning and Newhouse (1985) assess the role of insurance on pharmaceutical consumption and expenditure using data from the Rand Health Insurance Experiment (HIE) within which the prices of healthcare services and pharmaceuticals were randomly varied by altering the coinsurance rates across patients (Manning, Newhouse, Duan, Keeler, Leibowitz, and Marquis, 1987). Using a two-part (hurdle) model, and looking at a

representative sample of 3,860 households in Dayton, Fitchburg, Franklin, and Seattle (US), Leibowitz, Manning and Newhouse (1985) find no significant variation in the proportion of generic prescriptions by insurance plan. Their lack of evidence gives "*no support to the proposition that less generous insurance will stimulate patients to search for generic drugs*" (page 1,068) and thus no support to the above defined moral hazard hypothesis.[2]

Hellerstein (1998) empirically tests the moral hazard hypothesis using data from the 1989 National Ambulatory Medical Care Survey (NAMCS) in the US. Physicians selected in the NAMCS survey recorded information on a random sample of their patients who visited their offices over a two-week period over the course of a year in 1989. The dataset consisted of 38,384 patient visits to 1,233 office-based physicians, for a total of 492 multisource prescription drugs corresponding to 149 different generic compounds for which both branded and generic versions were available. Hellerstein (1998) estimates a random effects (RE) probit model for whether physicians prescribed the branded or generic version of the drugs, and, controlling for the characteristics of the physician, finds no evidence of moral hazard in insurance for multisource prescription drugs in the NAMCS data.

Lundin (2000) analyses the effect of health insurance on the probability of physician prescribing a generic or branded version of a drug in Sweden. Making use of prescriptions data (n=6,142) on seven different drugs collected from two pharmacies in Tierp (Sweden) in 1992 and 1993, Lundin (2000) estimates a RE probit model for whether physicians prescribed the branded or generic version of the drugs and finds some support for both the physicians' altruism and moral hazard hypotheses: higher coverage decreased (increased) the probability of prescribing a generic (branded) version of a drug.

Mott and Cline (2002) consider a sample of 6,450 prescriptions from 86 community pharmacies in a US Midwestern state and, using a RE panel logit model, find a significantly *higher* proportion of generic prescriptions among patients covered under Medicaid compared to uninsured patients. This is exactly the opposite of what the moral hazard hypothesis would predict. Mott and Cline (2002) interpret this as evidence that, in the double agency situation, the physicians *"appeared to act as better economic agents for Medicaid"* (page 670).

Granlund (2009) considers a random sample of 350,180 prescriptions from the Vasterbotten county council in Sweden and, using a logit model, finds that physicians were more likely to oppose generic substitution if all pharmaceutical costs were borne by the insurance rather than

[2] Also Dranove (1989) does not find any evidence of moral hazard when looking at the choice between old and new drugs treating the same disease under open or restricted formularies in Illinois, US (rather than at the choice between generic versus branded versions of the same drug).

by the patient. Thus, under the double agency hypothesis, physicians appeared to act as stronger agents for their patients rather than the insurer, which would be consistent with the moral hazard hypothesis. Granlund (2009) data, however, are not a panel, and therefore do not allow to look at repeated prescriptions for the same physician and patient. Given that in Sweden the copayment rates are a function of previous pharmaceutical expenditure, Granlund (2009) cannot rule out that "*the results were caused, for example, by physicians being more likely to veto substitution the more pharmaceuticals a patent was using*" (page 1649).

Liu, Yang, and Hsie (2009) consider a random sample of data for 200,000 National Health Insurance beneficiaries in Taiwan and, using a probit model, find that a lower reimbursement price level leads to an increase in generic substitution in oral hypoglycemic agents prescribed for diabetes.

As explained above, we innovatively contribute to this literature because we test physicians' moral hazard and altruism in generic versus branded prescription behavior by: i) using the "universe" of drug prescriptions in Finland contained in a national panel register with linked panel data between patients and their own physicians, so that we can characterise the full set of drugs competing in the market and the entire choice set of alternatives available to physicians and patients, and draw conclusions at a level that is representative of the population; ii) focusing on one therapeutic class of drugs – statins - that requires repeated prescriptions to target a chronic condition; iii) directly controlling for a broad range of physician, patient, firm and drug characteristics – including prices - so that we can mitigate potential confounders; iv) directly observing repeated prescriptions for all physician-patient pairs over time, so that we can explicitly model habit-dependent prescriptions in panel data estimations; and; v) distinguishing between dispensed and prescribed drugs, so that we can identify the physician's choice between generic and branded of the drugs in a way that is not confounded by what occurs in the pharmacy.

3. Institutional background

The regulatory requirements in Finland are such that generics have exactly the same amount of the same active ingredient, exactly the same dosage form (e.g. tablets, syrups, etc.), and are "bioequivalent" to the originator branded product (Lääkelaki 395/1987)[3]. Marketed drugs

[3] According to the European Medicines Agency: "two medicinal products containing the same active substance are considered bioequivalent if they are pharmaceutically equivalent or pharmaceutical alternatives and their bio-

receiving reimbursement from statutory health insurance are subject to price cap regulation in wholesale prices. In the Finnish legislation, maximum wholesale prices are called "reasonable wholesale prices" (Sairausvakuutuslaki 1224/2004). The reasonable wholesale price for a generic product can be at most 50 percent of the wholesale price defined for the branded product (Sairausvakuutuslaki 1224/2004). Price cap regulation thus requires wholesale prices not to exceed reasonable levels. Retail prices, or pharmacy prices, are then calculated from wholesale prices using a regressive rule - called a "price list for drugs" - which is defined in the legislation (Valtioneuvoston asetus lääketaksasta 713/2013). Besides this rule, retail prices are affected by a value added tax.

After receiving market approval, pharmaceuticals are prescribed by physicians. According to two decrees of the Finnish Ministry of Social Affairs and Health (Sosiaali- ja terveysministeriön asetus lääkkeiden määräämisestä 726/2003, 1088/2010), physicians in Finland are required to prescribe drugs specifying not only the drug name (e.g. Zocor, ot its generic equivalents), but also the dosage form (e.g. pills or injections), the specific strength of the drug (e.g. 10 mg), and the total amount of the drug (e.g. package size in case of pills).

Physisians in Finland are paid through a mix of payment methods that include negotiated salaries (in primary and secondary care), capitation (in primary care) and fee-for-service for minor procedures (in primary care) and therefore their income is not affected by the version (i.e. branded or generic) of the drug that they prescribe.

Prescribed drugs are dispensed in community pharmacies. Pharmacies are heavily regulated by the government, that establishes the retail drug prices to be offered in all pharmacies (Izhak, 2019).

All individuals who live in Finland (both Finnish citizens and permanent residents) are entitled to statutory health insurance, which is universally provided by KELA, the Social Insurance Institution of Finland. According to the current law (Sairausvakuutuslaki 1224/2204), KELA reimburses expenditures on drugs prescribed by physicians, dentists, but also nurses who have limited or temporary rights to prescribe medicines for the treatment of a disease.

Between 2003 and 2010, the KELA health insurance had three reimbursement classes for pharmaceutical expenditures: basic reimbursement, low special reimbursement, high special reimbursement. The reimbursement rates are defined as the proportion of pharmaceutical expenditure reimbursed by KELA. Table 1 below summarises the reimbursement rates in Finland for the years of our analysis.

---

availabilities (rate and extent) after administration in the same molar dose lie within acceptable predefined limits. These limits are set to ensure comparable *in vivo* performance, i.e. similarity in terms of safety and efficacy".

Whether a patient is entitled to a high or low special reimbursement class for a specific drug is decided by HILA, the Pharmaceutical Pricing Board in Finland. HILA is a regulatory authority that decides on pricing and reimbursement of pharmaceutical products in Finland. HILA consists of representatives from KELA, the Ministry of Finance, the Ministry of Social Affairs and Health, FIMEA (the Finnish Medical Agency), and the National Institute for Health and Welfare, appointed for 3 years by the Ministry of Social Affairs and Health. When a drug enters the market, the pharmaceutical company applies for a marketing authorisation to FIMEA. If the pharmaceutical company wants its pharmaceutical product to be reimbursed by KELA, it needs to apply to HILA. HILA negotiates on, and finally approves, the maximum price, and also decides on the reimbursement category.

Typically, all pharmaceutical products with a proven therapeutic value are granted the basic reimbursement by HILA. HILA allows a pharmaceutical product to be reimbursed under the special reimbursement classes if the product is necessary for the treatment of a specific chronic disease that is of high relevance within the epidemiological profile of the country. In particular, a decree of the Finnish Council of State (Valtioneuvoston asetus lääketieteellisin perustein vaikeiksi ja pitkäaikaisiksi arvioitavista sairauksista, joiden lääkehoidon kustannuksista sairausvakuutuslain 5 luvun 5 §:n 2 momentin perusteella korvataan 65 tai 100 prosenttia 1149/2016) lists the co-morbidities and chronic diseases that allow patients' pharmaceutical costs to be covered either in the low or in the high special reimbursement class. This list is informed by what are the top conditions that drive morbidity in Finland. To qualify for the low special reimbursement rate, the pharmaceutical product must be necessary for the treatment of a chronic disease for a patient (Sairausvakuutuslaki 1224/2004). To qualify for the high special reimbursement, the product must be necessary with either a replacement or a remedial effect in the treatment of a chronic disease for a patient (Sairausvakuutuslaki 1224/2004).[4]

For example, a patient who suffers from type III dyslipoproteinemia or from chronic coronary disease will be entitled to a low special reimbursement rate for statins. Both these chronic diseases are treated with statins. However, statins are also used for primary prevention, for example in patients who present risk factors for cardiovascular diseases even if those patients do not suffer from from type III dyslipoproteinemia or from chronic coronary disease. Therefore, a patient who presents risk factors for cardiovascular diseases (e.g. abnormal lipid levels in the blood, high bood pressure, smoking: Bibbins-Domingo et al., 2016) will be

[4] For example, insulin products provide an example of drugs with replacement effects, because they compensate the deficiency of insulin in the treatment of diabetes patients. Epilepsy drugs can be remedial because their use can reduce or even cure epileptic seizures.

prescribed statins but will be entitled only to the basic reimbursement. Instead, a patient who suffers from from type III dyslipoproteinemia or from chronic coronary disease – that are chronic conditions classified as being of epidemiological interest to the Finnish health system – will be prescribed statins under a low special reimbursement rate. As a result, when looked from the perspective of a specific patient using drugs, the insurance coverage in Finland is exogenously determined according to that patient's sets of co-morbidities and chronic conditions and to the pharmaceutical products used to treat those conditions.[5] Therefore, both the insurance and the insurance coverage in Finland are exogenous to the choices of patients or physicians, and in particular to the choices between branded and generic versions of the drugs.

Table 1: Reimbursement classes in the Finnish health insurance

	2003-2005	2006-2010
Special reimbursement		
- high	100%	100%
- low	75%	72%
Basic reimbursement	50%	42%

Considering the policies that target the pharmaceutical sector, generic substitution (GS) and reference pricing (RP) are two major policy reforms that have been implemented in the Finnish pharmaceutical market. GS was implemented in the beginning of 2003 (therefore constant during our period of analysis). According to the policy pharmacies had to inform patients about substitutable pharmaceutical products, and to suggest a substitution of the prescribed pharmaceutical product in form of a cheaper interchangeable product in the market (Lääkelaki 395/1987). Active ingredients, amounts of active ingredients, and biological equivalence are the criteria that define the classes of interchangeable products according to a decree of the Finnish Ministry of Social Affairs and Health (Sosiaali- ja terveysministeriön asetus lääkkeen määräämisestä 1088/2010). The list of interchangeable products is administered by FIMEA. Patients have the right to decline the substitution at the pharmacy. Physicians are also entitled to veto substitution at the pharmacy for medical reasons, when they issue the prescription. In the GS system, insurance reimbursement is based on the dispensed product, and the decline of substitution has no impact on how patients are reimbursed from health insurance. Given that it

[5] Therefore, both the insurance and the insurance coverage in Finland are exogenous to the choices of patients or physicians, and in particular to the choices between branded and generic versions of the drugs. There is also direct evidence that, in each reimbursement class, there is heterogeneity and variation in the physician's choices between branded and generic versions of the drugs: see, for example the descriptive statistics of generic prescriptions over the total number of prescriptions split by reimbursement class (either basic or low special reimbursement class) in Table A2 in the Online Appendix A2.

affects dispensing at the pharmacy rather than prescription by physicians GS is not a concern for our analysis as we focus on prescriptions rather than dispensing data.

RP was introduced in April 1, 2009 in Finland. The RP is a pharmaceutical demand side control scheme where the patient (or insurance) is financially responsible for the difference between the price of the purchased drug and a predetermined 'reference price' if the chosen pharmaceutical product is more expensive than its reference price. If the price of the pharmaceutical product is lower than the reference price, the health insurance reimbursement is based on the retail price of the pharmaceutical (Sairausvakuutuslaki 1224/2004).[6]

4. Theoretical framework

Although we use a different setting to test predictions, the theoretical framework is based on Hellerstein (1998). We consider a physician $i = 1,2...I$ (she) and a patient $j = 1,2...J$ (he). The physician acts as a double agent for the patient and the health insurer (Blomqvist, 1991; Hellerstein, 1998; Lundin, 2000). The physician has diagnosed the patient and chosen a therapeutic treatment that is effective in curing the patient. For each drug prescription the physician next faces a choice between a branded and a generic version of the drug, denoted as b and g, respectively.

By consuming the version $s \in \{b, g\}$ of the drug, the patient j obtains utility:

$$U_{js} = \left[u(q_s) - (1 - r_j)p_s\right]Q_s \qquad (1.1)$$

where q_s is the quality of the version s; Q_s is the quantity of drug s consumed; the function $u(q)$ measures the patient's utility[7] of consuming one unit of the drug with quality $q \geqslant 0$; p_s is the unit price of the version s; and r_j measures the fraction of the price covered by the patient's

[6] See Galizzi, Ghislandi, Hokkanen, Kangasharju, Linnosmaa, Miraldo and Valtonen (2009) and Galizzi, Ghislandi and Miraldo (2011) for reviews of the RP experiences in Finland and internationally, respectively.

[7] To estimate the model, we make no assumptions on the shape of the utility function u(q). However, we do assume that both physicians and patients perceive both versions of the good as being substitutes. The regulatory requirements in Finland are such that generics have exactly the same amount of the same active ingredient, exactly the same dosage form (e.g. tablets, syrups, etc), and are "bioequivalent" to the originator branded product (Lääkelaki 395/1987). Therefore, the quality of branded and generics drugs is the same. Physicians are trained to be aware of these regulatory requirements, and therefore it is plausible to presume that they perceive both versions as substitutes. However, patients, who are less informed than their physicians, could potentially perceive the quality of branded and generics to differ. Since we do not observe patients' preferences nor perceived quality of the drugs in our data, we have assumed that the quality of branded and generics is perceived as being the same for patients. The potential limitation of this assumption is discussed in the Conclusion Section.

health insurance. The term $(1-r_j)p_sQ_s$ thus measures the total copayment of patient *j* consuming a quantity Q_s of the version *s* of the drug. Since in Finland the branded and generic versions are bioequivalent, it is assumed throughout all the following analysis that $q_b = q_g$ (see also Hellerstein, 1998; and footnote 5).

By choosing the version $s \in \{b, g\}$ of the drug, the physician obtains random utility:

$$V_{ijs} = I_i + \gamma_1\left[u(q_s) - \left(1 - r_j\right)p_s\right]Q_s - \gamma_2 r_j p_s Q_s + \varepsilon_{ijs} = v_{ijs} + \varepsilon_{ijs} \tag{1.2}$$

where I_i refers to physician's labour income, and the terms $(1-r_j)p_sQ_s$ and $r_jp_sQ_s$ measure the copayment of patient *j* consuming the version *s* of the drug and the corresponding insurance expenditure, respectively. In line with Finland's institutional settings, it is assumed throughout the article that the insurance coverage is determined independently of the version of the drug prescribed by the physician, and that physician income is not affected by the version of the drug prescribed. As explained above, physicians are paid through a mix of payment methods that include negotiated salaries, capitation, and fee-for-service for minor procedures and therefore their income is not affected by the version (branded or generic) of the drug prescribed. That physician income, patient's utility, and insurance expenditures enter the physician utility function in an additively separable form facilitates the derivation and illustration of the comparative static results.

The parameter γ_1 in the utility function (1.2) measures the physician's altruism towards the welfare of the patient. The parameter γ_2, on the other hand, measures the degree to which the physician takes into account the consequences of her treatment choices on insurance expenditures.

The parameter γ_1 takes a value of zero for a selfish physician (potentially a negative value for an improbable "spiteful" physician) while it takes positive values for an altruistic physician, increasing with the level of her altruism. The hypothesis of altruistic physicians is therefore supported empirically if γ_1 is positive and differs statistically from zero.

The parameter γ_2 can take negative, zero, or positive values. If $\gamma_2 > 0$, the physician internalizes the consequences of her decisions on the insurer's expenditure, acting as an agent for the insurer, thus restraining pharmaceutical expenditure. If $\gamma_2 = 0$, the physician completely disregards any possible financial consequences of her decisions for the insurer. Finally, if $\gamma_2 < 0$, the physician acts as an opportunistic agent and takes advantage of the health insurance as a mean to finance patient's consumption of pharmaceuticals by prescribing more branded drugs.

While the altruism hypothesis is defined by looking at the parameter γ_1 only, the ex-post moral hazard hypothesis is defined by looking at the relationship between the two parameters γ_1 and γ_2., as discussed below in greater detail.

The random term ε_{ijs} in the physician's utility function captures unobservable factors affecting the physician's choice between the two versions of the drug. Such factors may be the advertising efforts of pharmaceutical companies to promote the sales of their products (Gonul et al., 2001) or the costs of prescribing generic versions of drugs (Hellerstein, 1998). We assume that the random terms ε_{ijs} are identically and independently distributed.

The rational physician *i* prescribes the generic drug version to patient *j*, if $V_{ijg} \geq V_{ijb}$. Assuming that the random terms ε_{ijs} are distributed as Extreme Value Type I (so that the difference between the generic and the branded error terms is logistically distributed), the probability of the physician prescribing the generic version of the drug is given by (see McFadden, 1974):

$$\Pr(s_{ij} = g) = \frac{e^{v_{ijg}}}{e^{v_{ijb}} + e^{v_{ijg}}} = \frac{\exp\{v_{ijg} - v_{ijb}\}}{1 + \exp\{v_{ijg} - v_{ijb}\}} \tag{1.3}$$

where

$$v_{ijg} - v_{ijb} = \gamma_1 u(q)(Q_g - Q_b) + [\gamma_1(1 - r_j)(p_b Q_b - p_g Q_g) + \gamma_2 r_j(p_b Q_b - p_g Q_g)] \tag{1.4}$$

Assuming that the quantity of the drug prescribed (i.e. the total number of DDDs) is determined by the patient's health need and is the same for both versions of the drug, i.e. $Q_b = Q_g = Q$, then the above utility difference simplifies to

$$v_{ijg} - v_{ijb} = [\gamma_1(1 - r_j)\Delta p + \gamma_2 r_j \Delta p]Q$$

where $\Delta p \equiv p_b - p_g$ is the price difference between the branded and generic versions of the drug. Given that the price difference Δp is not affected by physician's prescriptions, the effect of the insurance coverage on the probability of prescribing the generic version is given by:

$$\frac{\partial Pr(s_{ij} = g)}{\partial r_j} = -\frac{exp\{v_{ijg} - v_{ijb}\}(\gamma_1 - \gamma_2)\Delta pQ}{(1 + exp\{v_{ijg} - v_{ijb}\})^2} = -\frac{exp\{v_{ijg} - v_{ijb}\}(\gamma_1 - \gamma_2)\Delta TotalExp}{(1 + exp\{v_{ijg} - v_{ijb}\})^2} \tag{1.5}$$

where $\Delta TotalExp = \Delta pQ = (p_b - p_g)Q$ denotes the difference in total expenditure - that is, the extra total cost of the prescription - by choosing a branded version of the drug.[8] It is natural to assume that the branded version of the drug is more expensive than the generic version (see e.g. Hellerstein 1998), which implies that $\Delta p > 0$. Then it follows from the expression (1.5) that an increase in the patient's insurance coverage will decrease (increase) the probability that the physician prescribes the generic (branded) version of the drug if $\gamma_1 \geq \gamma_2$, and the physician gives a higher weight to patient welfare than to insurance expenditure. The main research hypotheses to be tested are as follows:

1. Empirical results are consistent with the *altruistic physician* hypothesis if the estimated coefficient γ_1 is significantly and economically greater than zero: i.e. if $\gamma_1 > 0$.

2. Empirical results are consistent with the ex-post *moral hazard* hypothesis if the estimated coefficients γ_1 and γ_2 are such that $\gamma_1 \geqslant \gamma_2$, that is, if the physician gives a higher weight to patient welfare than to insurance expenditure. In particular, this holds if one of the following sub-cases occurs:

    a. $\gamma_1 = 0$ and $\gamma_2 < 0$: the physician is not altruistic, but she takes advantage of the insurance as a mean to finance patient's consumption of pharmaceuticals by prescribing more branded drugs; we label this sub-case as the "financially careless" physician;
    b. $\gamma_1 > 0$ and $\gamma_2 < 0$: the physician is altruistic, and she takes advantage of the insurance a mean to finance patient's consumption of pharmaceuticals by prescribing more branded drugs; we label this sub-case as "pure ex-post moral hazard";
    c. $\gamma_1 > 0$, $\gamma_2 > 0$, but $\gamma_1 \geqslant \gamma_2$: the physician is altruistic, she internalizes the consequences of her decisions on the insurer's expenditure, but she attaches a higher weight to the patient's utility than to the insurer's expenditure; this is a

[8] Our simple theoretical framework can potentially accommodate also an econometric model where the probability of prescribing a generic is explained by the relative prices of the branded and generic products, rather than by their differences like in equation (1.5) above. This would only require to impose the extra assumption that the total drug expenditure enters the physician's utility function in a logarithmic form. Such an assumption, however, would also imply that the physician's utility function is strictly decreasing and convex with respect to drug expenditure for reasonable values of γ_1 and γ_2, and that the marginal disutility from additional drug spending is decreasing for the physician, which may not be realistic. We thank an anonymous reviewer to raise this point.

case of "double agent" caring about both the patient and the insurance, but of an "imperfect double agent" who, in her trade-offs, leans more towards the patient.

We next empirically test these hypotheses using national prescriptions data from Finland.

5. Data

Data on pharmaceutical prescriptions was obtained from KELA, the Social Insurance Institution of Finland. The original data contain information on all statin drugs that were prescribed and dispensed in outpatient settings in Finland during each year between 2003 and 2010. An original feature of our data is that in the Finnish national register we not only directly observe what was dispensed at the pharmacy (including package size and strength) but, in case it differs from what was prescribed by the physician, we also directly observe the product that was originally prescribed by the physician (including package size and strength). In this study we only focus on prescriptions for lipid modifying agents ("statins"), formally Anatomical Therapeutic Class[9] (ATC) C10.

In the period from 2003 to 2010, a total number of 4,502,107 statin prescriptions were issued in Finland.[10] More specifically, in the period 2003 to 2010, six statins were prescribed in Finland: in decreasing order of total number of prescriptions, these were Simvastatin (ATC C10AA01, 83.02% of the prescriptions), Atorvastatin (C10AA05, 7.2% of the prescriptions), Fluvastatin (C10AA04, 5.1% of the prescriptions), Lovastatin (ATC C10AA02, 2.3% of the prescriptions), Pravastatin (C10AA03, 1.49% of the prescriptions), and Rosuvastatin (C10AA07, 0.75% of the prescriptions) (see Table 2).

The dataset contains information on the characteristics of dispensed pharmaceutical products, patients, and physicians. We have access to information about the name, strength, form, producer, ATC-class, number of sold packages, and Defined Daily Doses (DDDs)[11] of the pharmaceutical products (in the above-mentioned ATC-classes) prescribed by physicians

[9] In the ATC classification system, products are classified into groups at five different therapeutic levels: the first level of the code indicates the anatomical main group; the second level indicates the therapeutic group; the third level indicates the therapeutic/pharmacological subgroup; the fourth indicates the chemical/therapeutic/pharmacological subgroup; the fifth level (that includes seven digits) indicates the chemical substance (WHO, 2016).

[10] This is excluding Cerivastatin (C10AA06), for which no generic substitution was available in Finland, and only one branded product was in the market in the period considered here.

[11] The WHO definition for Defined Daily Dose (DDD) is: "*a technical unit of measurement defined as the assumed average maintenance dose per day for a drug used for its main indication in adults*" (WHO, 2016; page 22).

and dispensed from all Finnish pharmacies each day for the period starting 1st January 2003 to 31st December 2010.

In addition, the dataset contains detailed information about the full price of the prescription and the amount reimbursed by the social insurer. Hence, both insurance coverage and coinsurance can be computed for each prescribed package in our dataset. In the case of substitution at the pharmacy we can also observe what the physician had originally prescribed, so that we are able to disentangle whether the possible generic substitution occurred by the initiative of the physician or the pharmacist.

Observations are defined at the level of an individual prescription, each of which contains the above information about the pharmaceutical product, and is linked to the patient and the prescribing physician characteristics. This creates an unbalanced panel where all the prescriptions for each physician-patient pair are followed over time.

The original data does not contain information on whether the prescribed product is either a branded or a generic version of the medicine. The most updated official information linking prescriptions with the versions was obtained from FIMEA and directly incorporated into the dataset. Given that generic substitution is possible only within the same 7-digit ATC class in Finland, in our empirical analyses we explicitly control for statins fixed effects by including dummy variables for each of the seven-digit ATC groups (the reference group being Simvastatin, ATC C10AA01, accounting for 83.02% of the prescriptions).

The expenditure difference between the branded and generic versions plays a key role in both the theoretical and empirical analyses (see Hellerstein, 1998; Lundin, 2000; and Section 2) and is expected to influence physicians' choices between the two versions of drugs. In our dataset we directly observe information about the price and quantity of the dispensed drug. These coincide with the price and quantity of the drug prescribed by the physician if there was no substitution at the pharmacy. For the prescriptions for which there was substitution at the pharmacy, we only observe the price of the dispensed drug and we need to reconstruct the price of the prescribed drug. We calculate the price per DDD of the prescribed drug as the average price per DDD of the same product (i.e. same name, producer, and strength) dispensed in the same quarter of the prescription. Given that prices per DDD might differ according to package size we have constructed the average price per DDD weighted by the quantities of DDDs sold per package size. The resulting prices are multiplied by the number of DDDs prescribed to obtain the $\Delta TotalExp$ associated with a given prescription.

For each prescribed drug we calculate the price of the alternative products in competition with the prescribed product, building on the principles developed by Lundin (2000). Lundin

(2000) considered as alternative price to a generic prescription the price of the branded competitor, and, as alternative price to a branded prescription, the price of the generic competitor with the largest market share. These prices were used by Lundin (2000) to calculate the $\Delta TotalExp$ that would have occurred if the alternative drugs were prescribed, by multiplying the alternative price by the number of DDDs prescribed.

We generalize the same principles as in Lundin (2000) by allowing prescribing physicians to have a broad knowledge of the prices (and expenditure) of alternative drugs (Kolassa, 1995). In Finland, in fact, physicians can access information about the average expenditure associated to all possible drug prescriptions from different online resources, including by logging into a dedicated platform provided by KELA.

In particular, if the prescribed drug was a generic version, we define the price of the alternative drug as the weighted average of the prices of the branded products (sold in the same quarter of the prescription) within the same seven-digit ATC class (i.e. the same active ingredient) and with the same strength. Note that, in our data, in each ATC class there is only one branded product. If the prescribed drug was a branded version, we define the price of the alternative drug as the weighted average of the prices of the generic products (sold in the same quarter of the prescription) within the same seven-digit ATC (i.e. the same active ingredient) and with the same strength.

The price of each alternative product - either generic or branded - is weighted in proportion of the share of the DDDs sold of that product over the total DDDs sold of the generic or branded versions, respectively, within that seven-digit ATC class in the same quarter of the prescription. In doing so, we have only considered those cases in which physicians had effective choices, i.e. when both the generic and branded versions were present in the market. Branded and generic versions of simvastatins, which is the biggest statin class in our data, were present in the market for all years 2003-2010. For some ATCs, like atorvastatins and rosuvastatins, for example, we know that generic products were present in our data only some years after 2003. For such statins, our estimations are based on data for those time periods for which both branded and generic products were present in the market.

Applying these principles, and observing the total number of DDDs prescribed, we calculated the price difference between the branded and generic versions for each prescribed drug as $\Delta p \equiv p_b - p_g$, and consequently the variation in the total expenditure of a prescription – $\Delta TotalExp$.

Information about patients in the dataset is quite rich. For each patient in the dataset, we observe the gender (*Gender*); the date of birth (from which we can calculate the age, *Age*; and

a dummy variable for whether the patient was over 75 years old, *Over75*); the taxable income (*Income*). In addition, we also have information on the illness severity of the patients. Illness severity is measured with a dummy variable equal to 1 if the patient suffers from either a difficult-to-treat or a severe, chronic and potentially life-threatening disease.[12]

For each drug prescribed, the expenditure difference $\Delta pQ = (p_b - p_g)\mathrm{Q}$ together with the individual rate of reimbursement of patient *j*, r_j, allows us to define the two key variables that measure the shares of the statins expenditure difference paid by patients (*PatOOP*) and by the health insurer (*InsExp*). In particular, the variation in the total expenditure associated with the prescribed drug for patient *j* is defined by $\Delta TotalExp_j = \Delta pQ_j$, with Q_j being total number of DDDs of the drug prescribed to patient *j*. The share of the expenditure difference paid by patient *j* is given by $PatOOP_j = (1-r_j)\Delta TotalExp_j$, while $InsExp_j = r_j\Delta TotalExp_j$ is the corresponding share of the expenditure difference paid by the health insurer.

Sources of variation

In our dataset, thus, the variation in the price (per DDD) and expenditure differences faced by the Finnish patients and physicians come from four main sources of variation: i) over time, because the prices (per DDD) of all the pharmaceutical products – branded and generics - vary in each quarter (and we have a panel where we observe all the prescriptions over time for each physician-patient pair); ii) at each point in time (e.g. a quarter), the price (per DDD) differences faced by the patients and physicians differ because physicians choose statins from different ATCs, that is, because at each point in time the price differences vary across the six types of statins in the market (being they simvastatin, atorvastatin, fluvastatin, lovastatin, pravastatin, rosuvastatin, each of which has a different ATC level 5 (seven-digit code) in our data); iii) at each point in time (e.g. a quarter), and within each ATC, the price (per DDD) differences faced by the patients and physicians vary across different products, i.e. in terms of strength of the active ingredient (e.g. 10mg versus 20mg), and across different package sizes, i.e. in terms of number of pills (e.g. 10 pills versus 20 pills); iv) at each point in time (e.g. a quarter), within ATCs, and within the same product – i.e. the same strength and the same package size - the effective out-of-pocket payments differences faced by the patients vary across different patients because patients have different (exogenous) co-payment rates.

[12] As a proxy for health status in the robustness checks we also run the specifications with *Over75*, a dummy equal to 1 if the patient is 75 years of age or above (results available from the authors upon request).

We observe in our data the variations ii)-iii) because, as explained in the Institutional Background section: a) in Finland physicians are required to prescribe drugs specifying not only the drug name (e.g. Zocor, or its generic equivalents), but also the dosage form (e.g. pills or injections), the specific strength of the drug (e.g. 10 mg), and the total amount of the drug (e.g. package size in case of pills); and b) in the Finnish national register we not only directly observe what was dispensed at the pharmacy (including package size and strength) but, in case it is different from what was prescribed by the physician, we also directly observe the product that was originally prescribed by the physician (including package size and strength).[13]

We exploit these sources of variation to identify the two main parameters of interest γ_1 and γ_2 in order to empirically test the hypotheses of physicians' altruism and moral hazard. Using the simple theoretical model described in Section 2, in fact, it can be seen that γ_1 is the coefficient of the share of the expenditure paid by the patients ($PatOOP_j$, i.e. $(1-r_j)\Delta pQ_j$), while γ_2 is the coefficient of the share of the expenditure paid by the insurer ($InsExp_j$, i.e. $r_j\Delta pQ_j$).

As discussed in Section 2, in our analysis, physician altruism is operationally measured by the coefficient of the variable *PatOOP*, while the moral hazard is operationally measured as the physicians' differential responsiveness to variables *PatOOP* and *InsExp*, and, in particular, as a relationship between their coefficients such that $\gamma_1 \geq \gamma_2$.

Our dataset also identifies prescribing physicians on the basis of a code (*sv-code*) that entitles a physician to practice the medical profession as a certified practitioner. Every physician with at least four years of university education can apply to receive such a code in Finland. In addition to the *sv-code*, we observe the date and the field of specialization of each physician which we use as a proxy for experience (*PhysExper*), measured as the number of years from the first specialization degree. In order to account for the specialization of the physicians, we group the physicians' practice areas in the four categories of general practice (*GP*), occupational healthcare (*OccupHC*), general medicine (*GenMed*), with the reference group being specialized care, that includes all other specializations (*SpecializedHC*).[14] Like Coscelli (2000) we also

[13] In the Online Appendix A1 we have included several graphs and descriptive statistics which provide direct evidence that there is substantial heterogeneity and variation in our data. In particular, we provide graphs for the time series of the mean prices per DDD for all prescriptions and by ATC (reporting separately the sample means for generic and branded prescriptions) (Figure A1 and Figure A2). In the Online Appendix A2 we also provide descriptive statistics of the price differences per DDD, as well as of the DDDs per prescription, for all prescriptions, and for prescriptions by ATC (Table A1). Tables A3-A8 in the Online Appendix A2 show the descriptive statistics of the prices per DDD for each drug name (e.g. Zocor, or its generic equivalents such as Lipcut simvastatin, for example) and provide evidence that the same drug name exhibits variation in the price per DDD due to the differences in the strength and in the package sizes.

[14] These are: cardiology, anesthesiology, surgery, neurology, psychiatry, diagnostic imaging, clinical and anatomical pathology, infectious diseases, pharmacology, oncology, gynecology and obstetrics, ears nose and throat medicine, neonatology and pediatrics, dermatology, geriatric medicine, and others.

explicitly control for the physician's prescribing habits (*PastBranded*), by calculating, for each prescription of a seven-digit ATC statin with a specific active ingredient, package size, and strength, the proportion of branded drugs prescribed by a given physician over the total prescriptions in the previous twelve months across all its patients.

Table 1 describes the main variables used in the empirical analysis and Table 2 presents the descriptive statistics. The dependent variable is the binary variable *Generic*, taking the value 1 if a generic version was prescribed, and 0 otherwise.

[Tables 1 & 2 in here]

Women accounted for 49.6% of the patients prescribed statins in our data. The mean age of patients using statins was 65.58 (with a standard deviation of 11.32 years), with about less than a quarter of the statins prescribed to patients aged over 75 years. The mean gross income among the patients in the data was 22,168.86 euro (with a standard deviation of 22,799.86 euro). In terms of disease severity, about 17.34% of the patients were *Severe*.

About 73.82% of the total statin prescriptions were generic versions. The average, per pack, expenditure difference between the branded and generic prescriptions was 42.49 euro (with a standard deviation of 33.10 euro). Patients paid on average about 53.4% of the price difference (22.69 euro), while the rest was paid by the insurer (19.79 euro).

In addition to the variables described in Table 1, we use some further explanatory variables. In particular, to account for exogenous changes in the economic, regulatory, and health policy context, we include dummy variables for each year from 2004 to 2010 (the reference year being 2003).[15] Furthermore, we also use the physician-specific variables described above (*PhysExper*, *PastBranded*, and the practice area dummies).

[15] A reference pricing (RP) system was introduced in 2009 in Finland. The RP is a pharmaceutical price regulation scheme where the patient (or insurance) is financially responsible for the difference between the price of the purchased drug and a predetermined 'reference price'. See Galizzi, Ghislandi, Hokkanen, Kangasharju, Linnosmaa, Miraldo and Valtonen (2009) and Galizzi, Ghislandi and Miraldo (2011) for reviews of the RP experiences in Finland and internationally, respectively. As discussed in Section 5, as a robustness check, we also run all the specifications excluding the data from 2009 onwards when the RP was introduced, and we find substantially the same results.

6. Econometric model

The dependent variable of interest is the binary variable y_{ijt}, which takes the value 1 if the drug prescribed by physician *i* to patient *j* at time *t* is the generic version, and 0 if it is the branded version. In order to directly test for the physician altruism and moral hazard hypotheses, in the different empirical specifications the probability that the physician *i* prescribes the generic (versus branded) version of a drug to patient *j*, $Prob(y_{ijt} = 1)$ is modeled as a function of the expenditure difference (between branded and generic) paid by the patients ($PatOOP_{ijt}$); the expenditure difference (between branded and generic) paid by the health insurance ($InsExp_{ijt}$); the total expenditure difference ($\Delta TotalExp_{ijt}$) defined as the sum of *PatOOP* and *InsExp*; the main patient-specific time-invariant characteristics Z_j (*Gender*, taking the value 1 for females) and time-variant patient characteristics Z_{jt} (*Age*, *Income*); the drug-specific dummy variables *D* (*Atorvastatin, Rosuvastatin, Fluvastatin, Pravastatin, Lovastatin*, five dummies capturing the seven-digit ATC classes of statins, with the reference drug being *Simvastatin*).

Further explanatory and control variables include patient's illness severity (*Severe*); year-specific dummy variables (the reference year being 2003); and physician-specific characteristics Ph_{it}. The latter are physician's practice areas (*GP*, *OccupHC*, *GenMed*), experience (*PhysExper*), and prescribing habits (*PastBranded*) as defined above.

Formally, the main econometric model thus takes the form:

$$Pr(y_{ijt} = 1) = \Lambda(\alpha + \gamma_1(1 - r_j)\Delta p \quad Q_{ijt} + \gamma_2 r_j \Delta p \quad Q_{ijt} + \beta_1 Ph_{it} + \beta_2 Ph_i + \delta_1 Z_{jt} + \delta_2 Z_j + \phi D \quad + \tau Y) \tag{1.6}$$

where Λ is the cumulative distribution function of the logistic distribution; r_j is the reimbursement rate of patient *j*; $\Delta p \quad Q_{ijt}$ is the expenditure difference between the branded and generic versions of the prescribed drug; Ph_{it} and Ph_i are vectors of physician-specific (time-variant and time-invariant) characteristics; Z_{jt} and Z_j refer to vectors of time-variant and time-invariant patient-specific variables; *D* is a vector of drug-specific dummies; and *Y* is a vector of year dummies.

As discussed in Section 2, the parameters γ_1 and γ_2 measure the weights that the physician places on the patient and health insurance expenditures, respectively. The specification (1.6) allows to directly estimate two coefficients for those parameters. As explained in Section 2, the

results of the empirical analysis give support to the physician altruism hypothesis if $\gamma_1 > 0$, and to the moral hazard hypothesis if $\gamma_1 \geq \gamma_2$.

In line with the theoretical model in Section 2, we estimate the logit specification of the empirical model (1.6). To take advantage of the unique longitudinal dimension of our dataset, we estimate a set of random-effects (RE) panel logit models, which look at each physician–patient pair *i-j* over time, and treat the pair-specific effects as unobserved random variables uncorrelated with the regressors:

$$\Pr(y_{i-jt} = 1 \mid x_{i-jt}, \alpha_{i-j}) = \Lambda\left(\alpha_{i-j} + x'_{i-jt}\beta\right) \tag{1.7}$$

where $\Lambda(z) = e^z/(1+e^z)$, the vector $x_{i\text{-}jt}$ contains the independent variables discussed above, and $\alpha_{i-j} \sim N(0, \sigma_\alpha^2)$. [16] To correct for possible error correlation over time for a given physician–patient pair, we use cluster-robust standard errors at the *i-j* pair level. This ensures that, in our setting, we cluster standard errors at the smallest unit of analysis.[17] The pair-specific effects are integrated out over the joint density function. Since there is no analytical solution to the integral, numerical methods are used in the estimation, in particular the adaptive 12-point Gauss-Hermite quadrature. Besides the estimated coefficients, we also calculate the corresponding average marginal effects (AMEs) using the delta method (Williams, 2012).

In our case, the RE panel logit model results in an unbalanced panel structure with the number of time observations for each doctor–patient pair being equal to the number of drug prescriptions in the 2003-2010 period under consideration. On average, the doctor–patient pairs have 5.77 drug prescriptions over that period (with a standard deviation of 5.91), with half of the observations having 4 or more prescriptions, and a quarter having 7 or more, up to a maximum of 116.

Notice that the estimation of a RE panel logit model entails the assumption that the physician–patient pair-specific effects are uncorrelated with the regressors. Relaxing this assumption would in principle require the estimation of a fixed-effect (FE) panel logit model, treating the pair-specific effects as unobserved random variables that potentially correlate with the regressors. In our case, however, the FE panel logit model is not a viable option, since

[16] Also Mott and Cline (2002) estimate RE panel logit models, while Hellerstein (1998) and Lundin (2000) estimate RE panel probit models.

[17] Cameron and Miller (2015) observe that the choice of the level at which to cluster "*mirrors the bias-variance tradeoff that is common in many estimation problems – larger and fewer clusters have less bias but more variability*" (p.333), and that "*there is no general solution to this tradeoff, and there is no formal test of the level at which to cluster*" (p.333). As we explain below, we have also replicated our estimations with cluster-robust standard errors at a physician level using a linear probability model, and using a population-averaged panel-data model.

jointly estimating the high number of incidental physician–patient fixed effects together with the other model parameters would lead to inconsistent estimations due to the few time points in our panel.

Robustness checks

We have, replicated our baseline estimations (*Models 1-8*) using a broad range of alternative models including, among others: a RE panel logit model focusing only on the general practitioners, the practice area with the largest number of physicians; a RE panel logit model with interaction terms between the years and the ATC dummies (*Model 9*); a linear probability panel model (LPM) with cluster-robust standard errors at physician level (*Model 10*); and a population-averaged logit model accounting for within-cluster correlation and with cluster-robust estimate of the variance matrix obtained using a generalized estimating equation (GEE) approach (*Model 11*) (Cameron and Miller, 2015).

Beyond the ATC- and the year-specific unobserved factors controlled for in our baseline specifications, there could still be other potential confounding unobserved factors driving both the price differences and the physician choice between the branded and generic version of the drugs. These potential factors can be related to unobserved insurance characteristics, patient characteristics, marketing efforts or other characteristics of pharmaceutical companies.

First, insurance characteristics and patient characteristics associated with insurance choice cannot be confounding factors given the nature of our institutional setting. In Finland, in fact, there is only one national social insurer that covers all patients; insurance coverage is universal; and patients do not choose insurance plan nor coverage. The differences in coverage rates are determined by whether the patient suffers from one of the chronic condition of epidemiological relevance in the Finish health system (see the Institutional Background section for further detail). Therefore, both the insurance and the insurance coverage in Finland are exogenous to the choices of patients or physicians, and in particular to the choices between branded and generic versions of the drugs. While less plausible, it could also be argued that the presence of chronic conditions and co-morbidities (that defines, directly or indirectly, the reimbursement class) also drives physician decisions. However, this is unlikely to be the case in our setting because there is evidence that, at any point in time, different patients face variation in their out-of-pocket payments for the same product (e.g. Zocor 10mg in 10 pills package). This can be seen in Table A13 in the Online Appendix A2. There, we collape the dataset by product (e.g. Zocor 10mg in 10 pills package), and by quarter, and we report the within variation of the

reimbursement rate for all products, and for branded and generic products separately: for the same product (e.g. Zocor 10mg in 10 pills package) in every year there is within variation of the reimbursement rate, such variation coming from the fact that different patients have different reimbursement rates because they have different chronic conditions and co-morbidities.

Given that insurance is decided at national level, a second potential confounding factor relates to some unobserved national-level policy not captured by the year dummies that drives not only drugs prices and insurance coverage, but also physician prescribing behaviour. During our period of analysis the only policy that can plausibly be a potential cause for concern is the RP policy (see Section 3 on the institutional background for further detail). RP affects decisions at the time of dispensing at the pharmacy rather than at the time the drug is prescribed by the physician. It is thus unlikely that RP affects physician decisions through routes other than the prices. However, one cannot rule this out completely, and for this reason we have run several specifications to assess whether our results are robust to the introduction of RP policy. In particular, we have run i) a baseline specification including all the quarters without controlling for RP; ii) a set of specifications with all the quarters and where we explicitly control for the RP policy with a dummy variable (*PostRP*) equal to 1 if the RP was in place, and 0 otherwise. In the Online Appendix A3 we have included a panel logit regression (*Model 16*, Table A14) where we have added the RP variable as a control variable to the baseline specification (i.e. *Model 4* in Table 3, the most complete specification); and a LPM specification where we also control for the RP variable (*Model 21*, Table A16) (both regressions include year and ATC fixed effects, as well as ATCs interacted with year fixed effects).

Thirdly, other factors such as advertising effort by pharmaceutical companies can also be potential confounding factors driving both prices and the decision of physicians to prescribe either a generic or a branded version of the drug.[18] While we cannot completely rule out these potential cofounders, we consider them unlikely because advertising in the pharmaceutical industry is typically done at drug name level (e.g. Zocor), rather than at the level of a specific product within that drug name (e.g. Zocor 10mg in 10 pills packages). Our empirical analysis, however, is conducted at the level of a specific product (e.g. Zocor 10mg in 10 pills packages),

[18] Note that one could potentially be worried with the role that direct to consumer (DTC) advertising could be playing in driving our results. However, a contribution of our study compared to most previous papers is that we use physician prescription data rather than dispensing data, where DTC advertising could indeed play a more substantial role. In principle, it could still be the case that DTC advertising would impact physician decisions through patients whose preferences are shaped or influenced by DTC advertising. However, while it is possible in other countries, DTC advertising on prescription drugs is actually forbidden in Finland. Therefore it is unlikely that DTC can be a confounder in the context of our analysis.

that is, of a specific ATC, with a specific strength, and with a specific package size within the ATC, because it models the choice between branded and generic versions of that specific product (i.e. Zocor 10mg in 10 pills packages versus generic version of that same ATC 10 mg in 10 pills packages). Therefore, because different products (e.g. Zocor 10 mg in 10 pills packages and Zocor 30mg in 10 pills packages) have typically different prices per DDD - even in the same quarter - we do have sources of heterogeneity and variation which are exogenous to the advertising at the level of the drug name (e.g. Zocor). To illustrate this we have built a panel at drug name level. In the Online Appendix A2 we have included Tables A3-A8 that show the descriptive statistics of the prices per DDD for each drug name, and confirm that the same drug name (e.g. Zocor or its generic equivalents such as Lipcut simvastatin, for example) exhibts variation in the price per DDD due to the differences in the strength and in the package size.[19]

Yet, as further robustness checks in order to control for potentially advertising and marketing expenditure efforts by the pharmaceutical companies, we have run the regressions with fixed effects for the drug name (e.g. Zocor) and for the firms (e.g. MSD). As advertising/marketing efforts are likely to be drug name- (or firm-) specific, the regressions with drug name (firm) fixed effects would thus account for different levels of advertising/marketing. In the Online Appendix A3 we have included a set of panel logit and LPM regressions with firm fixed effects (*Model 12* in Table A14, and *Model 17* in Table A16), and drug name fixed effects (*Model 13* in Table A14, and *Model 18* in Table A16). All models include ATC and year fixed effects, and *Models 12*, *17*, and *18* also include interactions between ATCs and year fixed effects.

Finally, we also run a set of models which explicitly control for the level of competition in each quarter, and in each quarter and within each ATC.[20] In the first set of regressions, we explicitly control for a continuous variable (*NDrugNames*) which counts the number of drug

[19] Incidentally, even in the (unlikely) case that pharmaceutical companies advertised drugs at product level (e.g. Zocor 10mg in 10 pills packages) rather than at a drug name level (e.g. Zocor), an exogenous source of variation would still remain, namely from the fact that different patients face different effective out-of-pocket (PatOOP) payments differences because they have different co-payment rates (i.e. reimbursement rates), which, as explained above, depend on the whether the patients suffers from diseases identified as being of special epidemiological interest by HILA, which, therefore, are exogenous to advertising and marketing efforts. To further illustrate this point, in the Online Appendix A2 (Table A13) we have included some descriptive statistics which provide further evidence that, in each year, different patients face variation in the PatOOP of the same product (e.g. Zocor 10mg in 10 pills package) due to the differences in their exogenous coverage rates. We did so by collapsing the dataset by product (e.g. Zocor 10mg in 10 pills package), and by quarter, and by reporting the within variation of the reimbursement rate for all products, and for branded and generic products separately. As it can be seen from Table A13, for the same product (e.g. Zocor 10mg in 10 pills package) in every year there is within variation of the reimbursement rates. Such variation comes from the fact that, as explained above, different patients have different reimbursement rates because they have different chronic conditions and co-morbidities.

[20] Tables A9-A12 in Online Appendix A2 report descriptive statistics for the number of generic and branded products in each point in time, using the variable *NProducts* defined below.

names (e.g. Zocor, or its generic equivalents such as Lipcut simvastatin, for example) present in the market in each quarter within each ATC. In the second set of regressions, we have constructed another, stricter, continuous variable (*NProducts*), which counts the number of products present in the market in each quarter, and in each quarter within each ATC: in particular, a product (e.g. Zocor 10 mg in 10 pills packages) is a different formulation of the same drug name (e.g. Zocor, or its generic equivalents such as Lipcut simvastatin, for example) in terms of strength of the active ingredient (e.g. 10mg versus 20mg), and of package sizes, i.e. in terms of number of pills (e.g. Zocor in 10 pills versus 20 pills packages). For the regressions using the variable *NDrugNames*, in the Online Appendix A3 we have included a panel logit model regression with ATC and year fixed effects, as well as with ATCs interacted with year fixed effects (*Model 14* in Table A14); and a linear probability model regression with ATC and year fixed effects, as well as with ATCs interacted with year fixed effects (*Model 19* in Table A16). For the regressions using the variable *NProducts*, in the Online Appendix A3 we have included a panel logit model regression with ATC and year fixed effects, as well as with ATCs interacted with year fixed effects (*Model 15* in Table A14); and a linear probability model regression with ATC and year fixed effects, as well as with ATCs interacted with year fixed effects (*Model 20* in Table A16)

All robustness checks results all reported in the Online Appendix A3. All estimations were conducted with Stata 13, using the High Performance Computer (HPC) at Imperial College London.

7. Results

Table 3 reports the results of the main estimations. We first estimate a baseline RE panel logit model (*Model 1*) where the probability of prescribing a generic drug is only a function of the share of the expenditure difference paid by patients, controlling for patients' age, gender, income and conditions' severity, for physicians' experience, practice areas, and prescribing habits, and for year- and drug-specific dummy variables. As it can be seen, the estimated coefficient of the patient share of the expenditure is significantly positive, suggesting that the likelihood of prescribing a generic version of a drug increases with the share of expenditure difference borne by the patient (i.e. $\gamma_1 > 0$). The estimated coefficient is, however, very small in size (0.0061813).[21]

[21] From this perspective, our results are thus qualitatively similar to Lundin's (2000) findings in Sweden for 1993. Our estimates of the parameters γ_1 are, however, larger in magnitude than Lundin's (2000) estimates in the corresponding specifications. Such differences in the results can be due to different datasets (as mentioned, Lundin,

As for the other variables, generic versions of the statins are less likely to be prescribed for older, richer, and sicker patients. Compared to simvastatin (the reference statin), generics are less likely to be prescribed for lovastatin, pravastatin, fluvastatin, atorvastatin, and rosuvastatin. Moreover, generic prescription significantly increases over time in Finland. Compared to physicians in specialized care, physicians working in general practices, occupational healthcare, and general medicine are more likely to prescribe generic versions of the statins. Finally, physicians who have prescribed more branded statins in the past are significantly less likely to prescribe generics, with a relatively large estimated coefficient.

The patient share of expenditure difference in *Model 1*, however, is correlated with the insurer expenditure difference (the Pearson correlation coefficient between *PatOOP* and *InsExp* is 0.71, $p<0.0001$), thus leading to a potential omitted variable bias problem. To deal with this, we then estimate another RE panel logit model (*Model 2*) where the probability of prescribing a generic version is a function of the *overall* expenditure difference paid by the patients and the insurer ($\Delta TotalExp$), controlling for the same set of variables as in *Model 1*. As it can be seen, the estimated coefficient of the overall expenditure difference is significantly positive, suggesting that the higher is the overall expenditure difference, the higher is the likelihood that physicians prescribe the generic version of the statin. However, the estimated effect is very small in size (0.0057377). All the effects of the control variables are substantially the same as in *Model 1*.

The estimated coefficient for the overall expenditure difference, moreover, is smaller in size than the estimated coefficient for the patient expenditure difference only (0.0057377 in *Model 2* compared to 0.0061813 in *Model 1*). To further explore this issue, in *Model 3* we estimate a RE panel logit allowing the probability of prescribing a generic drug to be a function of the share of the expenditure paid by the insurer, controlling for the same set of variables as in *Models 1-2*. As it can be seen, the estimated coefficient of the insurer share of the expenditure difference is significantly positive. All the effects of the control variables are substantially in line with the estimates in *Models 1-2*.

While still small in size, the coefficient of the insurer expenditure is approximately twice larger than the estimated coefficient for the patient expenditure (0.0139223 in *Model 3* compared to 0.006183 in *Model 1*). To further explore this difference, we then estimate a further RE panel logit model (*Model 4*) where the probability of prescribing a generic version is a

2000, does not have access to the universe of drugs prescriptions, nor to income and other patients' and physicians' characteristics), different modeling choices, or to differences in the socio-economic or regulatory context between Finland in 2003–2010 and Sweden in 1993.

function of the share of the expenditure difference paid by the insurer, *and* of the share paid by the patient, controlling for the same set of variables as in *Models 1-3*. The estimations accounting for both shares of the expenditure differences show that, while the estimated coefficient of the insurer expenditure is again significantly positive, the estimated coefficient of the patient expenditure is significantly negative. All the effects of the control variables are substantially the same as in *Models 1-3*. A likelihood-ratio test strongly rejects the null hypothesis that the coefficients of the insurer and patient expenditure are the same, and suggests that the fit of the restricted *Model 2* is significantly lower than the fit of the unrestricted *Model 4* ($p<0.0001$).

We have also replicated the estimations excluding some of the control variables such as the physicians' practice areas (*Model 5*), past branded prescriptions (*Model 6*), and experience (*Model 7*), and considering only the prescriptions from physicians in general practices (the larger group) (*Model 8),* with substantially similar results.

This set of results suggests that, when the analysis correctly accounts for both the patient's and the insurer's shares of the expenditure, the share of expenditure difference paid by the patient has a *negative* impact on the likelihood of physicians prescribing generic versions of the statins. We can therefore reject the hypothesis of physician altruism in our national prescriptions data in Finland.

Moreover, when the analysis simultaneously accounts for both the patient's and the insurer's shares of the expenditure difference, the estimated coefficient of the insurer's share of expenditure difference is always unambiguously larger than the estimated coefficient for the patient expenditure. A chi-squared test strongly rejects the null hypothesis that there is no difference in the estimated coefficients ($p<0.0001$). This directly points against the hypothesis of moral hazard in our Finnish prescriptions data.

Our lack of evidence of moral hazard in Finland is in line with Leibowitz, Manning and Newhouse (1985), Hellerstein (1998), and Mott and Cline (2002) who all find no evidence of moral hazard in the US, but is in contrast with Lundin (2000) and Granlund (2013) who both find evidence of moral hazard in Sweden.

Moreover, the estimated coefficients for the patient and insurer shares of pharmaceutical expenditure are so small in size that their effects would not be considered economically meaningful from a policy or business perspective. The average marginal effect (Table 5) of the patient out-of-pocket payment in *Model 4* is equal to -0.0003979 ($p<0.0001$): keeping the values of all the other independent variables constant, an increase in €1 in the patient expenditure difference *decreases* the probability of prescribing the generic version of the statins by about

0.0004%, an imperceptible change, especially if one keeps in mind that the average out-of-pocket payment is of about €22.69. Similarly, the average marginal effect of the insurer expenditure difference in *Model 4* is equal to 0.0006706 ($p<0.0001$): keeping the values of all the other independent variables constant, an increase in 1€ in the insurer expenditure difference increases the probability of prescribing the generic version of the statins by about 0.0007%, a negligible change (the average insurer's expense share is about €19.76) (Tables 2 and 5).

The estimated coefficients and the average marginal effects of the two expenditure shares variables are orders of magnitude smaller than the coefficients and marginal effects of other variables that appear to be key explanatory drivers of generic prescribing in Finland. As observed, generic versions of the statins are less likely to be prescribed for older, richer, and sicker patients. Moreover, less experienced physicians, physicians practicing in specialized care, and physicians who have prescribed more branded statins in the past are significantly less likely to prescribe generics. In all the regressions, the role of the past branded prescriptions is very prominent and with a large economic effect. The average marginal effect of the share of branded drugs in the total of past prescriptions in *Model 4* is -0.2243469 ($p<0.001$): an increase in 1% in the proportion of past branded drugs decreases the likelihood of prescribing the generic version of the statins by about 0.22% (Table 5).[22]

The estimated coefficients, signs, and average marginal effects of the two expenditure shares variables (as well as of the other control variables) obtained in all the robustness checks and replications are substantially equivalent to the estimated coefficients, signs, and marginal effects obtained in the baseline RE panel logit models presented in Table 3. Table 4 illustrates this for *Model 4*, presenting it together with the analogous estimations obtained using a RE panel logit model with interaction terms between years and ATC dummies (*Model* 9, where the estimated coefficients of the ATC*year interaction terms are omitted for the sake of space); a LPM panel model with cluster-robust standard errors at a physician level (*Model 10*); and a population-averaged logit model accounting for within-cluster correlation and with cluster-robust estimate of the variance matrix obtained using a GEE approach (*Model 11*). Analogous estimations for each of the other models in Table 3 are available on request.

A range of further robustness checks have been conducted, in particular to control for: the introduction of the RP; firm fixed effects; drug name fixed effects (to capture potential unobserved marketing efforts); and the level of competition in the market (see the above "Robustness checks" sub-section in Section 5 for detail). Results from all the robustness checks

[22] The effect of past branded drugs is closely in line with what reported by Coscelli (2000) for drugs prescriptions in general.

estimations replicate the main findings described above (see, for example, *Models 12-21* in Tables A14-A16 of the Online Appendix): in all the estimations the estimated coefficients and average marginal effects associated with (physicians') moral hazard and altruism are nearly zero, and directly reject those hypotheses (i.e. the estimated coefficient of out-of-pocket payment is negative, while the coefficient of the insurance expenditure is positive).

8. Conclusions

We operationally formulate and empirically test the hypotheses of physician altruism and moral hazard using a national panel register with all statins prescription records in Finland. We model the probability that physicians prescribe generic versus branded versions of statins for their patients as a function of the shares of the difference in prices that patients have to pay out of their pocket and that are covered by the insurance. We first illustrate a simple theoretical model on physician decision-making to explicitly define the research hypotheses of physicians' altruism and moral hazard. We next estimate the probability that physicians prescribe the generic version of statins using a set of RE panel logit, LPM, and GEE models while controlling for a wide range of physician, patient, and drug characteristics.

The results of all our estimations provide no evidence of physician altruism or moral hazard in the Finnish statins market: although, due to the large number of observations, the estimated coefficients associated with the shares of the statins expenditure paid by the patients and by the insurer are statistically significant, their size is very close to zero, and their effects would not be considered economically meaningful from a policy or business perspective. When the analysis correctly accounts for both the patient and the insurer shares of the statins expenditure, and controls for a broad range of physician, patient, and drug characteristics, the estimated coefficients directly reject the hypotheses of physician altruism and moral hazard. Moreover, the average marginal effects of altruism and moral hazard are negligible, and are orders of magnitude smaller than the marginal effects associated with other key explanatory factors, such as the class of the prescribed statins, the year of prescriptions, and the physician specialization.

We find, however, strong and robust evidence that the physicians' decision to prescribe branded versions of statins in Finland is a self-reinforcing pattern, in the sense that physicians who have prescribed more branded drugs in the past are less likely to switch to generic versions. The role of past branded drugs is very prominent and has a very large economic effect.

To the best of our knowledge, ours is the first national panel register of prescriptions in which the two hypotheses of moral hazard and altruism have been explicitly tested in regard to

the physician choice between generic and branded drugs. It is also the first time in which the habits dependence of prescribing branded drugs has been documented using a national panel register.

Our results add further support to the studies to date which have found no evidence on moral hazard in drug prescriptions markets (Leibowitz, Manning and Newhouse, 1985; Hellerstein, 1998; Mott and Cline, 2002).

Our analysis contributes to the existing body of evidence in several significant ways. First, from a methodological perspective, our analysis illustrates the importance of considering the universe of drugs prescriptions, rather than selected samples, in order to characterise the full set of drugs competing in the market and the whole set of alternatives faced by the physicians. Second, it also reinstates the importance of considering longitudinal data for prescriptions to fully account for repeated prescriptions and habits formation, especially in a context of chronic conditions; of disentangling generic substitution decisions made by the physician and by the pharmacist; and of controlling for a broad range of patients, physicians, and drugs characteristics, in particular by linking prescriptions records to data on pharmaceuticals market prices. In doing so, our study also confirms the largely untapped potential of empirically analysing national administrative registers and of linking them with other data records.

Third, our results show that is important to separately model the expenditure shares paid by the insurer and by the patients when testing moral hazard in drug prescriptions. When the analysis correctly accounts for both shares, the estimated coefficients and the marginal effects clearly reject the hypothesis of moral hazard.

At the same time, our results complement and qualify the findings from other streams of the economics literature that have found evidence of heterogeneity in altruistic motivation towards the patients' health benefits (Hennig-Schmidt, Selten, and Wiesen, 2011; Godager and Wiesen, 2013; Galizzi et al., 2015; Brosig-Koch, Hennig-Schmidt, Kairies-Schwarz, and Wiesen, 2016, 2017). While the majority of these studies are lab experiments with relatively small samples of medical students, Brosig-Koch, Hennig-Schmidt, Kairies-Schwarz, and Wiesen (2016) find behavioral patterns for physicians and medical students that suggest stronger altruistic motivation for physicans than for students.

Our research findings speak to these and other streams of the literature by suggesting that habits persistence seems to be the major obstacle to generics prescription in markets such as the Finnish market for statins. Further research is needed to test whether physician altruism and moral hazard depends on the healthcare context (e.g. drug prescription versus treatment choice), or the nature of the diseases (e.g. cardiovascular diseases versus mental health).

There are several caveats to our analysis. First, it could be that the duration of prescription of a branded drug affects the "sluggishness" in substituting a branded drug with a cheaper generic version. Since our data is left censored, because we do not observe physicians' prescription prior to 2003, we can only capture this effect partially with our variable *PastBranded*. This variable, however, is not suitable to capture potential habit formation that is formed years before 2003. Nonetheless, if habits do play a role, then it is plausible to presume that *PastBranded* is strongly and positively correlated with that past experience with branded drugs. Therefore, as we move accross time and we observe physicians prescription bevahiour over time, *PastBranded* increasingly captures more of that effect, as well as of the variation of that effect among prescribing physicians.

Second, our theoretical and empirical models rests on some specific operational definitions of physicians' moral hazard and altruism. There are, however, several alternative definitions of altruism and moral hazard in physicians (Galizzi, Godager, Linnosmaa, Tammi, and Wiesen, 2015). For example, one can design experiments to separately identify physicians' preferences for patients' health benefits from preferences for patients' co-payments (Ge, Godager, Wang, and Wiesen, 2018).

Third, our empirical results inherently rely on the crucial assumption that, for the patient and for the physician, the quality, or at least the *perceived* quality, is the same across the branded and the generic version of the drug. We do not believe this is a major cause of concern in our setting. While we cannot completely rule out that perceived quality differences, between generics and branded, exist for patients, there is evidence that patients in Finland do perceive generic drugs as being as effective and safe as branded drugs (Heikkila, Mantyselka, Hartikainen-Herranen, and Ahonen, 2007; Heikkila, Mantyselka, and Ahonen, 2011). There is also evidence that patients tend to follow physicians' decisions rather than to exert choice over versions of products (Hartikainen-Herranen and Ahonen, 2005; Heikkila, Mantyselka, Hartikainen-Herranen and Ahonen, 2007). Therefore, even if these differences were to exist, any differences in perceived quality by patients would be less relevant if the physicians are the decision maker.

Also, the regulatory requirements in Finland are such that generics have exactly the same amount of the same active ingredient, exactly the same dosage form (e.g. tablets, syrups, etc), and are "bioequivalent" to the originator branded product (Lääkelaki 395/1987). In this context, physicians in Finland (as any physician) are trained to be aware that the regulatory requirements are such that the branded and generic versions have the same composition, and are thus perfect substitutes. In our study, we assume that, within the physician-patient pair, the key decision

maker is indeed the physician (one of the advantages of our data is that we have prescription data rather than dispensing data), and therefore differences in perceived quality between branded and generic are less of a concern than in other settings in which patients are the key decision makers. For these reasons, also in our theoretical framework we assume that physicians know that branded and generic versions of the same drugs contain exactly the same molecule ingredients, and therefore see them as perfect substitutes.

Having said this, while we believe that, realistically, patients' role in prescriptions decisions is very limited in Finland, it is still possibly the case that patients' potential perceived differences in quality accross branded and generics influence physicians' prescription decisions. This could be a cause of concern if those preferences for branded arise on unobserved factors that drive both observed price differences and prescription behaviour. Register and market data do not traditionally include enough information to be able to control for preferences and perceived quality, and thus this is a limitation of our study of and the existing literature. Assesing the extent to which patient preferences differ accross versions of the drugs and whether those perceptions impact prescription decisions is an interesting area for future research that lends itself to be assessed through controlled laboratory or field experiments.

Acknowledgments. We gratefully acknowledge financial support from the Academy of Finland (grant number 138723) and gratefully thank KELA for sharing the data. We thank for helpful comments and suggestions the Editor Michael Chernew, two anonymous reviewers, Silvia Balia, Pietro Biroli, Kit Carpenter, Federico Crudu, Gianni De Fraja, Davide Dragone, Stefan Felder, Annika Herr, Stefan Lipman, Matteo Lippi Bruni, Mario Macis, Charitini Stavropoulou, Matt Sutton, Silvia Tiezzi, the participants to the iHEA conference in Milan, the Royal Economic Society conference in Bristol, the EuHEA conference in Maastricht, the APES confereence in Lisbon, the IBEO workshop in Alghero, and the London Health Economics Group seminar in London. We are also grateful to Jaana Joensuu for her comments on the Finnish health insurance system.

References

Aalto-Setala, V. (2008). The impact of generic substitution on price competition in Finland. *European Journal of Health Economics*, 9(2), 185-191.

Appelt, S. (2015). Authorized generic entry prior to patient expiry: reassessing incentives for independent generic entry. *Review of Economics and Statistics*, 97(3), 654-666.

Arrow, K.J. (1963). Uncertainty and the welfare economics of medical care, *American Economic Review*, 53(5), 941-973.

Bibbins-Domingo, K., Grossman, D.C., Curry, S.J., Davidson, K.W., Epling, J.W. Jr, García, F.A., Gillman, M.W., Kemper, A.R., Krist, A.H., Kurth, A.E., Landefeld, C.S., LeFevre, M.L., Mangione, C., Phillips, W.R., Owens, D.K., Phipps, M.G., Pignone, M.P. (2016). Statin Use for the Primary Prevention of Cardiovascular Disease in Adults: US Preventive Services Task Force Recommendation Statement. *JAMA*. 316 (19): 1997–2007.

Blomqvist, A. (1991). The doctor as double agent: information asymmetry, health insurance, and medical care. *Journal of Health Economics*, 10(4), 411-432.

Brosig-Koch, J., Hennig-Schmidt, H. Kairies-Schwarz, N. and Wiesen, D. (2016). Using artefactual field and lab experiments to investigate how fee-for-service and capitation affect medical service provision. *Journal of Economic Behavior & Organization*, 131(PB), 17–23.

Brosig-Koch, J., Hennig-Schmidt, H. Kairies-Schwarz, N. and Wiesen, D. (2017). The Effects of Introducing Mixed Payment Systems for Physicians: Experimental Evidence. *Health Economics*, 26(2), 243–262.

Cameron, A.C., Miller, D.L. (2014). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, 50(2), 318-372.

Chalkley, M., Malcolmson, J.M. (1998). Contracting for health services when patient demand does not reflect quality. *Journal of Health Economics*, 17(1), 1-19.

Chone, P., Ma, C.A. (2011). Optimal health care contract under physician agency. *Annals of Economics and Statistics*, 101-102, 229-256.

Coscelli, A. (2000) The importance of doctors' and patients' preferences in the prescription decision. *Journal of Industrial Economics*, 48(2), 349-369

Dranove, D. (1989). Medicaid drug formulary restrictions. *Journal of Law and Economics*, 32(1), 143-162.

Feldstein, S. (1973). The welfare loss of excess health insurance. *Journal of Political Economy*, 81(2), 251-280.

Frank, R.G., Salkever, D.S. (1997). Generic entry and the pricing of pharmaceuticals. *Journal of Economics and Management Strategy*, 6(1), 75-90.

Ellis, R.P., McGuire, T.G. (1986). Provider behaviour under prospective reimbursement. *Journal of Health Economics*, 5(2), 129-151.

Galizzi, M.M., Ghislandi, S., Hokkaken, J., Kangasharju, A., Linnosmaa, I., Miraldo, M., and Valtonen, H. (2009). Reference Pricing in Finnish Pharmaceutical Markets: Pre-Policy Evaluation. Report of the Ministry of Social Affairs and Health, Finland, 2009:25.

Galizzi, M.M., Ghislandi, S, and Miraldo, M. (2011). Effects of Reference Pricing in Pharmaceutical Markets: a Review. *PharmacoEconomics*, 29(1), 17-33.

Galizzi, M.M., Godager, G., Linnosmaa, I., Tammi, T., and Wiesen, D. (2015). Provider altruism in health economics. Finnish National Institute for Health and Welfare, THL Discussion Article 4/2015, Helsinki.

Granlund, D. (2009). Are private physicians more likely to veto generic substitution of prescribed pharmaceuticals? *Social Science & Medicine*, 69(11), 643-1650

Godager, G. and Wiesen D. (2013). Profit or patients' health benefit? Exploring the heterogeneity in physician altruism, *Journal of Health Economics*, 32(6), 1105-1116.

Gonul, F.F., Carter, F.J., Petrova, E., Srinivasan, K. (2001). Promotion of prescription drugs and its impact on physicians' choice behavior. *Journal of Marketing*, 65(3), 79-90.

Heikkila, R., Mantyselka, P., Hartikainen-Herranen, K., Ahonen, R. (2007). Customers' and physicians' opinions and experiences with generic substitution during the first year in Finland. *Health Policy*, 82(3), 366-374.
Heikkila, R., Mantyselka, P., Ahonen, R. (2011). Do people regard cheaper medicines effective? Population survey on public opinion of generic substitution in Finland. *Pharmacoepidemiology and Drug Safety*, 20(2), 185-191.
Hellerstein, J. (1998). The importance of the physician in the generic versus trade-name prescription decision. *RAND Journal of Economics*, 29(1), 108-136.
Hennig-Schmidt, H., Selten R., Wiesen, D. (2011). How payment systems affect physician's provision behaviour – an experimental investigation, *Journal of Health Economics*, 30(4), 637-646.
Hennig-Schmidt, H., Wiesen, D. (2014). Other-regarding behaviour and motivation in health care provision: an experiment with medical and non-medical students. *Social Science and Medicine*, 108, 155-165.
Iizuka, T. (2012). Physician agency and adoption of generic pharmaceuticals. *American Economic Review*, 102(6), 2826-2858.
Izhak, O. (2019). Extra costs of integrity: pharmacy markups and generic substitution in Finland. Dusseldorf Institute for Competition Economics Discussion Paper No 307, Dusseldorf University Press.
Kolassa, E.M. (1995). Perceptions of Prescription Drug Prices: Their Accuracy and Effect on the Prescribing Decision. *Journal of Research in Pharmaceutical Economics*, 6(1), 23-37.
Leibowitz, A., Manning, W.G., Newhouse, J.P. (1985). The Demand for Prescription Drugs as a Function of Cost-Sharing. *Social Science and Medicine*, 21, 1063-1070.
Liu, Y.M., Kao Yang Y.H., Hsieh, C.R. (2009). Financial Incentives and Physicians' Prescription Decisions on the Choice between Brand-name and Generic Drugs: Evidence from Taiwan. *Journal of Health Economics* 28(2): 341-349.
Lundin, D. (2000). Moral Hazard in Physician Prescription Behavior. *Journal of Health Economics*, 19(5), 639-662
Ma, C.A. (1994). Health care payment systems: cost and quality incentives. *Journal of Economics and Management Strategy*, 3(1), 93-112.
Ma, C.A., Riordan, M.H. (2002). Health insurance, moral hazard, and managed care. *Journal of Economics and Management Strategy*, 11(1), 81-107.
Manning, W.G., Newhouse, J.P., Duan, N., Keeler, E.B., Leibowitz, A., Marquis, S. (1987). Health insurance and the demand for medical care: evidence from a randomized experiment. *American Economic Review*, 77(3), 251-277.
McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, 3(4), 303-328.
McGuire, T.G. (2000). Physician agency. In Culyer, A.J., and J.P. Newhouse (Eds.), Handbook of Health Economics, Amsterdam: North Holland, Volume 1A: pp. 461-536.
Mott, D.A., Cline, R.R. (2002). Exploring generic drug use behavior: the role of prescribers and pharmacists in the opportunity for generic drug use and generic substitution. *Med Care* 2002; 40(8): 662-674
Pauly, M.. (1968). The economics of moral hazard: comment. *American Economic Review*, 58(3), 531-537.
Pavcnik, N. (2002). Do pharmaceutical prices respond to potential patient out-of-pocket expenses? *The RAND Journal of Economics*, 469-487.
WHO. (2004). Global status report on noncommunicable diseases 2014. World Health Organization, Switzerland. ISBN 978 92 4 156485 4.
WHO. (2016). Guidelines for ATC classification and DDD assignment 2016. WHO Collaborating Centre for Drug Statistics Methodology. Oslo, 2015.

Williams, R. (2012). Using the margins command to estimate and interpret adjusted predictions and marginal effects. *Stata Journal*, 12(2), 308-331.
Zweifel, P., Manning, W.G. (2000). Moral hazard and consumer incentives in health care. In Culyer, A.J., and J.P. Newhouse (Eds.) Handbook of Health Economics, Amsterdam, North-Holland, Chapter 8: pp. 409-459.

Laws and decrees:

Lääkelaki, 395/1987

Sairausvakuutuslaki, 1224/2004

Sosiaali- ja terveysministeriön asetus lääkkeen määräämisestä 726/2003.

Sosiaali- ja terveysministeriön asetus lääkkeen määräämisestä 1088/2010.

Valtioneuvoston asetus lääketaksasta, 713/2013

Valtioneuvoston asetus lääketieteellisin perustein vaikeiksi ja pitkäaikaisiksi arvioitavista sairauksista, joiden lääkehoidon kustannuksista sairausvakuutuslain 5 luvun 5 §:n 2 momentin perusteella korvataan 65 tai 100 prosenttia, 1149/2016

Tables

Table 1: Variables Description

Label	Description	Type
Dependent variable		
Generic	Type of drug prescribed	Dummy Variable =1 if a generic was prescribed
Patients Characteristics		
Age	Patient age at the time of prescription	Continuous variable
GenderD	Patient gender	Dummy variable =1 if female
Severe	Patient's disease severity	Dummy variable =1 if the patient suffers from chronic or life-threatening diseases
Income	Patient income (in €1,000)	Continuous variable
Doctor's Characteristics		

PhyExp	Number of years elapsed since the year of doctor's first specialization	Continuous variable
PastBranded	Share of branded statins prescribed by the doctor in the year before the observed prescription. This variable is built using the observed prescription data during the period of analysis.	Continuous variable
Speciality	Doctor's specialization	Categorical Variable: -Internal Medicine -Occupational Healthcare -General Practice -Specialized Healthcare (reference category)

Prescription Characteristics		
Simvastatin	Prescribed Molecule	Dummy variable =1 if the prescribed ATC is simvastatin (reference ATC)
Lovastatin	Prescribed Molecule	Dummy variable =1 if the prescribed ATC is lovastatin
Pravastatin	Prescribed Molecule	Dummy variable =1 if the prescribed ATC is pravastatin
Rosuvastatin	Prescribed Molecule	Dummy variable =1 if the prescribed ATC is rosuvastatin
Atorvastatin	Prescribed Molecule	Dummy variable =1 if the prescribed ATC is atorvastatin
Fluvastatin	Prescribed Molecule	Dummy variable =1 if the prescribed ATC is fluvastatin

ΔTotalExp	Difference between the expenditure of the prescribed drug and the average expenditure of alternative drugs. If the prescribed drug is a generic (branded) the alternative drugs are all the branded (generic) drugs with the same ATC available in the market in the same quarter	Continuous variable
PatOOP	Difference between the expenditure of the prescribed drug and the average expenditure of all alternative drugs borne by the patient	Continuous variable
InsExp	Difference between the expenditure of the prescribed drug and the average expenditure of all alternative drugs borne by the insurer	Continuous variable
Insurance	Share of TotalExp borne by the patient	Continuous variable varying between 0 and 1
Coinsurance	Share of TotalExp borne by the third party payer	Continuous variable varying between 0 and 1

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Prescription	4502107				
Characteristics					
Generic		0.7382357	0.439595	0	1
ATC					
Simvastatin		0.8302895	0.3753783	0	1
Lovastatin		0.0231276	0.1503088	0	1
Pravastatin		0.0149757	0.1214553	0	1
Fluvastatin		0.0514606	0.2209353	0	1
Atorvastatin		0.0725614	0.2594152	0	1
Rosuvastatin		0.0075853	0.0867629	0	1
ΔTotalExp		42.49185	33.10957	0	1,110.539
PatOOP		22.69508	17.86012	0	588.889
InsExp		19.79677	18.09465	0	800.47
Insurance		0.4542174	0.129022	0	0.7500463
Coinsurance		0.5457826	0.129022	0.2499537	1
Physician	4502107				
Characteristics					
GenMed		0.1003101	0.3004131	0	1
OccupHC		0.112546	0.316037	0	1
GP		0.57663	0.494093	0	1
Specialized HC		0.2105139	0.4076737	0	1
PhyExp		10.9193	9.194629	0	59
PastBranded		0.3355692	0.3431442	0	1
Patient	4502107				
Characteristics					
Gender		0.4962103	0.4999857	0	1
Age		65.58071	11.32961	2	105
Over75		0.2400538	0.427159	0	1
Income (*in €1,000*)		22.16886	22.79986	0	8,246.447
Severe		0.1734126	0.3786036	0	1

Table 3: Panel logit models, estimated coefficients.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
TotalExp		0.0057377***						
		(0.0001577)						
PatOOP	0.0061813***			-0.0149784 ***	-0.0149819***	-0.0134367***	-0.0134606***	-0.0159815***
	(0.0003016)			(0.0004911)	(0.000491)	(0.0005015)	(0.0005019)	(0.0010409)
InsExp			0.0139223***	0.0252395***	0.0251749***	0.0241434***	0.0241593***	0.024353***
			(0.0002942)	(0.0004883)	(0.000488)	(0.0004983)	(0.0004986)	(0.001093)
Gender	0.356982***	0.3649912***	0.3674062***	0.3583398***	0.3747045***	0.4168037***	0.4160139***	0.4850877***
	(0.020602)	(0.0206164)	(0.0205909)	(0.0205044)	(0.0204788)	(0.0240726)	(0.0241014)	(0.0797202)
Age	-0.0726591***	-0.0723191***	-0.0720481***	-0.0720001***	-0.0722455***	-0.0745021***	-0.0745319***	-0.0798756***
	(0.0010432)	(0.0010434)	(0.0010417)	(0. 0010372)	(0.0010294)	(0.0012542)	(0.0012559)	(0.005854)
Income	-0.0042855***	-0.0043247***	-0.0043203***	-0. 0042347***	-0.0044113***	-0.0041529***	-0.0040981***	-0.0081596***
	(0.0007358)	(0.0007401)	(0.0007403)	(0.000733)	(0.0007267)	(0.0007291)	(0.0007231)	(0.0019612)
Severe	-2.315163***	-2.429637***	-2.635821***	-2.98108***	-2.984693***	-3.069958***	-3.074293***	-3.40967***
	(0.02311)	(0.0231241)	(0.0240127)	(0.0273387)	(0.0273046)	(0.0312267)	(0.0312865)	(0.1764103)
PhyExp	0.0068201***	0.006971***	0.0070927***	0.0071264***	0.008955***	0.0046682***		0.0152518***
	(0.0011055)	(0.0011055)	(0.001104)	(0.0011)	(0.0010607)	(0.0012439)		(0.0042539)
PastBranded	-8.438741***	-8.440886***	-8.442153***	-8.444363***	-8.497856***			-10.40095***
	(0.0488479)	(0.0488547)	(0.0487784)	(0.0485957)	(0.0485693)			(0.5092497)
2004	0.8210964***	0.7615122***	0.752562***	0.8445008***	0.8380543***	1.980788***	1.984456***	1.050807***
	(0.0180427)	(0.0180043)	(0.0178941)	(0. 0180886)	(0.0180552)	(0.05191999)	(0.0192192)	(0.0597564)
2005	1.894044***	1.91853***	1.957456***	2.016127***	2.004441***	4.084843***	4.091996***	2.250754***
	(0.024086)	(0.0240731)	(0.0241144)	(0.0243071)	(0.0242236)	(0.0294117)	(0.294671)	(0.1107482)
2006	1.97657***	1.980326***	1.979327***	1.969185***	1.956288***	4.974504***	4.985685***	1.859887***
	(0.0286663)	(0.0286526)	(0.0286401)	(0.0286343)	(0.0285324)	(0.0355849)	(0.0356502)	(0.1187349)
2007	2.485366***	2.483874***	2.479889***	2.471856***	2.456002***	6.248345***	6.263889***	2.338929***
	(0.0338907)	(0.0338647)	(0.033829)	(0.0337881)	(0.0336638)	(0.0421952)	(0.0422753)	(0.1386065)
2008	2.806835***	2.796089***	2.787042***	2.783246***	2.764728***	7.135354***	7.155088***	2.696327***
	(0.0388279)	(0.0387909)	(0.0387288)	(0.0386443)	(0.0385061)	(0.0486898)	(0.0487532)	(0.1506443)

2009	2.806835***	2.883533***	2.880621***	2.895039***	2.877299***	7.338351***	7.362245***	2.897007***
	(0.0419253)	(0.0418738)	(0.0417891)	(0.0416957)	(0.0415396)	(0.0541889)	(0.0541858)	(0.1657142)
2010	4.499049***	4.449373***	4.430668***	4.476684***	4.456799***	9.373606***	9.403166***	4.292762***
	(0.049336)	(0.0491621)	(0.0489732)	(0.0489952)	(0.0488199)	(0.0647791)	(0.0648022)	(0.177993)
Lovastatin	-1.350222***	-1.243771***	-1.186988***	-1.239988***	-1.237555***	-0.6596904***	-0.6596127***	-4.977928***
	(0.0432737)	(0.043489)	(0.0436724)	(0.0439451)	(0.0438944)	(0.0459056)	(0.0459227)	(0.3803468)
Pravastatin	-6.865257***	-6.959501***	-7.031089***	-7.040238***	-7.015719**	-13.46846***	-13.48368***	-17.37889***
	(0.0763826)	(0.0764378)	(0.0764365)	(0.0762822)	(0.0761636)	(0.1078473)	(0.1081688)	(1.037798)
Fluvastatin	-9.491939***	-9.420699***	-9.394411**	-9.464645***	-9.425502***	-15.00142***	-15.02172***	-24.15806***
	(0.0739212)	(0.0738117)	(0.0736182)	(0.0735893)	(0.0732832)	(0.1175944)	(0.1179734)	(1.579057)
Atorvastatin	-5.349495***	-5.32898***	-5.2993***	-5.258578***	-5.213393***	-13.23238***	-13.24201***	-9.776092***
	(0.0557)	(0.055608)	(0.0554435)	(0.055199)	(0.0547422)	(0.0808054)	(0.0810635)	(0.05515249)
Rosuvastatin	-12.61254***	-12.58126***	-12.54554***	-12.51229***	-12.43436***	-22.23379***	-22.25426***	-23.17944***
	(0.193993)	(0.1942888)	(0.1940726)	(0.1927892)	(0.1919854)	(0.2904339)	(0.291585)	(1.525567)
GenMed	0.4427684***	0.2607368***	0.2576107***	0.2570418***				
	(0.0382728)	(0.0333909)	(0.0333607)	(0.0332463)				
OccupHC	0.4427684***	0.4465528***	0.4503431***	0.4537148***				
	(0.0382728)	(0.0383083)	(0.0382567)	(0.0380633)				
GP	0.4694149***	0.4745974***	0.4772594***	0.4745771***				
	(0.02279)	(0.0227992)	(0.0227727)	(0.0226911)				
Constant	11.74415***	11.64025***	11.61409***	11.7518***	12.09773***	7.554166***	7.596641***	20.91477***
	(0.092357)	(0.0922924)	(0.0920659)	(0.091778)	(0.0907848)	(0.0950069)	(0.0949748)	(1.243739)
lnsig2u	3.66142	3.661855	3.659576	3.65303	3.652251	3.970104	3.972566	5.10301
LogLikelihood	-775535.63	-774754.57	-734389.68	-773482.97	-875722.87	-808329.8	-808330.68	-435469.08
Wald Test	57651.60	57999.88	54791.63	59196.83	37958.69	36921.72	36750.88	3490.09
Observations	4502107	4502107	4502107	4502107	4502107	4502107	4502107	2596050

Note: Panel logit models, with robust standard errors, results reported as estimated coefficients. Lnsig2u is the logged variance of the random effect. Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01. All models include year and ATC fixed effects. Model 5 does not control for physicians' practice areas. Model 6 does not control for past branded prescriptions. Model 7 does not control for physicians' experience. Model 8 considers only the physicians in general practices.

Table 4: Panel logit, linear probability, and logit models, estimated coefficients.

	Model 4	Model 9	Model 10	Model 11
PatOOP	-0.0149784 ***	-0.017364***	-0.0008923***	-0.0075146***
	(0.0004911)	(0.0004854)	(0.0000398)	(0.0002342)
InsExp	0.0252395***	0.0241057***	0.001304***	0.010649***
	(0.0004883)	(0.0004802)	(0.0000452)	(0.0002429)
Gender	0.3583398***	0.361198***	0.0133352***	0.0542702***
	(0.0205044)	(0.0205553)	(0.0007607)	(0.007344)
Age	-0.0720001***	-0.0734937***	-0.0025558***	-0.0207533***
	(0. 0010372)	(0.0010465)	(0.0000472)	(0.000339)
Income	-0. 0042347***	-0.0040041***	-0.000106***	-0.0021982***
	(0.000733)	(0.0007194)	(0.0000261)	(0.0002123)
Severe	-2.98108***	-2.947552 ***	-0.121704***	-1.040741***
	(0.0273387)	(0.0270136)	(0.0019296)	(0.0117879)
PhyExp	0.0071264***	0.0062966***	0.0001155	0.0009941**
	(0.0011)	(0.0011116)	(0.0000917)	(0.0003971)
PastBranded	-8.444363***	-6.62796***	-0.3493978***	-3.779854***
	(0.0485957)	(0.0458773)	(0.0048093)	(0.014856)
2004	0.8445008***	1.364078***	0.0426904***	-0.0195097**
	(0. 0180886)	(0.0201293)	(0.0021315)	(0.0176483)
2005	2.016127***	2.647173***	0.0920883***	0.1334447***
	(0.0243071)	(0.0277214)	(0.0025236)	(0.0091388)
2006	1.969185***	3.054214***	0.096848***	0.1193368***
	(0.0286343)	(0.0324758)	(0.0030148)	(0.0102554)
2007	2.471856***	3.662521***	0.1029457***	0.2959456***
	(0.0337881)	(0.038134)	(0.0031921)	(0.0118726)
2008	2.783246***	4.148327***	0.1008338***	0.3686679***
	(0.0386443)	(0.0440147)	(0.003329)	(0.0131915)
2009	2.895039***	4.800786***	0.092775***	0.3179832***
	(0.0416957)	(0.0496416)	(0.0034702)	(0.0130175)

2010	4.476684*** (0.0489952)	5.466386*** (0.0567813)	0.1298342*** (0.0035715)	0.8834101*** (0.0147275)
Lovastatin	-1.239988*** (0.0439451)	-0.9168158*** (0.0485921)	-0.1097724*** (0.0068721)	-0.140508*** (0.0183095)
Pravastatin	-7.040238*** (0.0762822)	-7.175563*** (0.075635)	-0.4221174*** (0.005867)	-0.7857091*** (0.0199526)
Fluvastatin	-9.464645*** (0.0735893)	-6.743221*** (0.0669891)	-0.4884869*** (0.0052338)	-1.666342*** (0.0168701)
Atorvastatin	-5.258578*** (0.055199)	-4.770334*** (0.0746124)	-0.2192238*** (0.0066209)	-0.5910383*** (0.0162439)
Rosuvastatin	-12.51229*** (0.1927892)	-13.842285*** (0.1988915)	-0.544811*** (0.0066943)	-2.858863** (0.0361528)
GenMed	0.2570418*** (0.0332463)	0.2815264*** (0.0334742)	0.009076** (0.0037694)	0.0108148 (0.0128831)
OccupHC	0.4537148*** (0.0380633)	0.55537*** (0.038306)	0.0106971*** (0.0026222)	0.0376327** (0.129601)
GP	0.4745771*** (0.0226911)	0.5124352*** (0.0227882)	0.0175713*** (0.002143)	0.0286033*** (0.0083611)
Constant	11.7518*** (0.091778)	10.35642*** (0.0892779)	0.9943234*** (0.0048724)	4.117671*** (0.0273379)
(Other) FE		ATC*Year		ATC*Year
lnsig2u	3.65303	3.662646		
LogLikelihood	-773482.97	-758938.16		
Wald Test	59196.83	61654.88	145204.60	298239.41
R^2 (overall)			0.4096	
Sigma_u			0.286415	
Sigma_e			0.164127	
Rho			0.752800	
Observations	4502107	4502107	4502107	4502107

Note: Models 4 and 9 are panel logit models, with robust standard errors, results reported as estimated coefficients. Lnsig2u is the logged variance of the random effect. Both models include year and ATC fixed effects. Model 9 also includes year-specific ATC fixed effects (ATC*Year). Model 10 is linear probability panel model, with cluster-robust standard errors at physician level. Model 11 is population-averaged logit model accounting for within-cluster correlation and with cluster-robust estimate of the variance matrix obtained using a generalized estimating equation (GEE) approach. Both Model 10 and 11 include year and ATC fixed

effects. Model 11 also includes year-specific ATC fixed effects (ATC*Year). Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01.

Table 5: Average marginal effects Model 4

	dy/dx
PatOOP	-0.0003979***
	(0.0000131)
InsExp	0.0006706***
	(0.0000131)
Severe	-0.0792003***
	(0.0007038)
PastBranded	-0.2243469***
	(0.0012169)
2009	0.0769144***
	(0.0010719)
PhyExp	0.0001893***
	(0.0000292)

Note: Panel logit models, with robust standard errors, results reported as average marginal effects (dy/dx calculated with the delta method). Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01