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RESEARCH ARTICLE

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Hospitals and the generic versus brand-name prescription decision in the outpatient sector

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Summary

Health care payers try to reduce costs by promoting the use of cheaper generic drugs. We show strong interrelations in drug prescriptions between the inpatient and outpatient sectors by using a large administrative dataset from Austria. Patients with prior hospital visits have a significantly lower probability of receiving a generic drug in the outpatient sector. The size of the effect depends on both the patient and doctor characteristics, which could be related to the differences in hospital treatment and heterogeneity in the physicians' adherence to hospital choices. Our results suggest that hospital decisions create spillover costs in health care systems with separate funding for inpatient and outpatient care.

KEYWORDS

generic drugs, hospitals, physician behavior, prescription decision

1 | INTRODUCTION

Medical drug expenditures make up a substantial proportion of the total health care costs in developed countries. As population aging poses challenges to sustainable health financing, health care payers try to reduce costs by promoting the use of cheaper generic drugs. Although the majority of medical drugs are consumed in the outpatient sector, hospitals have a substantial impact on overall drug use because the drug choices after hospital discharge often follow the hospital decisions. In this paper, we study whether and to what extent hospitals influence the decisions in the outpatient sector to prescribe generic versus brand-name drugs.

In 2012 (or the latest year for which data are available), the Organization for Economic Co-operation and Development (OECD) countries spent on average 17% of their health care expenditures on pharmaceuticals (OECD, 2013), making it the third biggest spending component after inpatient and outpatient care. Even if one observes a slight decline in percentage after 2009, medical drug consumption has shown strong dynamics in the past. Since 2000, the average spending on pharmaceuticals has risen by almost 50% in real terms (OECD, 2011, 2015). The diffusion of new drugs and the aging population have been identified as the major contributors to the increased pharmaceutical expenditure. Competition from generic drugs in the pharmaceutical market is obviously a desirable policy objective of countries to reduce their medication costs. The consumption of nonbranded drug varieties containing the same active ingredients of branded drugs typically brings substantial savings to pharmaceutical buyers. In the United States, for example, the first generic competitor typically offers a 20% to 30% lower price than its branded counterpart. Subsequent entrants may provide discounts of up to 80% or even more. Similar price drops have been found in the European countries as well (OECD, 2009).[1] For Austria, Heinze et al. (2015) show that health insurance providers could save 18% (72 million € of 401 million €) of prescription

[1]Several countries additionally implemented tendering for off-patent medicines in the outpatient sector, in which the drugs that are reimbursed are selected via a competitive bidding process, with the goal of further price reductions (Dylst, Vulto, & Simoens, (2011)).

costs for antihypertensive, lipid-lowering, and hypoglycemic medicines through same-ingredient generic substitution. Thus, promoting the use of generics has been an important measure in OECD countries to reduce their pharmaceutical spending in recent years.

A growing body of the literature has examined the choice between generic and brand-name drugs. Several studies have found the doctors' and patients' preferences important, with a strong brand loyalty or state dependence in the choice of drugs (e.g., Coscelli, 2000; Hellerstein, 1998). Additional empirical evidence suggests that economic incentives also play a role. Lundin (2000) shows that doctors take into account the costs of their patients. Patients who incur high out-of-pocket costs are less likely to prefer brand-name drugs compared with those who get most of their costs reimbursed. Furthermore, Liu, Yang, and Hsieh (2009) and Iizuka (2012) find that for physicians who prescribe and dispense drugs, their profit incentives affect their prescription behavior. In many countries, pharmacists are allowed to substitute prescribed medicines with cheaper equivalent alternatives. Furthermore, Brekke, Holms, and Straume (2013) show that the pharmacies' product margins on branded versus generic drugs have a strong effect on the generic market share.

Another potential impact on generic prescribing may be caused by the implementation of payment for performance schemes in several OECD countries in an attempt to obtain better value for money and improve the efficiency of their health care systems. Recent examples from France, the United Kingdom, and the United States demonstrate that payment for performance interventions have proved successful in the substitution for brand-name medication by generic drugs. For a detailed description of these programs and their evaluation, see, for example, Cashin, Chi, Smith, Borowitz, and Thomson (2014).

1.1 | The hospital effect

To our knowledge, the role of hospitals in this context has not been studied. Moreover, hospitals have not been given high priority in policies meant to increase the market share of generics. As regards generic drug consumption, hospitals represent a market segment on its own and influence the type of drugs the patients receive in the outpatient sector after hospital discharge. First, a patient may ask for the same well-tolerated medication that he or she received during inpatient treatment and/or as discharge prescription. Second, in many health care systems, patients receive a discharge letter or discharge summary containing information about diagnoses and inpatient treatment and recommending the physician who should continue the patient's therapy, further treatment, and medication after hospital discharge. And third, the hierarchy between different groups of physicians may also play an important role in this context. Hospital specialists are considered as experts in their medical field. They are excellently trained, have extensive knowledge, and longstanding experience in the treatment of illnesses in their field of expertise. In general, they are held in high esteem by outpatient care physicians. This is in particular true for outpatient general practitioners (GPs) who may be more reluctant to deviate from decisions of their hospital colleagues. For these reasons, outpatient care physicians can be expected to follow the hospital doctors' recommendations in terms of suggested medication. Empirical evidence suggests that the interaction between the inpatient and outpatient sector is relevant. Prosser, Almond, and Walley (2003) interviewed 107 GPs in the United Kingdom on why they prescribed newly approved drugs. The pharmaceutical representative was the reason most cited, followed by hospital consultants and the observation of hospital prescribing. Similarly, Gallini, Legal, and Taboulet (2013) find that university hospitals have a significant influence on the pharmaceutical consumption in surrounding communities.

Pharmaceutical companies have recognized the potential impact of hospital decisions on outpatient prescription behavior. They have stepped up their marketing activities in hospitals through rebates and the free-of-charge dissemination of (brand name) drugs in an attempt to promote subsequent prescriptions by outpatient care physicians. This strategy is rational from the companies' perspective if the decrease in profits through rebates and discounts in kind can be expected to be overcompensated by an increase in profits generated in the outpatient sector (Ford, 2012; Gallini et al., 2013). Vogler, Zimmermann, Leopold, Habl, and Mazag (2013) collected official list prices and actual hospital prices in five European countries, including Austria, and found significant price discounts and rebates in all analyzed countries. In cases in which brand-name and generic drugs were both available, they found higher price reductions for brand-name drugs.

We analyze the hospital effect on the generic versus brand-name prescription decision in the outpatient sector, that is, the probability that a patient receives the generic version of a drug. For this purpose, we define three alternative indicators to capture this potential influence: (a) a prior hospital visit, (b) a hospital visit with a diagnosis that matches the drug prescription, and (c) a discharge prescription from a hospital with a corresponding active ingredient. Using a large administrative dataset of patient, doctor, and hospital information based on more than 15 million prescriptions in Austria, we find a strong hospital impact on the generic versus brand-name drug choice. Patients previously hospitalized have a significantly lower probability of receiving a generic drug in the outpatient sector, with the level of effect depending on both patient and doctor characteristics such as age and income of patients, whether the outpatient care physician holds a contract with a health insurance fund, and whether he or she runs a primary care pharmacy.[2]

The remainder of the paper is organized as follows. Section 2 presents our research design, including the institutional setting of our empirical analysis, a short description of the data, and the estimation strategy. Our estimation results are presented in Section 3. Section 4 discusses our results and concludes the paper.

2 | RESEARCH DESIGN

2.1 | Institutional setting

In Austria, the Bismarck-type health care system provides universal access to services for the whole population. With very few exceptions (e.g., a small daily allowance in the hospital), the mandatory health insurance covers all expenses for medical care, including visits to GPs and specialists in the outpatient care sector, inpatient treatment in hospitals, and prescription medicines. Nine provincial health insurance funds (in German, "Gebietskrankenkassen") are responsible for insuring all private employees and their dependents, representing approximately 75% of the population.[3] The expenses of the outpatient sector are funded by wage-related social security contributions from employers and employees, whereas hospitalization expenses are cofinanced by social security contributions and general tax revenues from different federal programs.

2.1.1 | Inpatient and outpatient medication

Different modes of financing exist to fund the expenses for medical drugs in the inpatient and outpatient sectors. The costs of medical drugs administered during hospitalization are covered by a diagnosis-related group–based remuneration scheme. According to this scheme, hospitals are reimbursed their inpatient care costs in case-based lump sums depending on the individual services provided and groups of diagnoses. This reimbursement scheme includes the costs of inpatient medication. The purchase of inpatient medical drugs is organized in a decentralized way. Basically, the hospital purchasing bodies negotiate the prices of medicines directly with the private manufacturers. Inpatient medical drug prices are not subject to price regulation. As a consequence, discounts, rebates, or even cost-free provision of medical drugs are common and regularly granted for medicines for which therapeutic substitutes exist (Vogler, Schmickl, and Zimmermann, 2013, p. 5). The economic incentive scheme seems clear; hospitals (and their staff doctors) have a strong interest in low purchasing prices, whereas pharmaceutical companies can be expected to push medicines that promise economic returns from the outpatient sector.

The situation in the outpatient sector is different. Regional health insurance funds reimburse the cost of every medical drug prescribed by outpatient care physicians. The reimbursement of these expenses is made directly to the dispensing pharmacy holding a contract with the health insurance fund. However, patients pay a prescription charge per medical drug to the pharmacy. In other words, patients are requested to pay either this prescription charge or the full price of the drug if it is below this deductible charge.[4]

Austria applies a positive list of medical drugs that can be reimbursed in the outpatient sector. This list is called the Reimbursement Code (in German, "Erstattungskodex"). Depending on the degree of automaticity in the reimbursement of medical drug expenses by the health insurance funds, the Reimbursement Code lists the expenses under three different sections. The "green box" includes drugs that are readily reimbursed. Doctors can prescribe these drugs without any formal approval by the health insurance funds. The prescription of drugs in the "yellow box" requires formal authorization by a chief physician of the health insurance fund. These drugs usually have an added therapeutic value and are not (yet) in the green box because of security concerns (e.g., long-run clinical studies are not available) or high prices. Finally, the "red box" of the Reimbursement Code includes drugs for which there is no reimbursement policy. Medicines in this last

[2] Outpatient care physicians are GPs or medical specialists who run their own medical practice outside a hospital.
[3] Furthermore, 16 social insurance institutions offer mandatory health insurance for certain occupational groups (farmers, civil servants, and self-employed workers) and employees of particular (large) companies. Affiliation with an institution is determined by place of residence and occupation and therefore cannot be freely chosen.
[4] Low-income patients with a net monthly income below 882.78 € (or below 1,015.20 € if they can prove that their above average health care expenditures are due to chronic disease) are exempted from this charge.

group are subject to a health technology assessment for a cost-benefit evaluation and are subsequently authorized or not on that basis (ISPOR, 2009).

The prices of medical drugs prescribed in the outpatient sector are regulated. According to the Austrian Price Act (in German, "Preisgesetz") and supported by the so-called pricing committee, the Federal Ministry of Health determines the prices of outpatient medication. These prices are maximum prices. For reimbursable medicines, the Main Association of Social Security Institutions (the umbrella organization of the Austrian social security and health insurance institutions) can further negotiate these prices with the manufacturers.[5] Whereas health insurance institutions have a clear interest in negotiating low prices from the pharmaceutical industry, the prescribing outpatient care physicians do not face an economic incentive for the prescription of either type of drug. They cannot influence the medication prices, nor do they receive a fee for their prescriptions.

Finally, the interface between the inpatient and outpatient sector is of particular importance. Patients treated in a hospital often receive a discharge prescription that is redeemed in a contracted pharmacy and, therefore, is reimbursed by the health insurance fund. Unlike in other countries, pharmacists in Austria are not authorized to substitute generic drugs for branded medication.

2.2 | Data

For our empirical analysis, we use the administrative register dataset provided by the *Upper Austrian Health Insurance Fund*. This dataset covers all the private sector employees (and their dependents) in the Upper Austria province.[6] The data include detailed individual information on medical attendance and medication in the outpatient sector. For each single drug prescription, we observe the patient's characteristics such as sex and age, an identifier for the prescribing physician, the prescription date, the Anatomical Therapeutic Chemical (ATC) classification system code for active ingredients (fifth level), and whether it is a brand-name or generic drug. Moreover, the register contains inpatient sector information such as the number and length of the patient's hospital stays and his or her admission diagnosis according to the *International Classification of Diseases, Tenth Revision* (ICD-10) advocated by the World Health Organization. Additional information on patient's income can be obtained from the income tax data provided by the Austrian ministry of finance.

Our empirical analysis covers the time period from 2008 to 2012, and we confine the sample to the active ingredients for which both brand and generic alternatives are available. The drugs included in the yellow and red box of the Reimbursement Code are excluded.[7] The discharge prescriptions of a hospital doctor following inpatient treatment are included in the sample. One important data restriction needs to be noted. Because we rely on the health insurance fund's reimbursement of medication expenses for prescription data, we do not observe the prescribed drugs that are priced below the prescription charges. These drugs are paid by the patients themselves and hence not recorded in the health insurance fund register.[8] We consider 15.9 million prescriptions for approximately 1 million patients for our sample. The sample includes 3,025 physicians prescribing 199 active ingredients; 60.1% of the prescribed drugs are generic.

2.3 | Empirical strategy

The unit of observation in the first part of our empirical analysis is the individual outpatient prescription. We model the choice between the generic and brand-name versions of a drug. We group the observed prescriptions by medical therapy, defined as consecutive prescription of the same active ingredient, and analyze whether prior hospitalization affects the drug choice. A therapy starts with the first prescription of a certain active ingredient (brand name or generic) by an outpatient care physician provided the active ingredient was not prescribed earlier within 1 year. The therapy ends as soon

[5]For the legal foundation and further institutional details, see Vogler et al. (2013).

[6]With 1.431 million inhabitants representing 16.8% of the Austrian population, Upper Austria is the third largest of the nine provinces (in German, "Bundesländer"). Both the average gross annual income of employees (31,803 €) and the employment rate (74.9% of working age population) are slightly above the national averages (31,234 € and 71.1%) (all numbers are from 2014; for details, see Statistik Austria, 2015, 2017). Per capita health care spending in 2015 (3,738 €) is 6% below the Austrian average of 3,973 €, whereas the life expectancy in good and excellent health for women (men) is 6 months higher (lower) than the country mean of 66.7 (65.9) years (Hofmarcher & Molnarova, 2017).

[7]Given that the prescription of drugs in the yellow box requires the formal authorization of a chief physician, health insurance funds can reject reimbursement on an individual level irrespective of previous hospital stay. In 2010, drugs in the green box account for 4,998 (84%) of the 5,980 drugs in the Reimbursement Code (Pharmig, 2016).

[8]The prescription charge is set yearly, and the amount is regulated by law. Between 2008 and 2012, it increased gradually from 4.8 € to 5.15 €. Due to data limitations, the estimated effects in the empirical analysis are not necessarily representative for cheap medications below this threshold.

TABLE 1 Matched ATC codes and ICD chapters

First-level ATC code and description		ICD-10 chapters
A	Alimentary tract and metabolism	II, XIII, XIX
B	Blood and blood-forming organs	IX, V, X
C	Cardiovascular system	IX, V, II
D	Dermatologicals	I, XII, XIX
G	Genitourinary system and sex hormones	XIV, II, IX
H	Systemic hormonal preparations	II, X, VII
J	Anti-infectives for systemic use	X, XIV, XIX
L	Antineoplastic and immunomodulating agents	II, XI, XIV
M	Musculoskeletal system	XIII, XIX, X
N	Nervous system	V, XIII, II
P	Antiparasitic products, insecticides, and repellents	XI, XIV, I
R	Respiratory system	X, II, IX
S	Sensory organs	VII, I, IX

Notes. This table shows the assignment of outpatient prescriptions to hospital diagnoses for the indicator variable "hospital stay with matched diagnosis." For any outpatient prescription with a given ATC code, the variable takes the value of 1 if there is a preceding hospital stay with any of the outlined ICD-10 diagnoses, and 0 otherwise. The links were determined using ATC codes and the three most common corresponding ICD-10 diagnoses of corresponding discharge prescriptions. Description of ICD chapters: I: Certain infectious and parasitic diseases; II: Neoplasms; V: Mental and behavioral disorders; VII: Diseases of the eye and adnexa; IX: Diseases of the circulatory system; X: Diseases of the respiratory system; XI: Diseases of the digestive system; XII: Diseases of the skin and subcutaneous tissue; XIII: Diseases of the musculoskeletal system and connective tissue; XIV: Diseases of the genitourinary system; and XIX: Injury, poisoning, and certain other consequences of external causes. ATC = Anatomical Therapeutic Chemical; ICD-10 = *International Classification of Diseases, Tenth Revision*.

as we notice that this ingredient has not been prescribed for more than 1 year. If the time period between two consecutive prescriptions is longer than 1 year, a new therapy is initiated. For the first prescription of a therapy, we estimate the following equation[9]:

$$g_{pt} = \alpha_0 + \alpha_1 h_{pt} + \zeta_p + \varsigma_{i(p,t)} + \rho_{d(p,t)} + \delta_{m(p,t)} + \nu_{pt}. \tag{1}$$

The dependent variable is a dummy for whether the outpatient prescription g_{pt} of patient p and therapy t was a generic ($g = 1$) or brand-name ($g = 0$) drug. The explanatory variable of interest h_{pt} indicates whether the therapy was initiated in hospital (h=1) or not (h=0). The set of control variables includes fixed effects for the patient (ζ_p) and for the active ingredient ($\varsigma_{i(p,t)}$), doctor ($\rho_{d(p,t)}$), and month ($\delta_{m(p,t)}$) of the corresponding prescription. The error term is denoted by ν_{pt}.

We define three alternative specifications for the hospital dummy. In its simplest form, h indicates whether the patient visited a hospital within 3 months prior to the therapy or not.[10] The second specification indicates that the previous hospitalization was not necessarily related to the subsequent medication therapy. In other words, the previous hospital stay could have nothing to do with the subsequent pharmacotherapy. Therefore, as an alternative, we consider only hospital stays with an ICD-10 classification code that is related to the ATC code of the active ingredient. For any outpatient prescription with a given ATC code, the indicator variable "hospital stay with matched diagnosis" is 1 when there is a preceding hospital stay with a corresponding ICD-10 diagnosis, and zero otherwise. Table 1 describes the assignment of an outpatient prescription to the corresponding hospital diagnoses for generation of the indicator variable. We assign each first-level ATC code the three most common corresponding ICD-10 diagnoses on the basis of discharge prescriptions. For example, a drug prescription for the active ingredient A (alimentary tract and metabolism) is assigned to ICD-10 chapters II (neoplasms), XIII (diseases of the musculoskeletal system and connective tissue), and XIX (injury, poisoning, and certain other consequences of external causes).

The third variant is based on the fact that we observe the discharge prescriptions for a subsample of hospital patients (representing 7.6% of all observations with hospital stays in our sample). In this specification, we consider only the hospital

[9] Alternatively, we include all consecutive prescriptions of a therapy.
[10] In a robustness check, we show how sensitive the results are when the number of months for a previous hospital stay is increased to six.

TABLE 2 Comparison of patients with and without a previous hospital stay

	(1) No previous stay	(2) Previous hospital stay	(3) Difference
Patient characteristics			
Age	47.9	61.8	−13.9
Female share	0.59	0.57	0.01
Outpatient expenditure in year of therapy			
Medical attendance	549.9	783.0	−233.1
Medication	487.2	1320.7	−833.5
Outpatient expenditure in previous year			
Medical attendance	477.8	650.6	−172.8
Medication	430.7	1004.4	−573.7
N	3,943,277	937,659	

Notes. This table shows the characteristics of patients with a previous hospital stay (column [2]) and without a previous hospital stay (column [1]) within 3 months before the first outpatient prescription.

stays following that the patients received a drug prescription issued by a hospital doctor, corresponding to continued medical therapy in the outpatient sector.[11]

2.3.1 | Identification of hospital effect

A crucial question of empirical strategy is whether to identify a hospital effect or rather reflect on (unobservable) patient characteristics. The selection of patients into hospitals may potentially invalidate the comparison of hospitalized patients with those who did not stay in hospital. One might argue that hospitalized patients and those not treated in hospitals receive different medicines or choose different (types of) outpatient care physicians. Both objections are met as we control for active ingredient and doctor fixed effects in Equation 1. Another objection is that hospitalization indicates bad health, and therefore, one might consider hospitalized patients sicker than those receiving only outpatient treatment. In fact, although we control for patient-fixed effects, which cover the time-invariant components of an individual's health stock such as genes or general health consciousness, (sudden) health shocks are the most frequent cause for hospitalization.

Table 2 shows the difference between hospitalized patients (column [2]) and their nonhospitalized counterparts (column [1]). The most striking difference is with regard to patients' age. Hospitalized patients are on average almost 14 years older than patients not treated in hospitals within 3 months prior to the first outpatient drug prescription. The strong presumption that hospitalized patients are sicker is based on the fact that the aggregate outpatient expenditure among this group is considerably higher. In the year of starting drug therapy, hospitalized patients spend on average 40% more on medical attendance than nonhospitalized patients (783.0 € vs. 549.9 €). The difference in expenditure for medical drugs is even larger. Given their mean of 1,320.7 €, hospitalized patients spend 2.7 times more than their nonhospitalized counterparts for medication in the same year. The higher outpatient health care service expenditure of hospitalized patients may be indicative of their worsening health condition and/or simply the fact that this group of patients are on average 14 years older than their nonhospitalized counterparts.

The fact that hospitalized patients are ceteris paribus sicker than their nonhospitalized counterparts should not impact the likelihood of their receiving a generic or brand-name prescription as long as the primary care physicians believe in the bioequivalence of the two drug types. Otherwise, they may favor sicker patients by prescribing brand-name drugs, which would then explain the significant hospital effect.[12] Moreover, in Section 3.1, we present sensitivity checks where we additionally control for the health status of individuals.

2.3.2 | Effect heterogeneity

To analyze the effect heterogeneity of hospital impact, we first estimate Equation 1 for different subsamples according to doctor and patient characteristics. In particular, we run separate regressions for split samples along the dimensions of

[11] Our data do not contain information on the complete inpatient drug therapy.
[12] Evidence for the belief among patients and physicians that generic drugs are less effective can be found in Kjoenniksen, Lindbaek, and Granas (2006), Shrank, Cox, Fischer, Mehta, and Choudhry (2009), and Shrank et al. (2011).

patients' age and income, doctors' age, and whether the physician runs a primary care pharmacy. Two different channels could explain the effect heterogeneity for patients: (a) the different treatment of groups of patients in the hospital translating into the outpatient sector, and (b) the outpatient physicians' adherence to hospital choices may depend on the doctors' and patients' characteristics. In a subsequent empirical analysis, we cover both channels. Equation 2 addresses the hospital treatment of the different groups of patients.

$$g^h_{pt} = \gamma_0 + \gamma_1 \boldsymbol{Y}_{pt} + \chi_{i(p,t)} + \tau_{m(p,t)} + \epsilon_{pt} \tag{2}$$

The dependent dummy variable g^h_{pt} indicates whether the hospital discharge prescription of patient p and therapy t is a generic (when the dummy is equal to 1) or brand-name drug. The coefficient of interest, γ_1, measures the impact of patient characteristics $\boldsymbol{Y}_{pt}$ (age and income) on the hospital prescription decision. We further control for active ingredient and month fixed effects, $\chi_{i(p,t)}$ and $\tau_{m(p,t)}$, respectively, and ϵ_{pt} reflects the error term.

Finally, we address the outpatient care physicians' adherence to hospital choices for the sample of patients, whose discharge prescriptions we observe, and analyze whether the physicians deviate from the hospital's choice of medication by estimating Equation 3:

$$a_{pt} = \beta_0 + \beta_1 \boldsymbol{X}_{d(p,t)} + \beta_2 \boldsymbol{Y}_{pt} + \lambda_{i(p,t)} + \sigma_{m(p,t)} + \mu_{pt}. \tag{3}$$

The dependent dummy variable a_{pt} is equal to 1 if the outpatient prescription is of the same type—generic or brand name—as the discharge prescription from the hospital and zero otherwise. $\boldsymbol{X}_{d(p,t)}$ and $\boldsymbol{Y}_{pt}$ represent respectively the characteristics of the doctors and patients. $\lambda_{i(p,t)}$ and $\sigma_{m(p,t)}$ denote respectively the fixed effects for the active ingredient and month. μ_{pt} denotes the error term. Following this specification, we examine whether certain characteristics, such as the age and income of the patient; the age and gender of the physician; whether the physician is a GP, holds a contract with a health insurance fund, practices in the city, or runs a primary care pharmacy; and whether the prescribing physician referred the patient to the hospital.

2.3.3 | Descriptives

Table 3 includes descriptive statistics of the dependent and explanatory variables for the full estimation sample (column [1]), the control group (column [2]), and the three different treatment groups (columns [3]–[5]). Although the treatment groups vary according to the abovementioned hospital dummy formulation, the control group always includes patients with no hospitalization within 3 months prior to the first outpatient drug prescription. Depending on our specification of hospital influence, the share of outpatient prescription potentially affected by prior hospital visits lies between 1.5% and 19.2% (for number of observations, see the table). Approximately 13% of drugs are prescribed by female physicians, more than 80% by GPs, 24% by physicians with a primary care pharmacy, and 6.5% by physicians who do not hold a contract with a health insurance fund.

TABLE 3 Descriptive statistics

	(1) Full sample	(2) Control	(3) Treatment groups: Hospital …	(4)	(5)
			Stay	Diagnosis	Discharge p.
Generic drug	0.611	0.627	0.542	0.510	0.423
Age of patient	50.6	47.9	61.8	62.4	62.8
Patient income (in 1,000)	22.4	23.2	19.2	19.6	20.7
Age of physician	52.9	52.9	52.9	53.0	53.4
Physician dispenses drugs	0.241	0.239	0.251	0.253	0.165
General practitioner	0.811	0.798	0.867	0.873	0.919
City practice	0.260	0.263	0.246	0.241	0.349
Female physician	0.131	0.131	0.131	0.132	0.144
Noncontracted physician	0.065	0.069	0.049	0.049	0.032
Number of first prescriptions	4,880,936	3,943,277	937,659	402,425	71,053

Notes. This table shows the descriptive statistics for the control and treatment groups (any hospital stay, hospital stay with matched diagnosis, and hospital discharge prescription) using the first outpatient prescription of a therapy. Because of missing information, the number of observations is only 3,920,927 for patient income; 4,163,325 for age of physician; and 4,573,476 for sex of physician.

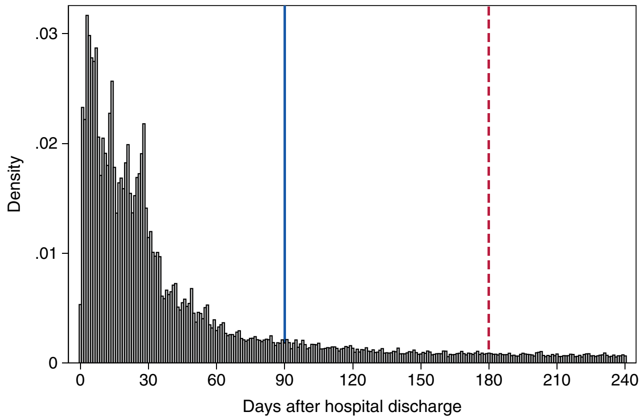

FIGURE 1 Time between discharge prescription and first outpatient prescription [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 1 gives the histogram for the distribution of number of days between a hospital discharge prescription and the first corresponding drug prescription (of the same active ingredient) in the outpatient sector for all patients in our sample who received a discharge prescription at the end of their hospital stay. The graphical representation clearly indicates that the majority of first drug prescriptions by outpatient care physicians after a previous hospital stay occur shortly after hospital discharge. The median of the time interval is 25 days, and the 75th percentile comes to only 52 days. Therefore, in our main specification, the hospital dummy is equal to 1 if a previous hospital stay ended within 3 months prior to the first outpatient prescription. This implies that hospitalization that ended before 3 months prior to the first outpatient drug prescription are coded as zero. We argue that hospital stays dated very far back may no longer influence the outpatient physicians' prescription behavior.[13]

Finally, Table 4 provides insight into how representative the subgroup of patients receiving a discharge prescription can be for all hospital patients. Both groups are of similar age and are also very comparable in terms of gender participation. The outpatient expenditure for medical attendance for both groups is very similar, and those who receive a discharge prescription on average spend 128.1 € per year more for medical drugs. The distribution of admission diagnoses may reveal minor differences, but both groups of patients show very similar disease patterns. For example, the three most frequent diagnoses for both groups are neoplasms, diseases of the circulatory system, and diseases of the musculoskeletal system.

3 | RESULTS

First, we examine the influence of previous hospital stays on outpatient prescription behavior based on three different hospital variables (Section 3.1) and study the effect heterogeneity in terms of patient and doctor characteristics (Section 3.2). Second, we consider the impact of the patients' socioeconomic characteristics on hospital prescription behavior and analyze to what extent doctors adhere to the discharge prescriptions issued to patients after a previous hospital stay (Section 3.3).

3.1 | Hospitalization effect on outpatient prescriptions

3.1.1 | First prescription

Our estimation of the effect of previous hospitalization on the first outpatient prescription for a particular drug therapy (Equation 1) is summarized in Table 5. The dependent variable is a binary indicator for a generic versus brand-name prescription. The table includes the results for three different hospital stay specifications. The dummy variable “hospital stay” is equal to 1 if the patient was hospitalized within a period of 3 months prior to the first outpatient prescription. The indicator variable “hospital stay with matched diagnosis” refers to the same time frame. However, the dummy is equal to 1 only if the ICD-10 classification code of hospital stay corresponds to the ATC code of the active ingredient for the

[13]We show below that the empirical results are not sensitive to variation in the length of this period.

TABLE 4 Comparison of hospital patients with and without a discharge prescription

	(1)	(2)	(3)
	Discharge prescription?		
	No	Yes	Diff.
Patient characteristics			
Age	53.7	53.2	0.4
Female share	0.55	0.52	0.03
Outpatient expenditure in year of hospital stay			
Medical attendance	624.2	636.5	−12.3
Medication	1214.3	1342.3	−128.1
Hospital diagnoses			
Neoplasms	14.21	13.12	1.10
Diseases of the circulatory system	10.97	12.18	−1.20
Diseases of the musculoskeletal system and connective tissue	9.47	13.25	−3.79
Injury, poisoning, and certain other consequences of external causes	9.38	11.79	−2.41
Diseases of the digestive system	8.01	7.00	1.01
Diseases of the eye and adnexa	7.44	1.08	6.36
Diseases of the genitourinary system	5.83	7.28	−1.44
Mental and behavioral disorders	5.72	6.92	−1.20
Diseases of the respiratory system	5.05	9.97	−4.92
Symptoms, signs, and abnormal clinical and laboratory findings	4.95	3.34	1.61
Pregnancy, childbirth, and the puerperium	4.64	1.44	3.19
Diseases of the nervous system	4.38	2.65	1.73
Certain infectious and parasitic diseases	2.22	2.94	−0.72
Endocrine, nutritional, and metabolic diseases	2.35	1.40	0.95
Diseases of the skin and subcutaneous tissue	1.44	1.85	−0.41
Diseases of the ear and mastoid process	1.18	2.35	−1.18
Factors influencing health status and contact with health services	0.86	0.26	0.60
Diseases of the blood and blood-forming organs	0.75	0.58	0.17
Congenital malformations, deformations, and chromosomal abnormalities	0.74	0.55	0.19
Certain conditions originating in the perinatal period	0.41	0.05	0.36
Codes for special purposes	0.00	0.00	0.00
N	1,669,425	213,431	

Notes. This table shows the characteristics of patients in hospitals who receive a discharge prescription (column [2]) and patients who do not receive a discharge prescription (column [1]).

particular drug prescription. The third variant "hospital discharge prescription" refers to the subsample of hospital stay within the same 3 months for which we observe a corresponding discharge prescription. Column (1) of Table 5 depicts the sample mean for the three different hospital variables, and columns (2)–(4) give the results for different sets of control variables (fixed effects for month, active ingredient, doctor, and patient).

The coefficients show a highly significant and negative hospitalization impact on the probability of a generic drug prescription by physicians in the outpatient sector for the three different definitions of hospital influence and different sets of control variables. Considering the "naive" hospital dummy definition and the specification controlling for all possible fixed effects, a patient's previous hospitalization reduces the probability of a subsequent generic drug prescription in the outpatient sector by 6.3 percentage points, which corresponds to 10.3% of the share of generic drugs.

These negative impacts increase to −8.7 and −23.6 percentage points respectively for the two other hospital dummy variables. This is the first indication that the prescription behavior of hospitals generates quantitatively relevant spillovers in the outpatient sector. In line with a priori expectations, the effect increases with a closer connection between hospital stay and drug prescription. Obviously, our naive hospital dummy also includes hospital stays that have no direct link with a subsequent drug prescription. A patient may have spent 2 days in hospital because of a broken leg and received antihypertensive drugs from his or her family doctor 2 months later. Hospital stays with matched diagnoses identify a

TABLE 5 Hospitalization effect on first outpatient prescription

	(1)	(2)	(3)
Hospital stay	−0.082***	−0.080***	−0.063***
	(0.001)	(0.001)	(0.001)
Hospital stay with matched diagnosis	−0.110***	−0.106***	−0.087***
	(0.001)	(0.001)	(0.001)
Hospital discharge prescription	−0.254***	−0.259***	−0.236***
	(0.002)	(0.002)	(0.002)
Controlling for fixed effects:			
Time	✓	✓	✓
Active ingredient	✓	✓	✓
Physician		✓	✓
Patient			✓

Notes. This table summarizes the hospital effect on the first outpatient medical therapy prescription. The dependent variable is a binary indicator for generic versus brand-name choice. Each entry represents the results from a separate regression with different explanatory variables of interest indicated on the left-hand side and controlling for different levels of fixed effects indicated at the bottom of the table. The number of observations is 4,880,936 for hospital stay regressions; 4,345,702 for hospital stay with matched diagnosis; and 4,014,330 for hospital discharge prescriptions. Robust standard errors are in parentheses. $^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

TABLE 6 Hospitalization effect on first outpatient prescription – varying time window

	(1)	(2)	(3)
Hospital stay in past 3 months	−0.082***	−0.080***	−0.063***
	(0.001)	(0.001)	(0.001)
Hospital stay in past 6 months	−0.065***	−0.064***	−0.048***
	(0.000)	(0.000)	(0.001)
Hospital stay in past 3 months (spec. II)	−0.084***	−0.082***	−0.065***
	(0.001)	(0.001)	(0.001)
Controlling for fixed effects:			
Time	✓	✓	✓
Active ingredient	✓	✓	✓
Physician		✓	✓
Patient			✓

Notes. This table summarizes the hospital effect on the first outpatient medical therapy prescription with varying time windows. The dependent variable is a binary indicator for generic versus brand-name choice. Each entry represents the results from a separate regression with different explanatory variables of interest indicated on the left-hand side and controlling for different levels of fixed effects indicated at the bottom of the table. The number of observations is 4,880,936 for hospital stay in the past 3 or 6 months, and 4,557,815 for hospital stay in the past 3 months (spec. II), where we exclude patients with hospital stays within 4 to 6 months prior to the outpatient prescription. Robust standard errors are in parentheses. $^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

closer connection between hospitalization and the active ingredient of a follow-up prescription such that the hospital impact increases quantitatively. However, even in this second specification, we cannot directly control for treatment and medication during hospitalization. In the third specification "hospital discharge prescription," we include only the hospital stay of patients who received a corresponding discharge prescription at the end of hospitalization. Although we do not have information on hospital medication in these cases either, we certainly know that these patients leave the hospital with a specific prescription that is redeemed in a local pharmacy. This is the most explicit indicator that the medical therapy of a patient starts in hospital. This specification reveals the strongest impact on the doctors' prescription behavior.

3.1.2 | Sensitivity check: time period

The results in Table 6 are not sensitive to the time period chosen to measure hospital stays. We rely on the simple "hospital stay" dummy and estimate Equation 1 with varying time periods. The first row of the coefficients replicates the main results presented in Table 5. The second row shows the impact of hospitalization on outpatient prescription decisions when the hospital stays are measured within 6 instead of 3 months. The quantitative and qualitative results remain basically unchanged. The significantly negative influence of hospitalization on the probability of receiving a generic follow-up drug prescription decreases from 6.3 to 4.8 percentage points. A third variation in the time frame is presented in the last row of the coefficients. In an alternative 3-month specification (II), we try to sharpen the distinction between "treated" (previous hospital stay) and "untreated" (no previous hospital stay) patients. The hospital dummy is again coded as 1 if the patient had a previous hospital stay within 3 months prior to the first outpatient drug prescription and zero otherwise. However, we exclude the patients who had a hospital stay within 4 to 6 months before the prescription. Again, as compared with the baseline version, the negative coefficient remains almost unchanged (−6.5 percentage points). Given these results and the fact that the majority of first prescriptions are issued in the first few weeks after hospitalization, we are confident that the period of 3 months for the identification of hospital stay is appropriate.

3.1.3 | Sensitivity check: Individual health

To address the concern that the identification of the results might be driven by differences in health states between patients, we offer two sensitivity checks in which we control for the severity of individual diseases. First, we include the covariates age, gender, expenditures for medical attendance, and expenditures for medication in the calendar year of the corresponding prescription to control for the difference in health states between patients, and we replicate the estimations of the effect of hospitalization on the first outpatient prescription. Table A1 in the appendix includes the estimation results. The regression output suggests that the individual health state and the probability of receiving a generic prescription are correlated. However, the quantitative impact is small. For example, an increase in expenditures for medical attendance (medication) by 1,000 € decreases the probability of receiving the generic version of a drug by 0.37 (0.35) percentage points when using discharge prescriptions as the treatment definition (see column [3]). More importantly, the point estimates for the hospital effect are very similar compared with our main analysis. A corresponding discharge prescription reduces the probability of a generic drug prescription in the outpatient sector by 25.7 percentage points. By comparison, we find effects between 23.6 and 25.4 percentage points in the main analysis.

Second, we explicitly identify control groups with similar observable characteristics compared with the treatment groups by using a matching procedure. This procedure does not require the specification of a functional form of the outcome equation, and it balances observable characteristics between treatment and control groups. For every treated observation, we use multivariate matching based on the Mahalanobis distance to find one ($M = 1$) or five ($M = 5$) nearest neighbors in the control group. We perform matching on the active ingredient, and the distance is then calculated from patients' age, gender, expenditures for medical attendance, expenditures for medication, and the month of the prescription.[14]

Table A2 shows descriptive statistics of the matched and unmatched data for the first treatment definition: whether or not a patient visited a hospital within 3 months prior to the outpatient prescription. The comparison reveals considerable differences between treated and control observations before matching. For example, treated patients are on average 14 years older and have substantially higher health care expenditures. After matching, the observable characteristics between the treatment and control groups are very similar. The average expenditures on medical attendance are 783 € for the treatment group and 775 € for the control group ($M = 1$), and the matching reduces the corresponding standardized differences from 31.5 to 1.1. Table A3 summarizes the matching estimates. The coefficients are very similar to the results of the main analysis presented in the manuscript. For example, the effect of a corresponding discharge prescription reduces the probability of a generic drug prescription in the outpatient sector by 24.4 ($M = 1$) or 24.5 ($M = 5$) percentage points. For comparison, the effects in the main analysis range between 23.6 and 25.4 percentage points.[15]

3.1.4 | All prescriptions

The estimation results based on all prescriptions of a therapy, and not just the first prescriptions, are depicted in Table 7. As earlier, the coefficients of interest are highly significant and the quantitative results are very similar to the results

[14]Matching is done with replacement, and if ties in the distance occur, all corresponding pairs are included, but the matched data are weighted to reflect the multiple matches.

[15]In another sensitivity check, we control for patient and physician characteristics in Equation 1 (using only fixed effects for active ingredients and the month of prescription). As can be seen from Table A4 in the appendix, the impact of hospitalization on the first outpatient medical prescription is basically unchanged in this alternative specification. Moreover, the coefficients of the control variables show statistically significant and quantitatively relevant effects for physician characteristics whereas the impact of patient characteristics is almost negligible.

TABLE 7 Hospitalization effect on all outpatient prescriptions

	(1)	(2)	(3)
Hospital stay	−0.083***	−0.082***	−0.057***
	(0.000)	(0.000)	(0.000)
Hospital stay with matched diagnosis	−0.113***	−0.110***	−0.080***
	(0.000)	(0.000)	(0.000)
Hospital discharge prescription	−0.217***	−0.214***	−0.182***
	(0.001)	(0.001)	(0.001)
Controlling for fixed effects:			
Time	✓	✓	✓
Active ingredient	✓	✓	✓
Physician		✓	✓
Patient			✓

Notes. This table summarizes the hospital effect on all medical therapy prescriptions. The dependent variable is a binary indicator for generic versus brand-name choice. Each entry represents the results from a separate regression with different explanatory variables of interest indicated on the left-hand side and controlling for different levels of fixed effects indicated at the bottom of the table. The number of observations is 15,945,098 for hospital stay regressions; 13,413,156 for hospital stay with matched diagnosis; and 11,694,960 for hospital discharge prescriptions. Robust standard errors are in parentheses. $^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

considering the first prescriptions only. Depending on the chosen specification, the impact of hospitals on the outpatient care physicians' decisions to prescribe a generic drug runs from −5.7 to −18.2 percentage points. Again, the lowest effect results from the naive hospital dummy specification, whereas the specification including only patients with discharge prescriptions provides the strongest negative impact on outpatient prescription behavior. On average, the coefficients for the whole sample of prescriptions are quantitatively slightly smaller than those for first prescriptions only. This could be because even if the outpatient care physicians' decision to prescribe a generic drug at the start of medical therapy is negatively affected by prior hospitalization, this influence levels off over time. The propensity to prescribe generic drugs in follow-up medication increases the further the hospital stay dates back.

3.2 | Effect heterogeneity

Table 8 gives separate regressions for a series of subsamples, splitting the data according to the physician's and patient's characteristics. We display the results for the specification using discharge prescriptions and estimate the hospital impact on first prescriptions. As regards the doctors, we distinguish between older and younger physicians (beyond or below 50 years old), male and female doctors, doctors in urban and rural areas, GPs and medical specialists, contracted and noncontracted (private) physicians, and finally physicians running and not running a primary care pharmacy. With regard to patients, we differentiate between older and younger patients (beyond or below 50 years old) and between high- and low-income patients.[16]

The coefficients reveal interesting heterogeneity in terms of both quality and quantity. At the physician level, we find significantly different effects for sex and age, but doctors practicing in urban and rural areas react similarly (their 95% confidence intervals overlap). The hospital effect is 2.0 percentage points stronger for males than for females and 1.7 percentage points stronger for younger than for older physicians.

The hospital impact for medical specialists (−18.8 percentage points) is smaller than that for GPs (−23.6 percentage points). Medical specialists are probably more self-conscious in their prescription behavior and less influenced by hospitals than their GP counterparts. However, the question whether the informal hierarchies between doctors working in the inpatient and outpatient sectors play a role in the physicians' prescription behavior cannot be answered unequivocally in this sort of quantitative analysis. An interesting result in this line of argument is revealed by the coefficients for the GPs who run and do not run their own primary care pharmacy. The negative and significant hospital dummy coefficient for physicians dispensing drugs from their attached apothecary is lower than that for physicians without a pharmacy (17.6 vs. 24.7 percentage points). Physicians who run their own pharmacies can be expected to be highly knowledgeable

[16]High-income patients have an income above the median income of their birth-year cohort in the respective calendar year.

TABLE 8 Heterogeneous effects

	(1) Mean	(2) Estimate	(3) *SE*	(4) 95% CI	(5) *N*
Physician characteristics					
Age					
Over 50	0.642	−0.231***	(0.003)	[−0.237, − 0.226]	2,364,237
Under 50	0.650	−0.248***	(0.005)	[−0.258, − 0.238]	1,049,962
Sex					
Female	0.629	−0.220***	(0.007)	[−0.234, − 0.207]	493,940
Male	0.636	−0.240***	(0.002)	[−0.245, − 0.235]	3,271,232
Type of physician					
General practitioner	0.639	−0.236***	(0.002)	[−0.241, − 0.231]	3,211,913
Specialist	0.561	−0.188***	(0.010)	[−0.209, − 0.168]	802,417
Drug dispensing of general practitioners					
Dispenses drugs	0.611	−0.176***	(0.005)	[−0.187, − 0.166]	953,533
Does not dispense drugs	0.651	−0.247***	(0.003)	[−0.252, − 0.242]	2,258,380
Type of physician					
Noncontracted physician	0.354	−0.146***	(0.025)	[−0.196, − 0.097]	275,282
Contract physician	0.643	−0.237***	(0.002)	[−0.241, − 0.233]	3,739,048
Place of medical practice					
City (population over 35,000)	0.648	−0.243***	(0.004)	[−0.250, − 0.235]	1,060,631
Rural area	0.615	−0.231***	(0.003)	[−0.237, − 0.226]	2,953,699
Patient characteristics					
Age					
Under 40	0.617	−0.248***	(0.007)	[−0.262, − 0.234]	1,364,816
40–70	0.639	−0.239***	(0.003)	[−0.245, − 0.233]	1,889,813
Over 70	0.595	−0.227***	(0.003)	[−0.234, − 0.221]	759,701
Income					
Low (under P10)	0.628	−0.216***	(0.009)	[−0.235, − 0.198]	318,957
Middle (P10–P90)	0.638	−0.239***	(0.003)	[−0.245, − 0.234]	2,552,186
High (over P90)	0.629	−0.254***	(0.010)	[−0.272, − 0.235]	319,029

Notes. This table summarizes the hospital effects on the first outpatient medical therapy prescription using discharge prescriptions. The dependent variable is a binary indicator for generic versus brand-name choice. Each line reflects the results from a separate regression for different samples indicated at the very left. Column (1) presents the corresponding sample mean of the dependent variable; columns (2)–(4) show the point estimates, robust standard errors; and the corresponding 95% confidence intervals. The number of observations is indicated in column (5). Additional covariates control for time, active ingredient, physician, and patient-fixed effects. $^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

about pharmaceuticals in general because they also dispense drugs. Thus, a potential explanation is that they are more self-confident in their prescription behavior and less reluctant to deviate from hospital prescription choices. Another potential explanation is that economic incentives (different profit margins for different types of drugs) play a role; however, we do not observe information on the profit margins of drugs in our data.

Finally, we find a large difference between the hospitalization impacts of contracted and noncontracted (private) doctors.[17] The impact of hospitalization on outpatient prescription behavior is −14.6 percentage points for the subgroup of noncontracted physicians and runs up to −23.7 percentage points for contracted doctors. This finding may suggest that noncontracted physicians in particular make self-determined decisions and therefore follow the hospital to a lesser extent. On the other hand, a mean of 0.35 for the proportion of generic drugs in the total prescriptions (see Table 8, column [1]) for this group of doctors indicates that noncontracted physicians generally prescribe a lower share of generic drugs. Given that these doctors have no direct contractual relationship with a health insurance fund, they may be generally less motivated or pressurized to prescribe cheaper generic drugs.[18] The lower impact of the hospital dummy for noncon-

[17]Contracted outpatient physicians hold a direct contract with the (regional) mandatory health insurance fund. These doctors' services are reimbursed by the health insurance funds in accordance with a predefined catalogue of medical services and attached fees. Patients visiting a noncontracted doctor (in German, “Wahlarzt”) pay their medical attendance fees themselves. They can subsequently submit a request for reimbursement of treatment costs to their health fund. The insurance fund covers up to 80% of the fees that they would have paid to their contracted physicians for the same medical service.
[18]Contracted doctors are regularly reminded by the health insurance funds of the fact that they may have caused substantial (above average) medication costs. Furthermore, there are guidelines for the economic prescription of pharmaceuticals, where contracted physicians are formally prompted to prescribe the most cost-effective product when several therapy options are available (ISPOR, 2009)

TABLE 9 Comparison of drug choice in hospitals and the outpatient sector

	Discharge prescriptions		Outpatient prescriptions	
	(1)	(2)	(3)	(4)
Patient under 40	−0.014***	−0.009***	0.016***	0.019***
	(0.002)	(0.002)	(0.001)	(0.001)
Patient over 70	−0.002	0.003	−0.012***	−0.017***
	(0.002)	(0.002)	(0.001)	(0.001)
High-income patient	−0.013***	−0.007***	−0.032***	−0.018***
	(0.003)	(0.002)	(0.001)	(0.001)
Low-income patient	0.005**	0.005**	0.000	−0.003***
	(0.002)	(0.002)	(0.001)	(0.001)
Constant	0.257***	0.254***	0.641***	0.640***
	(0.001)	(0.001)	(0.000)	(0.000)
Controlling for fixed effects:				
Time	✓	✓	✓	✓
Active ingredient	✓	✓	✓	✓
Hospital/physician		✓		✓
N	267,260	267,260	3,129,858	3,129,858
Mean of dept.	0.253	0.253	0.640	0.640

Notes. This table summarizes the effects of patient characteristics on hospital discharge prescriptions (columns [1] and [2]) and outpatient prescriptions with no prior hospital stay (columns [3] and [4]). The dependent variable is a binary indicator for generic versus brand-name choice. Additional covariates controlling for different levels of fixed effects are indicated at the bottom of the table. Robust standard errors are in parentheses. $^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

tracted doctors may therefore simply reflect their similarity with hospitals (patients receive brands irrespective of previous hospital stays).[19]

With regard to patients, the results show that both the income and age of patients matter for the hospital impact on the propensity to receive a generic or brand-name drug. A previous hospital stay reduces the likelihood of a generic follow-up prescription by 22.7 percentage points for the oldest patients (beyond 70 years old) and by 24.8 percentage points for the youngest patients (below 40 years old). The negative impact for patients in the lowest decile of the income distribution amounts to 21.6 percentage points. The figure increases to −25.4 percentage points for the highest income decile. The result of negative hospital impact increasing with a patient's income and decreasing with his/her age can be explained in two ways. First, the different age and income groups of patients are treated differently during hospitalization. Second, if at least some doctors are not convinced that generic drugs with the same active ingredient are (bio-) equivalent to brand-name drugs, the doctors may follow the hospital's recommendation more closely and prescribe the brand-name versions for the younger and high-income patients. Similarly, a stronger socioeconomic background of patients (income) could help them carry through the brand-name prescription of the hospital. In the next step, we address these two channels, that is, the treatment of different groups of patients in hospitals and the outpatient care physicians' adherence to hospital choices.

3.3 | Hospital treatment and outpatient physicians' adherence

Equation 2 reveals the impact of patient characteristics on the probability of receiving a generic discharge prescription at the end of hospitalization. Columns (1) and (2) of Table 9 depict the results for this regression. When we control for month, active ingredient, and hospital fixed effects, we find a significant and negative impact for young and high-income patients. The propensity to leave the hospital with a generic discharge prescription is 0.9 percentage points lower if the patient is below 40 years of age (as compared with the middle age group). The likelihood of a generic discharge prescription is 0.7 percentage points lower for high-income patients (beyond the 90th percentile) and 0.5 percentage points higher for low-income patients than for the middle income group. The effects are statistically significant, but their quantitative

[19]In Section 3.3, we provide a more thorough analysis to disentangle the hospital effect from the preference effect. We show that the smaller hospital effect for noncontracted physicians is primarily driven by deviations from hospitals' generic drug prescriptions.

impact is moderate. The results support our previous finding of the largest negative hospital effect for the youngest group of patients and for those with the highest net income.

For comparison reasons, columns (3) and (4) of Table 9 include equivalent estimations for all outpatient prescriptions of those with no previous hospital stay. In contrast to hospital medication, the propensity of old patients to receive a generic prescription in the outpatient sector is 1.7 percentage points lower than for the youngest patients and 1.9 percentage points higher than for the middle age group. Moreover, high-income patients are 1.8 percentage points less likely to receive a generic prescription from their outpatient care physician than their middle income counterparts. Patients in the lowest income group are also less likely to receive a generic prescription, but the quantitative effect is minor. Overall, the results indicate a significant impact of patients' socioeconomic characteristics on inpatient and outpatient prescription behavior.

Our final set of estimation results includes an analysis of whether doctors deviate from the hospital choice in their prescription behavior. From the subsample of patients who received a discharge prescription after hospitalization, we estimate Equation 3 and analyze whether the characteristics of patients and doctors influence the physician's adherence to the hospital choice (see Table 10). The dependent variable in column (1) is a binary indicator equal to 1 if the first follow-up prescription of a doctor in the outpatient sector and the hospital discharge prescription coincide; that is, both prescriptions contain either a generic drug or a brand-name drug.

At the patient level, adherence to the hospital's medication decision is significantly weaker for the youngest patients (−1.5 percentage points) and stronger for high-income patients (2.1 percentage points). As regards physician characteristics, we find a weaker adherence for female physicians (−1.3 percentage points) and the physicians who practice in one of the three largest cities of Upper Austria, Linz, Wels, and Steyr (−1.7 percentage points); the physician's age does not have an impact. The adherence of GPs is 2.3 percentage points higher than that of medical specialists.

TABLE 10 Physicians' adherence to hospital choices

	(1) Adherence	(2) Adh. to brand name	(3) Adh. to generic
Physician characteristics			
Physician over 50	−0.005	−0.001	−0.002
	(0.004)	(0.005)	(0.004)
Female physician	−0.013***	−0.010	−0.009
	(0.005)	(0.006)	(0.005)
City practice	−0.017***	−0.021***	0.002
	(0.003)	(0.004)	(0.003)
General practitioner	0.020**	0.025**	0.022**
	(0.009)	(0.011)	(0.011)
Noncontracted physician	0.131***	0.246***	−0.129*
	(0.031)	(0.037)	(0.070)
Physician dispenses drugs	−0.064***	−0.078***	−0.038***
	(0.005)	(0.006)	(0.005)
Physician referred to hospital	−0.005	−0.008*	−0.000
	(0.004)	(0.005)	(0.004)
Patient characteristics			
Patient under 40	−0.015**	−0.012	−0.020**
	(0.007)	(0.008)	(0.010)
Patient over 70	0.004	0.004	0.002
	(0.003)	(0.004)	(0.003)
High-income patient	0.021***	0.032***	−0.004
	(0.005)	(0.007)	(0.006)
Low-income patient	0.002	0.001	0.001
	(0.005)	(0.007)	(0.006)
N	52,994	38,804	14,190
Mean of dept.	0.817	0.766	0.955

Notes. This table summarizes the effects of patient and physician characteristics on physicians' adherence to discharge prescriptions. The dependent variable is a binary indicator for adherence and nonadherence. Column (1) depicts overall adherence to the type of discharge prescriptions. Column (2) depicts adherence to a brand-name discharge prescription and column (3) to a generic discharge prescription. All regressions include fixed effects for time and active ingredient. Robust standard errors are in parentheses. $^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

The point estimates for two other physician characteristics reveal large and interesting effects. Physicians running a primary care pharmacy follow the hospital recommendations to a lesser extent. The effect is highly significant and quantitatively important, with an estimated coefficient of −6.4 percentage points. This result is in line with the abovementioned interpretation that these doctors have a broad pharmacological knowledge and a good overview of medication alternatives, implying that they may be more often willing to deviate from the hospital choice.

Noncontracted doctors have a 13.1 percentage point higher adherence to the discharge prescription than the physicians holding a contract with a health insurance fund. As already mentioned, noncontracted doctors may be less pressurized to prescribe generic drugs. They have a strong preference for brand-name drugs and more often seem to follow the hospitals in prescribing the more expensive original drugs. Furthermore, many noncontracted outpatient care physicians are directly affiliated to a hospital. It is common for hospital doctors in Austria to run a private part-time ordination in the outpatient sector. The particularly close relationship of this group of doctors with hospitals may also explain their high degree of adherence to previous inpatient medication decisions.

For further insight, we split the sample into patients leaving hospital with a generic discharge prescription (column [3]) and those leaving with a brand-name prescription (column [2]) and analyze the physicians' adherence to the two categories separately. We see that noncontracted private physicians have a 24.6 percentage point higher adherence to hospital brand-name prescriptions than contracted doctors. On the contrary, the corresponding coefficient for adherence to generic prescriptions is negative and significant at the 10% level (−12.9 percentage points). This group of doctors generally does not follow the prescription choices of hospitals but rather indicates a strong preference for brand-name pharmaceuticals. In contrast, columns (2) and (3) of the table reveal that the negative impact on adherence of physicians who run their own primary care pharmacy can be observed for both drug categories. In other words, the results do not indicate a clear preference of these physicians for either type of medication but rather express their pharmaceutical competence and willingness to deviate from the prescription behavior of hospital doctors. Another argument is that primary care pharmacies tend to have less variety of drugs in their stock and therefore the prescription behavior of doctors is less influenced by hospitals.

A separate analysis of the prescription adherence for two drug categories also helps explain the stronger hospital impact for high-income and young patients. As abovementioned, these patients receive less generic drugs during hospitalization (according to their discharge prescriptions). The tendency toward brand-name drugs is reinforced by the prescription behavior of primary care physicians. As column (2) shows, physicians follow the prescription of brand-name drugs for high-income patients more closely (3.2 percentage points), but we do not observe any reinforcing or weakening effect for generic hospital prescriptions for this group of patients. As regards the youngest patients, we find no significant effect on the physicians' adherence to brand-name prescriptions. However, the significantly negative coefficient of −2.0 percentage points for adherence to generic hospital prescriptions also generates a reinforcing effect for brand-name prescriptions in the outpatient sector for these patients. Our results support the hypothesis that inpatient and outpatient doctors treat higher socioeconomic groups differently, be it due to their belief that generic drugs are not (bio-) equivalent or for some other reason.

4 | DISCUSSION AND CONCLUSIONS

We find a strong influence of hospitalization or hospital drug use on the prescription behavior and drug consumption in primary health care. Patients with previous hospital stay have a significantly lower propensity to receive a generic drug in their first follow-up prescription compared with those with no prior hospital stay. The quantitative effects run from −6.8 percentage points (based on a simple hospital dummy) to −20.3 percentage points (based on the subsample of hospital stays with a discharge prescription).

The strong hospitalization impact on the decision of outpatient doctors to prescribe generic or brand-name drugs indicates that physicians are not in general convinced of the (bio-) equivalence of the two types of medication. Moreover, deviating from hospital choices could be costly. Because outpatient doctors have to put some effort to convince their patients on an alternative medication, physicians generally prefer to follow the hospital prescription. These results support the hypothesis that pharma companies have succeeded in their marketing efforts to promote brand-name drugs in the hospital sector. The beneficial provision of drugs in hospitals or even the free-of-charge distribution of drugs reduces the costs of hospitals. However, as our analysis shows, any such conduct increases the expenditure of outpatients and puts a substantial strain on the budgets of health insurance funds. If the provision of inpatient and outpatient health care service is operated separately for each group without any transfer payment, the whole procedure would not be incentive compatible, and most likely not cost minimizing.[20]

Our empirical analysis also reveals heterogeneous results for the different patient groups and doctor characteristics. The negative hospital effect on generic drug prescription in the outpatient sector is stronger for young and high-income patients. As for physicians, our estimations reveal a substantial influence of supply-determined circumstances. The hospital effect is lower for the physicians running their own pharmacy and for the noncontracted outpatient physicians. However, although the doctors with pharmacies tend to deviate from hospital medication decisions irrespective of drug type (brand-name or generic), noncontracted doctors seem to have a strong preference for brand-name drugs.

The finding that doctor characteristics play an important role both qualitatively and quantitatively is another evidence that well-developed (Bismarckian) health care systems are supply-side driven to a large extent. We hypothesize that the different behavior of primary care physicians may have to do with the hierarchy in doctor groups. One could argue that medical specialists (as compared with GPs) and the doctors running a pharmacy (as compared with physicians who do not sell medical drugs) command higher pharmacological competence and hence are more self-confident in their prescription behavior and follow their hospital colleagues to a lesser extent.

The lesson to be learnt from a health policy perspective is to closely examine the imperfections at the interface between the inpatient and outpatient sector. These two levels of health care service provision are in general interconnected, either directly in systems where one single authority is responsible for the service provision at both levels or indirectly via spillovers in systems with only superficially separated inpatient and outpatient sectors. Distinct funding systems generate inefficiencies and misallocation of services between outpatient care physicians and hospitals. This analysis reveals that the system creates extra costs with regard to the funding of medication.

This analysis also illustrates a dilemma of health insurance funds. In principle, health insurance funds discourage the prescription of brand-name drugs in the outpatient sector through their reimbursement policy and require their contracted doctors to prescribe generic drugs whenever available. However, this policy has not been successfully implemented for several reasons. First, the negotiation process between social insurance institutions and pharmaceutical companies on the admission of drugs to the reimbursement scheme is complex. For example, the acceptance of an individual drug often means the implicit acceptance of some other drugs (of the same company), by which it is almost impossible for the health insurance funds to exclude single brand-name products from reimbursement without any negative repercussion. The final list of drugs that automatically qualify for reimbursement (included in the green box) requires compromises; that is, not all drugs in the green box are the cheapest ones. Second, all the outpatient practitioners and specialists in Austria are self-employed. Thus, to some extent, the health insurance funds must accept the doctors' medical choices even if their choices lead to higher costs.

In a second-best world, where the role of health insurance funds is limited to their imposition of cheaper generic drugs, regulating the pharmaceutical industry's marketing activities in public hospitals through the prohibition of no-cost distribution, or even the attempt to promote the use of generic drugs in these hospitals, could be cost saving. A better documentation of the quantities and prices of drugs used in hospitals is an important prerequisite to improve transparency and to better evaluate the implications of regulatory measures.

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[20]A serious analysis of the overall cost consequences would require an empirical comparison of the cost decreases and increases in the inpatient and outpatient sector. Because we cannot observe the prices and quantities for hospital medication, this analysis is not possible.

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APPENDIX A

TABLE A1 Sensitivity analysis: Controlling for patient characteristics

	(1)	(2)	(3)
Hospital stay	−0.0785***		
	(0.0005)		
Hospital stay with matched diagnosis		−0.1041***	
		(0.0008)	
Hospital discharge prescription			−0.2572***
			(0.0018)
Age	0.0001***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)
Female	−0.0044***	−0.0060***	−0.0068***
	(0.0004)	(0.0004)	(0.0004)
Medical attendance (in 1,000 €)	−0.0015***	−0.0027***	−0.0037***
	(0.0003)	(0.0004)	(0.0004)
Medication (in 1,000 €)	−0.0036***	−0.0035***	−0.0035***
	(0.0003)	(0.0004)	(0.0005)
N	4,880,936	4,345,702	4,014,330

Notes. This table summarizes the hospital effect on the first outpatient medical therapy prescription. The dependent variable is a binary indicator for generic versus brand-name choice. Further control variables are fixed effects for active ingredients, physicians, and the month of the prescription. Robust standard errors in parentheses. $^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

TABLE A2 Balance of patient characteristics for treatment "hospital stay"

	(1) Before matching	(2) After matching ($M = 1$)	(3) After matching ($M = 5$)
Age			
Mean of treated obs.	61.78	61.78	61.78
Mean of control obs.	47.88	61.71	61.65
Standardized difference	70.73	0.40	0.70
Female			
Mean of treated obs.	0.57	0.57	0.57
Mean of control obs.	0.59	0.57	0.57
Standardized difference	−2.76	−0.04	−0.09
Expenditure for medical attendance			
Mean of treated obs.	782.97	782.97	782.97
Mean of control obs.	549.91	774.61	768.63
Standardized difference	31.51	1.13	1.94
Expenditure for medication			
Mean of treated obs.	1320.71	1320.71	1320.71
Mean of control obs.	487.18	1246.14	1196.36
Standardized difference	25.73	2.30	3.84

Notes. This table summarizes patient characteristics of the matched and unmatched data. Column (1) shows the means of treated and control observations and the standardized difference before matching. Columns (2) and (3) are after matching to one or five nearest neighbors.

TABLE A3 Matching estimates of hospitalization on first outpatient prescription

	(1) $M = 1$	(2) $M = 5$
Hospital stay	−0.080***	−0.080***
	(0.001)	(0.001)
Hospital stay with matched diagnosis	−0.104***	−0.105***
	(0.001)	(0.001)
Hospital discharge prescription	−0.244***	−0.245***
	(0.002)	(0.002)

Notes. This table summarizes the matching results for the hospital effect on the first outpatient medical therapy prescription. Each entry shows the average treatment effect on the treated from a separate nearest neighbor matching estimation with different treatment definitions indicated on the left-hand side. Column (1) shows estimates from one-to-one matching ($M = 1$), and column (2) shows the estimates from one-to-many ($M = 5$) matching (i.e., every treated observation is matched to its five nearest neighbors). Standard errors are in parentheses. $^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

TABLE A4 Sensitivity analysis: Controlling for patient and physician characteristics

	(1)	(2)	(3)
Hospital stay	−0.0811***		
	(0.0006)		
Hospital stay with matched diagnosis		−0.1070***	
		(0.0009)	
Hospital discharge prescription			−0.2681***
			(0.0019)
Patient characteristics			
Age	0.0002***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)
Female	−0.0039***	−0.0056***	−0.0063***
	(0.0004)	(0.0004)	(0.0005)
Medical attendance (in 1,000 €)	−0.0025***	−0.0036***	−0.0045***
	(0.0004)	(0.0004)	(0.0005)
Medication (in 1,000 €)	−0.0040***	−0.0038***	−0.0037***
	(0.0004)	(0.0004)	(0.0005)
Physician characteristics			
Physician dispenses drugs	−0.0347***	−0.0400***	−0.0458***
	(0.0005)	(0.0005)	(0.0006)
General practitioner	−0.0225***	−0.0167***	−0.0108***
	(0.0007)	(0.0007)	(0.0007)
Noncontracted physician	−0.1022***	−0.0987***	−0.0772***
	(0.0051)	(0.0054)	(0.0057)
City practice	0.0281***	0.0286***	0.0305***
	(0.0005)	(0.0005)	(0.0005)
Over 50	−0.0137***	−0.0126***	−0.0114***
	(0.0005)	(0.0005)	(0.0005)
Female physician	−0.0190***	−0.0197***	−0.0198***
	(0.0006)	(0.0007)	(0.0007)
N	4,163,314	3,699,628	3,414,191

Notes. This table summarizes the hospital effect on the first outpatient medical therapy prescription. The dependent variable is a binary indicator for generic versus brand-name choice. Further control variables are fixed effects for active ingredients and the month of the prescription. Robust standard errors in parentheses. $^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.