R&D MANAGEMENT

The impact of increasing internet penetration on prescription choices and response to pharmaceutical detailing: a 10-year empirical investigation

Utkarsh Shrivastava[1,*], Daniel Zantedeschi[2], Wolfgang Jank[2] and Philip Stern[3,4]

[1]Haworth College of Business, Department of Business Information Systems, Western Michigan University, 49001, Michigan, Kalamazoo, USA. utkarsh.shrivastava@wmich.edu
[2]Muma College of Business, School of Information Systems and Management, University of South Florida, 33613, Florida, Tampa, USA, danielz@usf.edu, wjank@usf.edu
[3]Ehrenberg-Bass Institute, UniSA Business, University of South Australia, 5000, South Australia, Adelaide, Australia.
[4]Business School, University of Exeter, EX4 4PY, Exeter, UK. phil.stern@marketingscience.info

This study investigates the implications of increased internet penetration on demand in the context of pharmaceutical prescribing. The internet has changed the information and tools available to make decisions in complex tasks such as those made by physicians, and any impact on prescribing patterns has implications for the marketing activities of drug manufacturers, necessitating a strategic rethink of business practices. This study conceptualizes the prescription decision-making process through the lens of expectancy value theory. The unique research design allows for the observation of contrasting internet penetration rates of geographically distributed physicians over an extended time period in multiple drug categories. Modeling physician behavior as a combination of learning, peer effects, and face-to-face detailing by pharmaceutical firms, the study finds that the growth of the internet has a significant moderating impact on detailing efforts. Interestingly, the study also documents the interaction between learning and peer effects, as well as how the internet ultimately reduces reliance on prior prescription behavior (prescribing inertia) for the four Cardiovascular drug categories under consideration. We discuss the implications of these findings for R&D managers, marketers, and policymakers.

1. Introduction

The prescription choices made by physicians play an essential role in the diffusion of pharmaceutical innovations, thus providing better health outcomes for patients. A new drug is considered a pharmaceutical innovation when it safely and effectively caters to inadequately met healthcare

needs (Morgan et al., 2008). Manufacturers secure benefits from their R&D investment by filing for patent(s) when their new drug satisfies a health care need through a unique biological mechanism. The number of patent filings by pharmaceutical companies indicates their innovativeness (Caner et al., 2017; van de Wal et al., 2020), but the adoption of pharmaceutical innovations is critical for the sustainability of R&D and the success of a pharmaceutical company. While Primary Care Physicians (PCPs) rarely engage in pharmaceutical research themselves, they evaluate R&D outcomes, side effects, and benefits of new drugs and are gatekeepers between drug manufacturers and patients (Khazzaka, 2019).

A physician's job is highly knowledge-intensive, often requiring familiarity with many diseases, their symptoms, and medications, along with the latest research published in the biomedical literature (Davenport and Glaser, 2002). PCPs are sophisticated knowledge workers who need to understand a plethora of facts that are constantly changing as research matures. Prior studies have investigated various aspects of physician prescribing, including the influence of peers (Yang et al., 2013), social networks (Nair et al., 2010), pharmaceutical promotion (Kappe and Stremersch, 2016), and prescribing inertia (Janakiraman et al., 2008). However, one important gap, addressed by this research, is the impact of increasing internet penetration on physician prescription choices.

Internet-enabled external connections bring diverse knowledge and expansion of the information network, which contributes to flexibility in thinking and decision-making (Cross and Cummings, 2004; Tang, 2016). The internet has increased user-generated content on the World Wide Web (Web), which has further accelerated internet adoption (Viard and Economides, 2015). Von Knoop et al. (2003) report that 80% of patients search online for potential treatments before consulting their physician. The internet has also contributed to an increase in patient assertiveness, resulting in increased questioning and the expectation that their physician will inform them about the pros and cons of the possible treatments for their medical condition (Cajita et al., 2016).

Physicians have also benefitted from online user-generated content, a survey of 4,033 physicians found that around 90% of the physicians use at least one website while about 65% use social media for professional support and advancement (QuantiaMD, 2011). These findings are reinforced by a more recent survey, which found that 88% use social media platforms, devoting 1 hr per day on average to them (Surani et al., 2017).

Pharmaceutical representatives are the traditional gatekeepers of R&D communications between drug manufacturers and PCPs, who, in turn, take the drug adoption or prescribing decision on behalf of the patients (Khazzaka, 2019). The development of physician social networks through interactions with representatives helps spread pharmaceutical innovations to the population (Whelan et al., 2013). The growth of the internet has brought about substantial changes in the role of the traditional gatekeepers as the carriers of relevant information (Whelan et al., 2010). In fact, in the current digital society, the role and the capabilities of the gatekeepers to control the information are diminishing (Singer, 2006). In the context of pharmaceutical detailing, it is a common perception that meetings with sales representatives are both time-consuming and inconvenient (Connelly et al., 1990; Janakiraman et al., 2008); this has encouraged physicians to seek drug-related information from online sources as well as their peers. Peer popularity of a drug may reinforce its quality perception (Tucker and Zhang, 2011); however, patient engagement and the democratizing effect of the internet (Ding et al., 2010) may undermine this and its subsequent prescription probability.

The absence of clinical information and high costs of gathering information has encouraged physicians to habitually prescribe from an armamentarium (mostly accessible or highly detailed) to minimize overall risk due to incomplete information (Chinburapa et al., 1993; Janakiraman et al., 2008; Berndt et al., 2015). Internet use may reduce reliance on previous prescribing by reducing information-gathering costs (Malone et al., 2004), increasing productivity and patient engagement in prescribing decisions (Wald et al., 2007; Ding et al., 2010).

The latest R&D findings and drug prescribing patterns are equally important (Doak and Assimakopoulos, 2007), with PCP prescription choices key to the diffusion of pharmaceutical R&D results. In this study, we ask: 'How have internet penetration, pharmaceutical detailing, peers, and prior prescribing affected prescribing behavior?'

The study examines prescription choices in 10 UK Government Office Regions (GOR) over a 10-year period. Four drug classes are considered to generalize the findings and account for competing brands, providing a robust analysis. Using a flexible mixed-random utility model, the study quantifies physician heterogeneity in detailing elasticity and internet access. In the following sections, we use prior theory to develop testable hypotheses and then describe the market and data utilized before specifying the variables and measures. Section 5 considers the model and estimation followed by the key results

in Section 6. We then discuss these results before providing a conclusion.

2. Theory development and hypotheses

The prescription process involves patient diagnostic information, drug alternatives, their attributes, and utility values. This study examines physician prescription decision-making using expectancy-value theory (Chinburapa et al., 1993), which proposes that doctors follow a linear and additive compensatory decision process to choose the best drug for a patient. This rule links drug attributes, patient diagnosis, and medical history to the medical outcome. The highest-utility drug is prescribed among a set of possible alternative medicines with different attributes.

Typically, four types of costs hinder physicians' prescription of customized or tailor-made prescription for their patients. These costs are associated with communication with patients, coordination between the providers, and the physicians' cognition and capability (Frank and Zeckhauser, 2007). Communication costs are incurred while eliciting patient symptoms, treatment preferences, medical history, and other information required for an informed prescribing decision. In the absence of appropriate communication or patient-related information, suboptimal prescribing may occur. The clinical needs of patients often require visits to multiple specialists, thereby increasing the potential for interaction between different therapies. Coordination costs arise when prescribing involves communication with other providers to identify the best treatment plan for a patient.

Cognition costs occur due to rational calculation or comparisons of the possible drug alternatives, their attributes, and matching them to the clinical needs and the preferences of the physicians. High cognition costs compel physicians to use some heuristic or the popular norm for making the prescription decision (Tversky and Kahneman, 1974; Frank, 1987; Shurtz, 2022). There can be several types of treatments for a patient's medical condition, and a physician may have substantial experience or expertise in a particular type of treatment. Capability costs are the costs incurred by a physician to hone their skills or become familiarized with novel treatments. In the presence of high capability costs, physicians typically prescribe their preferred treatments.

Prescribing inertia hinders innovation adoption, Berndt et al. (2015) analyzed monthly antipsychotic prescription data from 2000 physicians and found that 41% of them prescribed a preferred drug to their patients. Physicians tend to prescribe a popular (or their preferred) drug to reduce information-gathering risks in a complex environment or one with incomplete drug and patient information. Urgency of the patient's problem and peer pressure to follow medical norms encourage doctors to seek external information (Robson and Robinson, 2015).

Through email services, electronic databases, and online forums, internet access has reduced decision costs for clinical information and guidance. Physicians can now share insights, discuss new ideas, and ask questions outside their local network. Internet-enabled technologies influence innovation by connecting individuals and organizations with external innovation resources, such as crowdsourcing (Randhawa et al., 2019; Patroni et al., 2022). Direct or online interactions help synthesize and apply new knowledge for decision-making or innovation (Shang et al., 2017). The rise in user-generated medical content on the internet has raised concerns about information overload and higher decision-making costs (Ahmed, 2018). Knowledge workers often rely on simple heuristics and cognitive shortcuts, leading to suboptimal decisions (Hansen and Haas, 2001), but online information processing has improved with internet use (Phan et al., 2017). Tools such as text search, information filters, topic tags, and recommendation engines support information search, and processing for better decision making. Online experts' opinions help synthesize complex information and guide decision-making heuristics (Nauhaus et al., 2021).

Therefore, increasing internet penetration has the potential to discourage physicians from persisting with previously prescribed drugs and allow for higher personalization of patient-level prescribing. Hence, the first hypothesis of the study is:

> **Hypothesis 1** The increase in internet penetration has decreased physicians' reliance on prior prescription choices.

Another research thread examines how drug marketing affects prescriptions. Most of these studies have focused on pharmaceutical promotion and prescribing. Azoulay (2002) found that detailing can turn minute differences in drug efficacy into market advantages at the brand level. Similarly, Berndt et al. (1995) found that face-to-face detailing has the highest sales elasticity compared with direct mailings and DTC advertising. Other studies find that the impact of detailing depends on the drug's effectiveness and side effects (Venkataraman and Stremersch, 2007) and the content of detailing meetings (Kappe and Stremersch, 2016). Wierringa et al. provide a useful review of drug promotion in aggregate prescribing (Wieringa et al., 2014).

Marketing is essential for promoting pharmaceutical R&D advances. Prior studies have viewed physicians as 'pharma customers,' and their interactions with representatives showcase R&D and innovative new drugs (Kyle et al., 2008; Khazzaka, 2019). Representatives act as R&D gatekeepers, presenting relevant pharmaceutical advances and outcomes to physicians. The R&D literature studies gatekeeping extensively (Livingston and Bennett, 2003; Whelan et al., 2010). A gatekeeper filters large amounts of information or messages into manageable amounts (Barzilai-Nahon, 2008).

The utility of detailing depends on its value, importance, timeliness, and accessibility (Robson and Robinson, 2015). In a choice-based decision process, doctors favor information that will help them complete a task (Feldman and Lynch, 1988). Thus, a sales representative's credibility, as perceived by physicians, will affect prescription decisions (Briñol and Petty, 2009). A study conducted by IBM (2006) found that 76% of doctors perceive sales meeting information to be biased, and 50% believe they are inconvenient.

Internet diffusion opens new channels for evidence-based medical information (Amdnews.com, 2010). Discussion forums, online portals, and peer groups are less biased than sales representatives. Signaling theory suggests that multiple opinion sources are less biased than a single contributor's (Donath, 2007).

Knowledge workers can now share insights, discuss new ideas, and ask questions outside their local network. Explicit knowledge spreads faster and is consumed more easily online than implicit experiential knowledge, which requires in-person human interaction (Enkel et al., 2020). The internet and web-based communication technologies have reduced the role of information gatekeepers (Whelan et al., 2010).

Internet cost-saving and productivity-boosting effects will reduce the reliance of PCPs on information garnered from sales representatives. Hence, we expect that increasing internet penetration will reduce the impact of detailing.

Hypothesis 2 The increase in internet penetration has reduced the positive effect of pharmaceutical detailing on the prescription choice of the detailed drug.

A separate research stream found that opinion leaders influence prescription choices (Nair et al., 2010) and found 'followers' less responsive to drug manufacturers' marketing than opinion leaders. Such peer effects in prescribing are more pronounced with similar age, experience, or background (Yang et al., 2013). The peer effect stems from similar medical training, networking, or community norms. The popularity of a product among peers reinforces its quality and features (Tucker and Zhang, 2011), and Ding et al. (2010) found that BITNET increased academic collaboration.

Physician-to-physician engagement using networking platforms in the United Kingdom grew to 184,000 instances by 2020 (Myers, 2020). Facebook has moderated virtual social networks of physicians with tacit and explicit medical practice knowledge (Wieringa et al., 2018). Hospital internet access provides equipment, services, and information and allows knowledge workers to collaborate and increase productivity (Menon et al., 2000). Centrality of a knowledge worker in the network determines the extent of diversified knowledge consumption, which influences its use and creativity (Tang, 2016). Doctors who consume online expert knowledge can become more central in the physician knowledge network (Tang, 2016).

Today, regulatory organizations encourage knowledge-sharing for evidence-based medicine. The UK's National Institute for Clinical Excellence (NICE) uses the internet to facilitate access to full-text documents and guidelines *via* electronic databases. In the digital era, a drug's popularity may trigger patient drug requests based on online information and word of mouth among patients and physicians (Dewan et al., 2010). The internet lowers the cost of obtaining information and increases access to others' knowledge, encouraging doctors to follow medical norms or peers.

Hence, our final hypothesis is:

Hypothesis 3 The increase in internet penetration has amplified the positive effect of peer popularity on the prescription choice of a drug.

3. Data and market

The study utilizes four different categories of prescription drugs commonly prescribed to treat cardiovascular diseases (CVD): (1) Statins, (2) Calcium Channel Blockers (CCB), (3) ACE Inhibitors (ACE), and (4) Angiotensin Receptor Blockers (ARBs). The primary dataset consists of the prescription choices of (and detailing to) 110 general practitioners spread across 10 Government Office Regions[1] of the United Kingdom from January 1997 to December 2006. Prescription and detailing records were obtained from a market research firm and comprised the daily records of new prescription decisions by physicians, detailing visits by salespeople and patient-specific

information; physician and patient demographics are anonymized. We know of no other continuous dataset with a similar length or detail. The second data source used in the study is the British Household Panel Survey (BHPS) (Bardasi et al., 2012; University of Essex, Institute for Social and Economic Research, 2014). BHPS is a nationally representative annual survey of approximately 10,000 households. BHPS data are used to measure internet penetration and the demographics of the patients in the physician's regions.

The study examines prescription drug molecules with at least 5% market share in each of the four categories across the 10 years under consideration (Janakiraman et al., 2008). Table 1 shows the generic name of the molecules for each drug category and their corresponding prescription share in the class. The combined market share of the selected molecules in each category ranges from 80% (Statins) to 98% (ARB).

Cardiovascular diseases accounted for about a third of non-communicable disease fatalities globally in 2019 (WHO, 2021). In the United Kingdom, the National Health Service (NHS) has provided free care at the point of delivery to the population since 1948, irrespective of the ability to pay. Except for emergencies, a General Practitioner (GP) referral is required for hospital treatments.

The NHS bears the cost of providing health care services to United Kingdom residents, which contracts virtually all GPs. Patients under 18, pregnant women, and those over 60 receive their medication free of charge. The rest of the population pays a fixed 'prescription charge', which bears no relationship to the cost of the medication to the NHS; thus, it is estimated that about 80% of all drugs in the United Kingdom are dispensed without charge to the patient. By the end of 1999, less than 12% of the UK population had any form of private medical insurance cover (Euro.who.int, 2016), but this is almost exclusively linked to surgical procedures and largely associated with employment benefits. The centralized nature of the health care system compels pharmaceutical companies to communicate directly with NHS for approval of new drugs and the conditions under which they can be prescribed (Magrini and Font, 2007).

The advertising of prescription-only drugs directly to the consumers (i.e., patients) is strictly regulated by the advertising regulation act of 1994. Unlike the United States, pharmaceutical companies are not permitted to advertise directly on broadcast media in the United Kingdom. Under certain conditions, they may answer specific questions and provide facts and reference materials without making product claims or references to the brand.

4. Variables and measures

The response variable of interest in our study is the prescription choice of the drug '*d*' by the physician '*i*' at occasion '*t*' in a drug category (C_{dit}) and focuses only on new prescription occasions and patients with the same medical diagnosis within each category, thus eliminating the influence of other medical conditions and follow-up visits on prescription choice.

Two types of explanatory variables are examined: molecule-specific and case-specific. The physician chooses one molecule (i.e., drug) from all the alternatives in the relevant category on each new prescription occasion. Detailing, prior prescription, and peer popularity of that drug can all play a key role in the prescribing decision; thus, molecule-specific variables can change on each prescription occasion. On the other hand, case-specific variables such as patient age, physician characteristics, and internet access remain the same for all the alternative molecules.

Our molecule-specific variables include (a) drug detailing, (b) prior prescriptions of the drug, (c) popularity of the drug, and (d) availability of generic variants; these are time-variant and differ across physicians on each prescribing occasion. Prior studies in marketing and advertising have utilized a stock variable to

Table 1. Category and molecules

Category	Molecules (*code – % share)	Total new prescriptions	Total details
Calcium Channel Blockers (CCBs)	Amlodipine (AMLO* – 44%), Felodipine (FELO – 25%), Adalat (ADAL – 14%), Tildiem (TILD – 7%)	9,122	4,939
ACE Inhibitor (ACE)	Ramipril (RAMI – 37%), Lisinopril (LISI – 31%), Perindopril (PERI – 13%), Enalapril (ENAL – 13%)	13,679	4,341
Statin	Simvastatin (SIMV – 43%), Atorvastatin (ATOR-29%), Pravastatin (PRAV- 8%)	16,374	7,453
Angiotensin II receptor blockers (ARB)	Olmesartan (OLME – 5.5%), Telmisartan (TELM – 7.5%), Valsartan (VALS – 18%), Losartan (LOSA – 19%), Irbesartan (IRBE – 23%), Candesartan (CAND-25%)	5,771	11,541

reflect memory decay and carryover effects from prior marketing actions (Berndt et al., 1997; Gönül et al., 2001; Janakiraman et al., 2008). Consistent with these studies, we operationalize the detailing of a drug '*d*' for physician '*i*' on a prescription occasion in the week '*t*' as a stock variable ($Detailing_{dit}$) (Berndt et al., 1997; Gönül et al., 2001) as:

$$Detailing_{dit} = DET_{dit-1} + \lambda_d Detailing_{di(t-2)} \quad (1)$$

In the above equation, DET_{dit} is the number of detailing meetings in the week '*t*-1' before the prescription occasion '*t*', $Detailing_{di(t-1)}$ is the stock of detailing in the week *t*-1, and λ_d is the decay factor to incorporate memory decay. We consider detailing meetings for the specific molecule under consideration.

Prior prescription experience of a drug informs the physician about the drug's effectiveness, and this learning is likely to be incorporated into physician decision-making. Like detailing, the impact of prior experience of the drug could also be affected by memory decay. Here, we operationalize and summarize past prescription choices (or prescription learning) as a stock function ($Learing_{dit}$) similar to detailing stock such that:

$$Learning_{dit} = Prescriptions_{dit} + \lambda_d Learning_{di(t-2)} (2)$$

In this equation, $Prescriptions_{dit}$ is the total number of times drug '*d*' is prescribed by the physician '*i*' in the week before the prescription occasion '*t*.' This variable 'learning' encompasses a physician's experience because of prior prescribing of the drug in question, after accounting for any memory decay.

The popularity of the drug is a dynamically measured variable (evaluated on each patient visit). It is equivalent to the percentage prescriptions written by other physicians for the drug in the previous 6 months. We tested this time windows for robustness by using quarterly and annual periods but did not observe significant variations in the model estimates.

The study also controls for the availability of the generic (GEN) variant of a drug in the market. The GEN variable is operationalized as a dummy taking a positive value when the generic variant becomes available in the market. Several case-specific variables may influence the choice of a prescription drug; these include:

a. Patient Age (Pat_Age): The age of the patient visiting the physician for the prescription.
b. Gender (Dr_Sex): A dummy variable and represents the sex of the prescribing physicians.
c. Year of Qualification (YOQ): The year in which the physician completed his / her medical studies. This variable controls the experience of the physician.
d. Size of practice (SOP): This refers to the size of the practice in which the physician is operating, measured by the number of practice partners.
e. Time (Year): To incorporate time trends, we also control for a time in years (YEAR) in all of our models.
f. Internet (INT): Internet penetration (INT) is another key case-specific variable in our study.

INT in a region is measured as the percentage of households with a broadband connection. Nowadays, mobile phones can also access the internet using an appropriate wireless network plan. However, by the end of 2006, approximately 61% of households in the United Kingdom had broadband internet connections, and while mobile phone usage was prevalent, mobile internet usage was extremely limited (Statista, 2022). Mobile internet usage grew rapidly after the introduction of touchscreen-based mobile phones in 2007, but this falls outside the timeline of this study (Kleinen et al., 2014). The INT is a time- and geographic-dependent variable (according to the GOR of the physician) and is measured annually. The interaction of internet access and the molecule-specific variables gives another set of molecule-specific variables (INTx$f(DET)$, INTx$f(PAST)$, INTxPOP), which are used to study the impact of INT on detailing, past prescriptions, and drug popularity.

5. Model and estimation

Physicians typically consider a finite set of drug alternatives to prescribe to their patients in a consultation. Thus, the multinomial logit model (MLM) (Gönül et al., 2001; Janakiraman et al., 2008) is appropriate for modeling physicians' choice probabilities. MLMs can be categorized into standard and mixed MLM. The standard MLM assumes a homogenous relationship between explanatory variables (e.g., detailing) and the choices (McFadden, 1980). However, physicians may differ in their sensitivity to marketing actions and standard MLMs cannot capture the heterogeneous relationships. Mixed MLMs can overcome this challenge as they allow for physician-level heterogeneity and correlation between the explanatory variables' slopes. Mixed MLMs also eliminate the restrictive assumption of independence from irrelevant alternatives (IIA) present in the standard MLM. Next, we explain our modeling framework in detail.

Let U_{dit} be the unobserved utility of prescribing a drug 'd' for physician 'i' during a prescription occasion 't'. This unobserved utility can be represented as a combination of a systematic (V_{dit}) and a stochastic component ($\in_{dit}$) such that

$$U_{dit} = V_{dit} + \in_{dit} \tag{3}$$

The systematic component V_{dit} is a function of observable explanatory and control variables as well as unknown parameters to be estimated, while the stochastic component ϵ_{di} is a random variable accounting for unobserved determinants of the utility. A physician would choose drug d^1 over any other drug d^n if: $V_{d^1it} + \epsilon_{d^1it} > V_{d^nit} + \epsilon_{d^nit}$ for all $n \neq 1$.

The observable part of the utility (V_{dit}) for a drug 'd' is represented as:

$$\begin{aligned} V_{dit} = {} & \beta_d^0 + \beta_i^1 Detailing_{dit} + \beta_i^2 Learning_{dit} + \beta_i^3 Popularity_{dit} + \beta_i^4 Gen_{dit} \\ & \beta_i^5 Detailing_{dit} \times INT_{it} + \beta_i^6 Learning_{dit} \times INT_{it} + \beta_i^7 Popularity_{dit} \times INT_{it} \\ & + \sum_{j=1}^{k} \alpha_j^1 Patient\_Age_{it} \times Drug_j + \sum_{j=1}^{k} \alpha_j^2 Dr\_Sex_{it} \times Drug_j + \sum_{j=1}^{k} \alpha_j^3 YOQ_{it} \times Drug_j \\ & + \sum_{j=1}^{k} \alpha_j^4 SOP_{it} \times Drug_j + \sum_{j=1}^{k} \alpha_j^5 TIME_{it} \times Drug_j + \sum_{j=1}^{k} \alpha_j^6 INT_{it} \times Drug_j \end{aligned} \tag{4}$$

In the above equation, the β coefficients are associated with the alternative and choice situation-specific variables, while α coefficients are associated with only choice-specific variables. At each choice occasion 't' the alternative specific variables, such as detailing, vary across drug alternatives while the choice specific variables, such as the age of the patient (Patient_Age), remain constant. We account for heterogeneity in the utility of prescription drugs with respect to the choice of specific variables by using drug-specific model coefficients (α_d^n). Furthermore, we account for the physician-specific heterogeneity concerning the effect of the alternative specific covariates through the physician-specific coefficients β_i^n (where n varies from 1 to 7 for each physician-specific coefficient in equation (4). The flexible specification of equation (4) allows for the incorporation of correlation between the β_i^n by assuming that the β_i^n are random draws from a multivariate normal distribution whose parameters are estimated from the data.

A correlated random coefficient specification can significantly improve the model fit (see Rossi and Allenby, 2003 for an overview). In this study, we test several model specifications and select the one that explains the largest variation in the observed data for in-depth analysis. There are repeated observations for each physician in the dataset. Therefore, we account for the longitudinal dimension in estimating the model parameters by using a panel likelihood function (Train, 2009).

In summary, the study accounts for heterogeneity in the relationship between the drug-specific variables and the prescription choice by a random-effect specification on the slopes (β_i^n). As a result, the model allows for the contribution of detailing, prior prescriptions, and drug popularity on the prescribing decision to be different for each physician, and the difference is captured by the individual level parameters β_i^n.

The detailing visits to doctors are planned to maximize marketing investment return. Sales representatives target easily approachable doctors who prescribe for more patients to maximize profits. Therefore, detailing visits are not assigned randomly but planned based on possibly unobserved physician-specific characteristics. The combination of detailing and internet access makes identification difficult. In equation (3), these variables may not be exogenous and may be correlated with unobserved factors (ϵ_{dit}).

To identify the effect of detailing and its interaction with internet access (also endogenous), we use the control function (*CF*) approach of Petrin and Train (2010). See Appendix A.1 'Identification Strategy' for details.

6. Results

6.1. Model performance

We now present our empirical results. For each of the drug categories under consideration, we estimate five different models. The multinomial choice models without random parameters (models 1 and 2) are estimated using Maximum Likelihood Estimation (MLE) (Train, 2009, p. 61). Models 3, 4, and 5 (which include random coefficients) are estimated using Simulated Maximum Likelihood Estimation (Train, 2009, p. 61). Model 1 is a baseline choice model that does not account for physician-level heterogeneity or correlation between Detailing, Learning, and Popularity, nor does it control the interaction between these

variables and the internet. Model 2 complements model 1 by considering the interaction of these key explanatory variables with the internet. Model 3 adds to model 2 by including all six random coefficients for the three key explanatory variables and their interaction terms with the internet. Notice that for model 3, we assume that the correlation between the random coefficients is zero; that is, we assume independence between the random coefficients. Model 4 builds on model 3 by allowing for correlation between the random coefficients of the three explanatory variables and their interaction terms with the internet. Finally, model 5 enhances model 4 by accounting for the endogenous nature of detailing to the physicians and its interaction with the internet by including the residuals from the first state regression of the endogenous detailing with exogenous variables and instruments.

All five models include the same set of case-specific control variables (patient's age, doctor's gender, year of qualification (YOQ), number of partners in the practice (SOP), time trend, and internet). Since these variables are case-specific, they each enter the model as an interaction term with the drug alternatives. This allows for control of observable heterogeneity in the effect of the variables for each drug alternative. We refrain from listing the estimates for the control variables in the tables below due to space limitations. However, the complete model summary is available in Appendix A.2. We set the discount rate, $\lambda_d = 0.98$ (specified in equations (1) and (2)) consistent with prior studies in this domain with the weekly observed data (e.g., Gönül et al., 2001). As a robustness check, we also considered two alternative discount rates, 0.90, and 0.95 and found that the discount rate 0.98 gives the best fit to the data for all five models and each of the four drug categories studied.

Tables 1–5 show the estimates for all five models for each of the four drug categories. The model fit statistics (AIC, Log-Likelihood, and McFadden R Squared) suggest that the random coefficients (in model 3) lead to a significant increase in model performance. The improvement in model performance (starting with model 3) suggests that physicians prescribe highly individually, and our models can quantify this degree of individuality. It is noteworthy that models 4 and 5 improve the model performance further. Recall that models 4 and 5 allow for the random parameters to be correlated with one another. Model 5 across all Tables 1–5 fits the observed data best, and so we use this model for deriving insights.

The variation explained by model 5 is 25%, 39%, 41%, and 43% for the prescription choices in Statins, CCB, ACE, and ARB categories, respectively. The interaction terms (Detailing: Internet and Learning: Internet) are significant and negative for all four drug categories under consideration. While the interaction term (Popularity: Internet) is significant and positive for Statins and ARB, it is not statistically significant for drugs in the CCB and ACE drug categories. These results suggest that internet access has a moderating effect on detailing, learning, and the impact of popularity, and we use simulations to quantify the implications.

Specifically, we use simulations to estimate the Average Marginal Effect (AME) of a 1% increase in the explanatory variables detailing, learning, and popularity on the probability of prescribing a drug. Table 6 describes the AME for all three explanatory variables (based on the coefficients from model 5). The lower and the upper bounds of the 95% confidence interval are also reported.

6.2. *The effect of detailing on prescription choice*

The first row in Table 6 shows that face-to-face detailing meetings positively impact the utility of prescribing the detailed drug. More specifically, we can see that, on average, a 1% increase in detailing leads to a 0.15%, 0.51%, 0.18%, and 0.74% increase in utility of prescribing a drug in the categories Statins, ACE, CCB, and ARB, respectively. These figures are consistent with the average elasticity of detailing of 0.39 reported in a review of around 28 prior studies in various drug categories (Kremer et al., 2008). These findings support Hypothesis 2 of the study for all four drug categories under consideration.

To understand how the internet influences the elasticity of detailing, we perform a counterfactual experiment. In this experiment, we hold internet access constant at minimum (21%), 1st quartile (32%), 3rd quartile (57%), and maximum (73%) levels and estimate the elasticity of detailing using the three-step iterative AME simulation procedure described earlier. Figure 1 contrasts the detailing elasticities for the different levels of internet penetration.

We can see in Figure 1 that, for all of four drug categories, the elasticity of detailing declines with increasing internet access. At the lowest level of internet penetration (i.e., 21%), a 1% increase in the detailing leads to an average increase of 0.44%, 0.75%, 0.38%, and 1.2% of the utility of prescribing a drug in the categories Statins, ACE, CCB, and ARB, respectively. However, at higher levels of internet penetration, this effect reduces; at 73% internet penetration, the effect of detailing reduces to −0.01%,

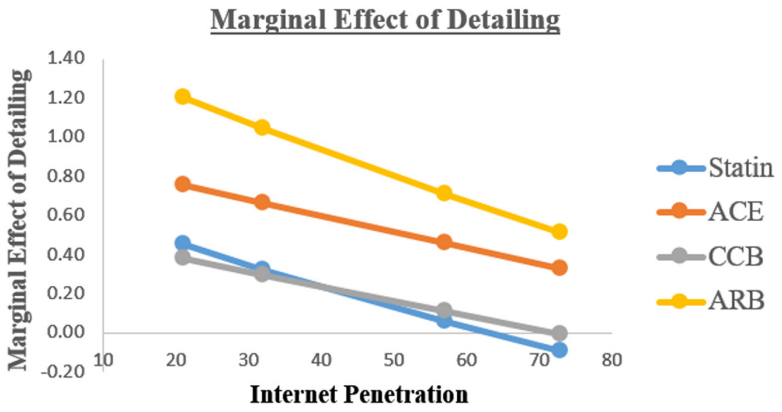

Figure 1. Marginal effect of detailing (high vs. low internet).

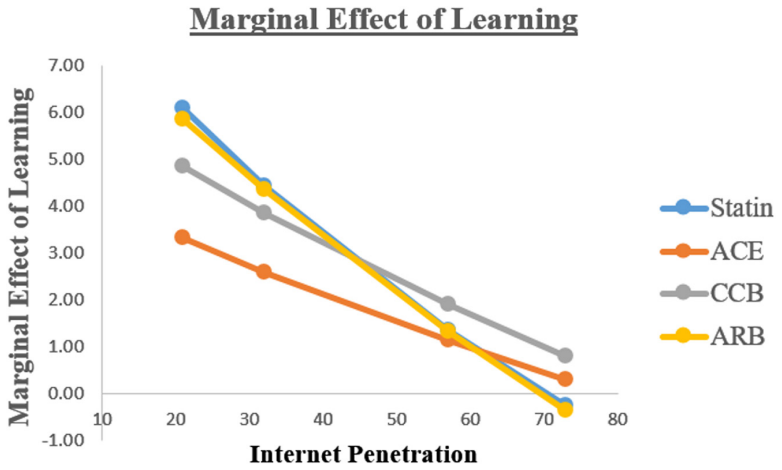

Figure 2. Internet vs. marginal effect of prior learning.

0.32%, −0.001%, and 0.50%, respectively. On average, we observe that a 25% increase in internet penetration from 32% (1st quartile) to 57% (3rd quartile) leads to a 53% decline in detailing's positive elasticity. These findings support the hypothesis that increasing internet penetration leads to an overall decrease in the effect of detailing on prescription choices.

6.3. *The effect of prior learning on prescription choice*

Table 6 (second row) observes that the marginal effect of prior learning on prescription choice is, on average, higher than detailing or drug popularity. More specifically, on average, a 1% increase in learning leads to 1.3%, 1.2%, 1.9%, and 1.2% increase in utility of prescribing a drug in Statins, ACE, CCB, and ARB drug categories, respectively.

Like in Section 6.2, we again perform a counterfactual experiment to understand how the internet influences prior learning elasticity. The results are shown in Figure 2. The study observes a declining trend in the elasticity of prior learning for all four drug categories. At the lowest levels of internet penetration (i.e., 21%), a 1% increase in the learning leads to an average increase of 6%, 3%, 4%, and 5% of the utility of prescribing a drug in the categories Statin, ACE, CCB, and ARB, respectively. However, at 73% internet penetration, the effect of a 1% increase in learning reduces to −0.2%, 0.2%, 0.7%, and −0.4%, respectively. On average, we find that a 25% increase in internet penetration from 32% (1st quartile) to 57% (3rd quartile) leads to a 62% decline in the positive elasticity of prior learning. The decline in prior learning elasticity is about 9% more than that of detailing for a 25% increase in internet penetration. Hence, the first hypothesis of this study is supported for all four categories of prescription drugs under consideration.

6.4. *The effect of drug popularity on prescription choices*

Table 6 (third row) shows that the average marginal effect of drug popularity on prescription choices

is significant and positive for three of the four-drug categories. A 1% increase in drug popularity leads to a 0.64%, 0.51%, and 0.61% increase in the utility of prescribing the drug in Statins, CCB, and ARB drug categories. While for drugs in the ACE category, the Average Marginal Effect of drug popularity is significant and slightly negative at −0.36%. ACE is a more established therapeutic subcategory with drugs of potentially similar efficacy. It appears that the prescription choices in this category are less reliant on popular opinion due to sufficient diffusion of knowledge about these drugs among physicians.

We again perform a counterfactual experiment to understand how the internet influences the elasticity of drug popularity. The results are shown in Figure 3. In contrast to our findings from the prior sections, the results are now mixed. The elasticity of drug popularity increases with the internet for drugs in Statin and ARB categories while decreasing for drugs in CCB and ACE categories. Therefore, Hypothesis 3 is only supported for drugs in categories Statin and ARB.

The study finds that a 25% increase in internet penetration from 32% to 57%, the elasticity of drug popularity increases from 0.3% to 0.7%, and from 0.01% to 0.7% for prescription drugs in the Statin and ARB categories, respectively (Figure 3). In contrast, drug popularity elasticity decreases from −0.1% to −0.4% and from 0.7% to 0.5% for molecules in CCB and ACE categories, respectively. In this 10-year study (from 1997 to 2006), six new prescription drugs were launched in the Statin and ARB categories, with just two launched in CCB and ACE categories. New product launch activity is directly related to research activity, and this has the potential to stimulate scientific collaborations and knowledge sharing among the profession (Ding et al., 2010).

The increase in internet access has facilitated collaboration among physicians, thereby compounding drug popularity in prescription choices. Hence, greater internet penetration would expose the physicians to a collective pool of shared information where the most popular drug benefits from positive word of mouth. Our finding is consistent with previous studies arguing that product popularity is self-reinforcing and influences consumer perception of product quality (Salganik, 2006; Cai et al., 2009; Chen et al., 2011).

6.5. *Robustness checks and alternative explanations*

The prescription pattern for a drug may be time-dependent. For instance, some drugs may exhibit seasonality (e.g., during the influenza season). While our models in Tables 2–5 control for the effect of time *via* the inclusion of the variable control '*week*', it is possible that the impact of time materializes differently. To that end, we explored additional model specifications with quarterly fixed effects (see Appendix A.2). The results of these specifications were similar and directionally consistent with our benchmark model 5, and they did not increase the overall model fit.

It is also possible that internet diffusion affects patient consultations rather than how physicians prescribe drugs. Hence, we also test if there is any relationship between the internet and the number of prescriptions written over time by the physicians; after controlling for the time trend, the relationship between internet access and the number of a prescription written in any of the four categories is not significant with an alpha level of 0.05

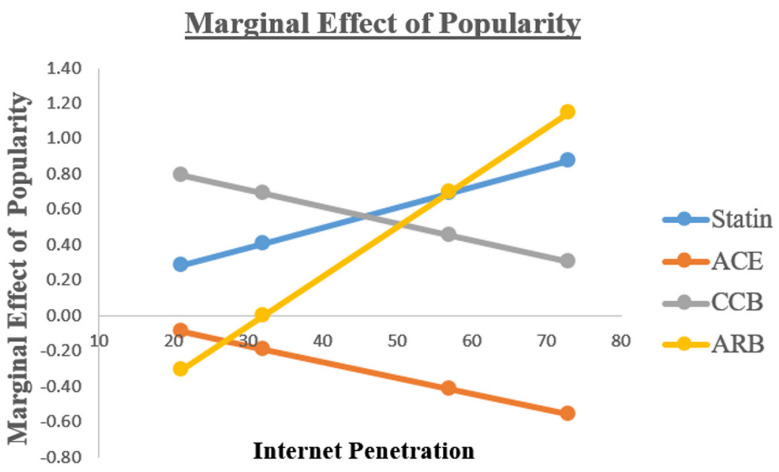

Figure 3. Marginal effect of drug popularity vs. internet penetration.

Table 2. Model statistics for statin

	Model 1	Model 2	Model 3	Model 4	Model 5
Detailing	–0.00	0.02*	0.01	0.01	0.058***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Learning	0.05***	0.18***	0.36***	0.38***	0.36**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.008)
Popularity	1.48***	0.82	0.93	0.04	0.127
	(0.13)	(0.53)	(0.61)	(0.66)	(0.663)
Detailing: Internet		–0.06**	–0.07***	–0.06**	–0.153***
		(0.02)	(0.02)	(0.02)	(0.022)
Learning: Internet		–0.23***	–0.55***	–0.55***	–0.549***
		(0.01)	(0.01)	(0.01)	(0.0153)
Popularity: Internet		1.73	1.77	4.44***	3.385**
		(0.94)	(1.08)	(1.18)	(1.185)
Residuals					–0.02*
					(0.0089)
Controls[1]	Yes	Yes	Yes	Yes	Yes
Random parameters	No	No	Yes	Yes	Yes
Correlated random parameters	No	No	No	Yes	Yes
AIC	25,022	24,555	22,724	22,485	22,505
Log Likelihood	–12,494	–12,257	–11,336	–11,201	–11,211
McFadden R. Squared	0.1596	0.17552	0.2374	0.24655	0.24593
Num. obs.	16,037	16,037	16,037	16,037	16,037

***$P<0.001$, **$P<0.01$, *$P<0.05$,
[1]Control variables: Patient_Age*Drug, Dr_Sex*Drug, YOG*Drug, SOP*Drug, Time (weeks)*Drug, Internet*Drug.

(P-value = 0.269).[2] See Appendix A.3 for robustness analyses.

7. Discussion

Increasing internet access and the subsequent rise in user-generated content have affected how physicians receive and process pharmaceutical R&D information in prescribing decisions. Yet, understanding exactly how the internet has affected physician prescribing behavior over time has been limited to date. This study contributes to filling this void by empirically estimating the moderation effect of the internet on the impact of prior learning, detailing, and drug popularity on prescription choices. 0.

A key finding from this study is that the increase in internet penetration over time has reduced the impact of face-to-face detailing on prescribing decisions. Across all four drug categories studied, we find that, on average, a 25% increase in internet penetration is associated with a 53% decrease in the elasticity of face-to-face detailing. A similar trend is also evident in the media industry, where new online resources reduce print advertising effectiveness (Chandra and Kaiser, 2014). However, no prior studies have considered the geographic variations in access to the internet in the prescribing region, which we incorporate in our analyses.

The study also finds that the internet makes physicians less reliant on their prior choices when making prescribing decisions. Habit or prescribing inertia of physicians has always been a concern for the regulatory bodies.

Interestingly, our findings also complement a recent study of the US pharmaceutical market (where DTCA for drugs is allowed), which found that physicians with access to drug information from reference databases prescribed a more diverse set of prescription drugs and adopted new medical innovations earlier (Arrow et al., 2016). Whether this decline in prescribing inertia leads to improved patient well-being or medical outcomes is still to be determined and presents a future area for investigation.

Finally, the study finds that the increase in access to the internet can increase the likelihood of prescribing a more popular prescription drug. A drug's popularity is akin to its attractiveness for a similar diagnosis among the prescribers' peers. There are many causes of popularity, including quality, effectiveness, promotion, or institutional factors. User-generated content on the internet plays an important role in highlighting a prescription drug's

Table 3. Model statistics for Calcium Channel Blockers (CCBs)

	Model 1	Model 2	Model 3	Model 4	Model 5
Detailing	0.04***	0.13***	0.27***	0.57***	0.37***
	(0.01)	(0.04)	(0.05)	(0.06)	(0.08)
Learning	0.11***	0.33***	0.60***	0.53***	0.69***
	(0.00)	(0.01)	(0.01)	(0.02)	(0.019)
Popularity	1.31***	1.87*	4.79***	6.47***	3.95***
	(0.25)	(0.77)	(0.95)	(1.10)	(1.03)
Detailing: Internet		−0.19*	−0.57***	−1.13***	−0.502***
		(0.08)	(0.10)	(0.13)	(0.1107)
Learning: Internet		−0.38***	−0.60***	−0.61***	−0.83***
		(0.02)	(0.02)	(0.03)	(0.0032)
Popularity: Internet		−1.56	−8.69***	−11.69***	−3.75
		(1.46)	(1.78)	(2.02)	(2.096)
Residuals					−0.129*
					(0.0612)
Controls	Yes	Yes	Yes	Yes	Yes
Random parameters	No	No	Yes	Yes	Yes
Correlated random parameters	No	No	No	Yes	Yes
AIC	15,975	15,569	12,933	12,811	12,784
Log Likelihood	−7,963.92	−7,757.92	−6,433.66	−6,357.73	−6,343
McFadden R. Squared	0.23323	0.25306	0.38056	0.38787	0.3869
Num. obs.	8,811	8,811	8,811	8,811	8,811

***$P<0.001$, *$P<0.05$.

popularity among physicians and their patients. The data limitations do not permit the direct analysis of the impact of specific services provided through the internet on prescription choices. However, the flexible model specification used in the study accounts for cross-correlations in physician sensitivity to detailing, prior learning, and drug popularity and captures physician-specific differences in drug choice.

7.1. Research implications

Our findings have implications for policymakers as well as drug manufacturers' marketing efforts to promote pharmaceutical innovations. For example, our counterfactual simulations show that failing to account for internet access can lead to an overestimation of detailing elasticity in high internet penetration regions and an underestimation of detailing elasticity in low internet penetration regions. To meet the sales target, marketers should either increase detailing in regions with high internet penetration or utilize non-traditional promotion channels.

The study demonstrates empirical evidence of changing physician prescribing habits, which can be used to accelerate the adoption of pharmaceutical innovations and R&D. Professional digital platforms can inform pharmaceutical companies about the importance of a physician in the knowledge network, which can then be strategically used to promote innovations for faster diffusion. As a result, the study has implications for the diffusion of innovation. The study lends empirical support to previous research by arguing for the specialization of gatekeeper functions to compete with modern sources of information (Whelan et al., 2010).

Understanding the effect of declining prescribing inertia among physicians with increasing internet penetration could also be useful for policymakers. How does this decrease in prescribing inertia affect the health of patients? Do patient drug requests prompted by online content contribute to this declining prescription inertia?

The role of pharmaceutical detailing is not eliminated but evolved. In the absence of the internet, physicians assimilated scant information on product research findings, but in the digital age, they have access to more reliable and extensive knowledge in the form of peer-to-peer learning, patient stories, and online forum feedback. This longitudinal study illustrates the shift in prescribing patterns among physicians because of the proliferation of the internet. The

Table 4. Model statistics for ACE Inhibitor (ACE)

	Model 1	Model 2	Model 3	Model 4	Model 5
Detailing	0.05***	0.27***	0.19***	0.16***	0.547***
	(0.01)	(0.03)	(0.03)	(0.03)	(0.04)
Learning	0.09***	0.21***	0.38***	0.42***	0.425***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.009)
Popularity	0.94***	2.92***	1.53	1.84*	0.365
	(0.27)	(0.76)	(0.88)	(0.91)	(0.979)
Detailing: Internet		−0.38***	−0.19***	−0.19***	−0.476***
		(0.05)	(0.05)	(0.06)	(0.0637)
Learning: Internet		−0.21***	−0.38***	−0.53***	−0.537***
		(0.01)	(0.01)	(0.02)	(0.016)
Popularity: Internet		−5.14**	−1.67	−3.00	−3.54
		(1.68)	(1.94)	(1.99)	(2.05)
Residuals					−2.52***
					(0.021)
Controls	Yes	Yes	Yes	Yes	Yes
Random Parameters	No	No	Yes	Yes	Yes
Correlated Random Parameters	No	No	No	Yes	Yes
AIC	23,938	23,541	20,232	20,127	20,041
Log Likelihood	−11,945	−11,743	−10,083	−10,015	−9,971
McFadden R. Squared	0.2950	0.3069	0.38056	0.4049	0.4115
Num. obs.	13,273	13,273	13,273	13,273	13,273

***$P<0.001$, **$P<0.01$, *$P<0.05$.

Table 5. Model statistics for Angiotensin II receptor blockers (ARB)

	Model 1	Model 2	Model 3	Model 4	Model 5
Detailing	0.09***	0.08*	0.15***	0.18***	0.376***
	(0.01)	(0.04)	(0.04)	(0.05)	(0.0543)
Learning	0.15***	0.54***	1.32***	1.32***	1.75***
	(0.00)	(0.02)	(0.03)	(0.05)	(0.053)
Popularity	0.95***	−0.63	−0.34	−6.22***	−5.29***
	(0.29)	(0.87)	(1.15)	(1.62)	(1.507)
Generic	5.83***	6.02***	6.00***	6.40***	6.76***
	(0.78)	(0.80)	(0.83)	(1.22)	(1.102)
Detailing: Internet		0.02	0.01	−0.16^{+}	−0.323*
		(0.07)	(0.08)	(0.08)	(0.085)
Learning: Internet		−0.66***	−1.22***	−1.94***	−2.57***
		(0.04)	(0.04)	(0.08)	(0.104)
Popularity: Internet		3.49	1.69	16.74***	16.63***
		(1.91)	(2.50)	(3.39)	(3.14)
Residuals					−0.109***
					(0.0209)
Controls	Yes	Yes	Yes	Yes	Yes
Random Parameters	No	No	Yes	Yes	Yes
Correlated Random Parameters	No	No	No	Yes	Yes
AIC	13,897	13,630	10,961	10,926	10,864
Log Likelihood	−6,909.87	−6,773.03	−5,432.92	−5,400.12	−5,352.4
McFadden R. Squared	0.2647	0.2792	0.4218	0.4253	0.4304
Num. obs.	5,614	5,614	5,614	5,614	5,614

***$P<0.001$, *$P<0.05$, $^{+}P<0.1$.

Table 6. Average marginal effects (in %) using Model 5

Variable\ molecule	STATIN			ACE			CCB			ARB		
	Mean	CI 2.5%	CI 97.5%	Mean	CI 2.5%	CI 97.5%	Mean	CI 2.5%	CI 97.5%	Mean	CI 2.5%	CI 97.5%
Detailing	0.15%	0.01%	0.28%	0.51%	0.47%	0.55%	0.18%	0.13%	0.23%	0.74%	0.61%	0.85%
Learning	1.33%	0.89%	1.76%	1.23%	1.03%	1.43%	1.94%	1.70%	2.18%	1.18%	1.03%	1.32%
Popularity	0.64%	0.63%	0.65%	–0.36%	–0.36%	–0.35%	0.51%	0.50%	0.51%	0.613%	0.61%	0.62%

abundance of explicit information sources necessitates the employment of specialists with experience in gatekeeping roles (Whelan et al., 2010). These findings should aid in the development of strategies to increase the adoption of pharmaceutical R&D by emphasizing online marketing and distinguishing the function of detailing visits to physicians.

Multiple developing nations have embraced advances in ICTs to boost their economies by promoting innovative startups that offer digital services, such as those related to knowledge management (Ben Khalifa, 2022). Additionally, pharmaceutical R&D companies should invest in knowledge management solutions to synthesize the vast amount of health care information available online in order to enhance their products (Ben Khalifa, 2022). The firms should promote and highlight R&D to the platform-visiting health professionals.

The healthcare industry is highly regulated, and the confidentiality of patient information is essential for maintaining patient–physician trust. Prior research has observed physicians' reluctance to interact with patients on online forums, suggesting that privacy regulations can affect patient–physician interactions in virtual communities (Ventola, 2014). Clarity on the rules of online engagement with patients and peers should inspire physicians to share their experiences with greater assurance. Governments around the world have also taken measures to censor groups, individuals, and online networks for political reasons. Online censorship and surveillance have a negative impact on digital engagement and should be avoided (Chan et al., 2022). In order to encourage experiential learning in online communities and forums, it is essential to implement regulation carefully.

Individuals and organizations alike are capitalizing on and leveraging the utilization of digital platforms to facilitate innovation and decision-making. However, the integration of Internet-based knowledge into organizational processes or individual decision-making presents a number of obstacles (Chesbrough, 2019). Future research should investigate how the internet's impact on prescribing options has affected patient outcomes.

8. Conclusion

The study finds significant variations in the prescribing patterns of the physicians and their response to the marketing actions of drug manufacturers. Physicians' prescription decisions play an important role in transferring pharmaceutical R&D to the patients. The significant decline in the responsiveness of the physicians to face-to-face detailing and

the stronger influence of peer prescription choices should encourage drug manufacturers to rethink their marketing strategy to improve the diffusion of pharmaceutical innovations to the general population. The reduced importance of prior prescription choices in new prescribing decisions with rising internet penetration demonstrates changes in the mindset of the providers and an intent to experiment with medical information available from online sources.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

Ahmed, I. (2018). *How Much Data is Generated Every Minute? [Infographic] [WWW Document]*. Social Media Today. Retrieved 17 September 2022, from https://www.socialmediatoday.com/news/how-much-data-is-generated-every-minute-infographic-1/525692/

Amednews.com. (2010) Amednews.com. Retrieved 23 May 2020, from https://amednews.com/article/20100104/business/301049966/7/.

Arrow, K.J., Bilir, L.K., and Sorensen, A. (2016) Information and Innovation Diffusion: The Case of Pharmaceuticals in the United States. Retrieved 25 December 2019, from https://www.ssc.wisc.edu/~sorensen/papers/ABS%20draft%2010jul2016.pdf

Azoulay, P. (2002) Do pharmaceutical sales respond to scientific evidence? *Journal of Economics and Management Strategy*, **11**, 4, 551–594.

Bardasi, E., Jenkins, S.P., Sutherland, H., Levy, H., and Zantomio, F. (2012) British household panel survey derived current and annual net household income variables. *Waves*, **1–18**, 1991–2009.

Barzilai-Nahon, K. (2008) Toward a theory of network gatekeeping: a framework for exploring information control. *Journal of the American Society for Information Science and Technology*, **59**, 9, 1493–1512. https://doi.org/10.1002/asi.20857.

Ben Khalifa, A. (2022) Impact of research and development (R&D) and information, and communication technology (ICT) on innovation and productivity evidence from Tunisian manufacturing firms. *Economics of Transition and Institutional Change*. https://doi.org/10.1111/ecot.12340.

Berndt, E.R., Bui, L.T., Lucking-Reiley, D.H., and Urban, G.L. (1997) The roles of marketing, product quality, and price competition in the growth and composition of the U.S. antiulcer drug industry. In: *The Economics of New Goods*. Chicago, IL: University of Chicago Press. pp. 277–328.

Berndt, E.R., Bui, L., Reiley, D.R., and Urban, G.L. (1995) Information, marketing, and pricing in the U.S. antiulcer drug market. *American Economic Review*, **85**, 2, 100–105.

Berndt, E., Gibbons, R., Kolotilin, A., and Taub, A. (2015) The heterogeneity of concentrated prescribing behavior: theory and evidence from antipsychotics. *Journal Of Health Economics*, **40**, 26–39. https://doi.org/10.1016/j.jhealeco.2014.11.003.

Briñol, P. and Petty, R. (2009) Source factors in persuasion: a self-validation approach. *European Review of Social Psychology*, **20**, 1, 49–96.

Cai, H., Chen, Y., and Fang, H. (2009) Observational learning: evidence from a randomized natural field experiment. *American Economic Review*, **99**, 3, 864–882. https://doi.org/10.1257/aer.99.3.864.

Caner, T., Cohen, S.K., and Pil, F. (2017) Firm heterogeneity in complex problem solving: a knowledge-based look at invention. *Strategic Management Journal*, **38**, 9, 1791–1811. https://doi.org/10.1002/smj.2615.

Cajita, M.I., Cajita, T.R., and Han, H.-R. (2016) Health literacy and heart failure: a systematic review. *Journal of Cardiovascular Nursing*, **31**, 121–130. https://doi.org/10.1097/JCN.0000000000000229.

Chan, M., Yi, J., and Kuznetsov, D. (2022) Government digital repression and political engagement: a cross-national multilevel analysis examining the roles of online surveillance and censorship. *The International Journal of Press/Politics*. https://doi.org/10.1177/19401612221117106.

Chandra, A. and Kaiser, U. (2014) Targeted advertising in magazine markets and the advent of the internet. *Management Science*, **60**, 7, 1829–1843. https://doi.org/10.1287/mnsc.2013.1830.

Chen, Y., Wang, Q., and Xie, J. (2011) Online social interactions: a natural experiment on word of mouth versus observational learning. *Journal of Marketing Research*, **48**, 2, 238–254. https://doi.org/10.1509/jmkr.48.2.238.

Chesbrough, H. (2019) *Open Innovation Results: Going Beyond the Hype and Getting Down to Business*. Oxford: Oxford University Press. https://doi.org/10.1093/oso/9780198841906.001.0001.

Chinburapa, V., Larson, L., Brucks, M., Draugalis, J., Bootman, J., and Puto, C. (1993) Physician prescribing decisions: the effects of situational involvement and task complexity on information acquisition and decision making. *Social Science & Medicine*, **36**, 11, 1473–1482.

Connelly, D.P., Rich, E.C., Curley, S.P., and Kelly, J.T. (1990) Knowledge resource preferences of family physicians. *The Journal of Family Practice*, **30**, 3, 353–359.

Cross, R. and Cummings, J.N. (2004) Tie and network correlates of individual performance in knowledge-intensive work. *Academy of Management Journal*, **47**, 6, 928–937. https://doi.org/10.5465/20159632.

Davenport, T.H. and Glaser, J. (2002) Just-in-time delivery comes to knowledge management. *Harvard Business Review*, **80**, 107–111.

Dewan, S., Ganley, D., and Kraemer, K.L. (2010) Complementarities in the diffusion of personal computers and the internet: implications for the global digital

divide. *Information Systems Research*, **21**, 925–940. https://doi.org/10.1287/isre.1080.0219.

Ding, W., Levin, S., Stephan, P., and Winkler, A. (2010) The impact of information technology on academic scientists' productivity and collaboration patterns. *Management Science*, **56**, 9, 1439–1461.

Doak, S. and Assimakopoulos, D. (2007) How forensic scientists learn to investigate cases in practice. *R&D Management*, **37**, 2, 113–122. https://doi.org/10.1111/j.1467-9310.2007.00467.x.

Donath, J. (2007) Signals in social supernets. *Journal Of Computer-Mediated Communication*, **13**, 1, 231–251.

Enkel, E., Bogers, M., and Chesbrough, H. (2020) Exploring open innovation in the digital age: a maturity model and future research directions. *R&D Management*, **50**, 1, 161–168. https://doi.org/10.1111/radm.12397.

Euro.who.int. (2016) http://www.euro.who.int/__data/assets/pdf_file/0007/98422/Private_Medical_Insurance_UK.pdf

Feldman, J. and Lynch, J. (1988) Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior. *Journal Of Applied Psychology*, **73**, 3, 421–435.

Frank, R. (1987) Shrewdly irrational. *Sociological Forum*, **2**, 1, 21–41. https://doi.org/10.1007/bf01107892.

Frank, R. and Zeckhauser, R. (2007) Custom-made versus ready-to-wear treatments: behavioral propensities in physicians' choices. *Journal of Health Economics*, **26**, 6, 1101–1127.

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

Hansen, M.T. and Haas, M.R. (2001) Competing for attention in knowledge markets: electronic document dissemination in a management consulting company. *Administrative Science Quarterly*, **46**, 1, 1–28. https://doi.org/10.2307/2667123.

IBM. (2006) https://www-935.ibm.com/services/us/imc/pdf/g510-3242-effective-e-detailing.pdf

Janakiraman, R., Dutta, S., Sismeiro, C., and Stern, P. (2008) Physicians' persistence and its implications for their response to promotion of prescription drugs. *Management Science*, **54**, 6, 1080–1093. https://doi.org/10.1287/mnsc.1070.0799.

Kappe, E. and Stremersch, S. (2016) Drug detailing and doctors' prescription decisions: the role of information content in the face of competitive entry. *Marketing Science*, **35**, 6, 915–933.

Khazzaka, M. (2019) Pharmaceutical marketing strategies' influence on physicians' prescribing pattern in Lebanon: ethics, gifts, and samples. *BMC Health Services Research*, **19**, 1, 80. https://doi.org/10.1186/s12913-019-3887-6.

Kleinen, A., Scherp, A., and Staab, S. (2014) Interactive faceted search and exploration of open social media data on a touchscreen mobile phone. *Multimedia Tools and Applications*, **71**, 1, 39–60. https://doi.org/10.1007/s11042-013-1366-3.

Kremer, S.T.M., Bijmolt, T.H.A., Leeflang, P.S.H., and Wieringa, J.E. (2008) Generalizations on the effectiveness of pharmaceutical promotional expenditures. *International Journal of Research in Marketing, Marketing and Health*, **25**, 234–246. https://doi.org/10.1016/j.ijresmar.2008.08.001.

Kyle, G.J., Nissen, L.M., and Tett, S.E. (2008) Pharmaceutical company influences on medication prescribing and their potential impact on the quality use of medicines. *Journal of Clinical Pharmacy and Therapeutics*, **33**, 5, 553–559. https://doi.org/10.1111/j.1365-2710.2008.00948.x.

Livingston, S. and Bennett, W.L. (2003) Gatekeeping, indexing, and live-event news: is technology altering the construction of news? *Political Communication*, **20**, 363–380. https://doi.org/10.1080/10584600390244121.

Magrini, N. and Font, M. (2007) Direct to consumer advertising of drugs in Europe. *BMJ*, **335**, 526. https://doi.org/10.1136/bmj.39310.506308.AD.

Malone, M., Harris, R., Hooker, R., Tucker, T., Tanna, N., and Honnor, S. (2004) Health and the Internet—changing boundaries in primary care. *Family Practice*, **21**, 189–191. https://doi.org/10.1093/fampra/cmh215.

McFadden, D. (1980) Econometric models for probabilistic choice among products. *The Journal of Business*, **53**, 3, S13–S29.

Menon, N., Lee, B., and Eldenburg, L. (2000) Productivity of information systems in the healthcare industry. *Information Systems Research*, **11**, 1, 83–92.

Morgan, S., Lopert, R., and Greyson, D. (2008) Toward a definition of pharmaceutical innovation. *Open Medicine*, **2**, 1, e4–e7.

Myers, M. (2020) What you need to know about Doctors.net.UK. Mike Myers. https://mikemyers.co.uk/doctors-net-uk/

Nair, H., Manchanda, P., and Bhatia, T. (2010) Asymmetric social interactions in physician prescription behavior: the role of opinion leaders. *Journal of Marketing Research*, **47**, 5, 883–895.

Nauhaus, S., Luger, J., and Raisch, S. (2021) Strategic decision making in the digital age: expert sentiment and corporate capital allocation. *Journal of Management Studies*, **58**, 7, 1933–1961. https://doi.org/10.1111/joms.12742.

Npalliance.org. (2013) Retrieved 4 February 2020, from http://npalliance.org/2013/05/14/how-drug-reps-size-up-doctors/

Patroni, J., von Briel, F., and Recker, J. (2022) Unpacking the social media–driven innovation capability: how consumer conversations turn into organizational innovations. *Information & Management*, **59**, 3, 103267. https://doi.org/10.1016/j.im.2020.103267.

Petrin, A. and Train, K. (2010) A control function approach to endogeneity in consumer choice models. *Journal of Marketing Research*, **47**, 1, 3–13. https://doi.org/10.1509/jmkr.47.1.3.

Phan, P., Wright, M., and Lee, S.-H. (2017) Of robots, artificial intelligence, and work. *Academy of Management Perspectives*, **31**, 4, 253–255. https://doi.org/10.5465/amp.2017.0199.

QuantiaMD (2011, September 8) *Over 65% of Physicians Have used Social Media to Support Their*

Professional Practice. Fierce Healthcare. https://www.fiercehealthcare.com/healthcare/over-65-physicians-have-used-social-media-to-support-their-professional-practice.

Randhawa, K., Wilden, R., and West, J. (2019) Crowdsourcing without profit: the role of the seeker in open social innovation. *R&D Management*, **49**, 3, 298–317. https://doi.org/10.1111/radm.12357.

Robson, A. and Robinson, L. (2015) The information seeking and communication model. *Journal of Documentation*, **71**, 5, 1043–1069.

Rossi, P.E. and Allenby, G.M. (2003) Bayesian statistics and marketing. *Marketing Science*, **22**, 304–328.

Salganik, M. (2006) Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, **311**, 5762, 854–856. https://doi.org/10.1126/science.1121066.

Shang, S.S.C., Yao, C.-Y., and Liou, D.-M. (2017) The effects of knowledge interaction for business innovation. *R&D Management*, **47**, 3, 337–351. https://doi.org/10.1111/radm.12130.

Shurtz, I. (2022) Heuristic thinking in the workplace: evidence from primary care. *Health Economics*, **31**, 8, 1713–1729. https://doi.org/10.1002/hec.4534.

Singer, J.B. (2006) Stepping back from the gate: online newspaper editors and the co-production of content in campaign 2004. *Journalism & Mass Communication Quarterly*, **83**, 265–280. https://doi.org/10.1177/107769900608300203.

Statista (2022) *Internet Penetration of Households 2000–2020*. Statista. https://www.statista.com/statistics/272765/internet-penetration-of-households-in-the-united-kingdom-uk/

Stock, J., Wright, J., and Yogo, M. (2002) A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, **20**, 4, 518–529. https://doi.org/10.1198/073500102288618658.

Surani, Z., Hirani, R., Elias, A., Quisenberry, L., Varon, J., Surani, S., and Surani, S. (2017) Social media usage among health care providers. *BMC Research Notes*, **10**, 1, 654. https://doi.org/10.1186/s13104-017-2993-y.

Tang, C. (2016) Accessed external knowledge, centrality of intra-team knowledge networks, and R&D employee creativity. *R&D Management*, **46**, S3, 992–1005. https://doi.org/10.1111/radm.12160.

Train, K.E. (2009) *Discrete Choice Methods with Simulation*, 2nd edn. Cambridge, MA: Cambridge University Press. https://doi.org/10.1017/CBO9780511805271.

Tucker, C. and Zhang, J. (2011) How does popularity information affect choices? A field experiment. *Management Science*, **57**, 5, 828–842. https://doi.org/10.1287/mnsc.1110.1312.

Tversky, A. and Kahneman, D. (1974) Judgment under uncertainty: Heuristics and biases. *Science*, **185**, 4157, 1124–1131. https://doi.org/10.1126/science.185.4157.1124.

University of Essex, Institute for Social and Economic Research. (2014). *British Household Panel Survey, Waves 1-18, 1991-2009: Conditional Access, Acorn Type 2013* [data collection]. UK Data Service. SN: 7447. https://doi.org/10.5255/UKDA-SN-7447-1.

Venkataraman, S. and Stremersch, S. (2007) The debate on influencing doctors' decisions: are drug characteristics the missing link? *Management Science*, **53**, 11, 1688–1701.

Ventola, C.L. (2014) Social media and health care professionals: benefits, risks, and best practices. *P T*, **39**, 491–520.

van de Wal, N., Boone, C., Gilsing, V., and Walrave, B. (2020) CEO research orientation, organizational context, and innovation in the pharmaceutical industry. *R&D Management*, **50**, 2, 239–254. https://doi.org/10.1111/radm.12394.

Viard, V.B. and Economides, N. (2015) The effect of content on global internet adoption and the global "digital divide.". *Management Science*, **61**, 3, 665–687. https://doi.org/10.1287/mnsc.2013.1875.

Von Knoop, C., Deborah, L., Silverstein, B., Tutty, M., (2003). *Vital Signs: E-health in the United States*. Boston, MA: The Boston Consulting Group, Inc.

Wald, H., Dube, C., and Anthony, D. (2007) Untangling the web – the impact of internet use on health care and the physician–patient relationship. *Patient Education and Counseling*, **68**, 3, 218–224. https://doi.org/10.1016/j.pec.2007.05.016.

Whelan, E., Golden, W., and Donnellan, B. (2013) Digitising the R&D social network: revisiting the technological gatekeeper. *Information Systems Journal*, **23**, 197–218. https://doi.org/10.1111/j.1365-2575.2011.00384.x.

Whelan, E., Teigland, R., Donnellan, B., and Golden, W. (2010) How internet technologies impact information flows in R&D: reconsidering the technological gatekeeper. *R&D Management*, **40**, 4, 400–413. https://doi.org/10.1111/j.1467-9310.2010.00610.x.

Who.int. (2021). WHO. [online] Available at: https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds) [Accessed 26 September 2022].

Wieringa, S., Engebretsen, E., Heggen, K., and Greenhalgh, T. (2018) How knowledge is constructed and exchanged in virtual communities of physicians: qualitative study of Mindlines online. *Journal of Medical Internet Research*, **20**, 2, e8325. https://doi.org/10.2196/jmir.8325.

Wieringa, J.E., Osinga, E.C., Conde, E.R., Leeflang, P.S.H., and Stern, P. (2014) Modeling the effects of promotional efforts on aggregate pharmaceutical demand: what we know and challenges for the future. In: Ding, M., Eliashberg, J., and Stremersch, S. (eds), *Innovation and Marketing in the Pharmaceutical Industry. International Series in Quantitative Marketing*. Volume 20. New York, NY: Springer. https://doi.org/10.1007/978-1-4614-7801-0_20.

Wooldridge, J.M. (2002) *Econometric Analysis of Cross Section and Panel Data*, 1st edn. Cambridge and London: MIT Press.

Yang, M., Lien, H., and Chou, S. (2013) Is there a physician peer effect? Evidence from new drug prescriptions. *Economic Inquiry*, **52**, 1, 116–137. https://doi.org/10.1111/ecin.12022.

Notes

[1] For completeness the 10 Government Office Regions considered in the study are: London, East Midlands, Yorkshire and Humber, South East, East of England, South West, Scotland, North West, West Midlands, Wales, North East. See https://publications.parliament.uk/pa/cm200607/cmselect/cmcomloc/352/35204.htm for additional details.

[2] Additionally, the in-sample evidence is consistent with general demographic trends for cardiovascular disease (CVD) in the UK over the last 20 years, which have been stable despite increasing internet penetration. Figure 5 from Bhatnagar *et al*. (2016) shows CVD prevalence during our study period.

Utkarsh Shrivastava is an Assistant Professor in the Department of Business Information Systems of the Haworth College of Business at Western Michigan University. Dr. Shrivastava holds a Ph.D. in Information Systems and Decision Sciences from the University of South Florida. His research concentrates in the areas of health informatics, business analytics, and technological solutions to societal problems. In particular, he has examined the application of AI for patient triaging, impact of privacy regulations in health information exchange, and the role of ICT in creating new businesses and reducing corruption. Shrivastava's research is published in several top-tiered peer-reviewed journals, including in several A* and A outlets in the ABDC journal list. He also has been the recipient of a US patent in the applications of AI in health care. Dr. Shrivastava has also served as the editor of international journals and chaired several international gatherings.

Daniel Zantedeschi is an Assistant Professor at the Muma College of Business, University of South Florida. He holds a Ph.D. degree from the University of Texas at Austin and has had previous appointments at the University of Pennsylvania and the Ohio State University. His research interests are in business analytics with applications to Marketing, Information Systems, and Public Health.

Wolfgang Jank is the Anderson Professor of Global Management in the School of Information Systems and Management. He teaches classes in statistics and data mining in the masters, MBA, and Executive MBA programs. An author of more than 80 refereed articles, Jank's research focuses on the application of statistics and data mining to data-driven problems in marketing, information systems, and operations management. He has published in journals such as the Journal of Forecasting, the INFORMS Journal of Computing, Marketing Science, the Journal of the American Statistical Association, the Journal of the Royal Statistical Society and the Annals of Applied Statistics. He was awarded the best Information Systems Publication in 2008. He has written three books and has presented his work at national and international meetings. Jank earned a PhD in statistics from the University of Florida and a master's degree in mathematics from the Technical University of Aachen (Germany). Prior to joining the Muma College of Business, he was an associate professor in the Department of Decisions, Operations & Information Technologies and served as the director of the Center for Complexity in Business at the University of Maryland's Smith School of Business.

Philip Stern is Professor and Senior Marketing Scientist at the Ehrenberg-Bass Institute at the University of South Australia and Chairs their European Board. He is also Professor of Marketing at Exeter Business School. He previously worked at Loughborough, Bangor and at Warwick Business School. He has published many articles in journals including Management Science, Journal of the Academy of Marketing Science, International Journal of Research in Marketing, European Journal of Marketing, Journal of Consumer Behaviour, International Journal of Forecasting, Industrial Marketing Management, Marketing Letters, Journal of Business Research, Journal of Advertising Research, Long Range Planning, British Journal of Management, Omega, Journal of Brand Management, Communications Law. He has managed and contributed to numerous executive courses for companies including Moneycorp, HSBC, TNT, Barclay's, Diageo, Unilever and Carlsberg. Philip is an active consultant and clients have included GfK, Glaxo Smith Kline, Novartis, Lilly Industries, Organon, Compufile, HMSL, Procter and Gamble, Bristol Myers Squibb, IMS, Premier Farnell and the National Audit Office.

APPENDIX A

A.1 IDENTIFICATION STRATEGY

Our methodological development posits that the endogenous $Detailing_{dit}$ component can be represented as a function of the variables entering the utility function (Molecule-specific and Case-specific variables) and instruments that do not directly affect the prescription utility but do impact the endogenous detailing and its interaction with the internet.

Therefore, the first instrument we employ is the number of patient visits (visits) in the last quarter (13 weeks) for

a physician. Marketing plans are typically reviewed on a quarterly basis to incorporate the latest market information. Hence, an increase in the number of patients visiting a physician could attract more detailing ('Npalliance.org', 2013). However, the number of patient arrivals in a quarter to a physician can be considered an outcome of an exogenous process, having no relationship with the perceived utility of prescribing a specific drug. In other words, we expect the instrument to affect the detailing received by the physicians but does not affect the attractiveness of any prescription drug under consideration, after controlling for the detailing. The endogeneity of detailing also renders the interaction $Detailing \times Internet$ potentially endogenous (Wooldridge, 2002, p. 234). We included the corresponding interactions between our instrument and the internet (visits × Internet) in our stage 1 model to address this concern, as suggested by Wooldridge (2002, Chap. 9).

First, the endogenous detailing variable, $Detailing_{dit}$, is regressed against all the observed explanatory variables in equation (4) and the instruments. The residuals from the first stage regression represent the control function or unobserved factors. In the second stage, the final model (equation 4) is estimated with a control variable, the first-stage residuals (or control function, *CF*).

The *CF* method is also useful for discrete choice models (Petrin and Train, 2010). We test the instrumental approach's validity using the F-test for the first-stage regression model's instruments. When the test statistic exceeds 10, it is reliable (Stock et al., 2002). Our smallest test statistic was 37 for Statin drugs, indicating a strong correlation between our instruments and the endogenous variable. Indeed, a doctor's patient visits in the previous quarter correlates with detailing for all four prescription drug categories.

A.2 MODEL 5 WITH QUARTERLY DUMMIES FIXED EFFECT

Table A2 below shows the estimates for model 5 with additional quarterly dummies to account for the seasonal effects. The inclusion of the quarterly dummies leads to a marginal change in the strength while preserving the direction of the relationship between the variables of interest.

Table A2. Model 5 with quarterly dummies

	Drug category			
	CCB	ACE	Statin	ARB
TILD:(intercept)	18.711			
	(16.511)			
FELO:(intercept)	−26.120*			
	(14.808)			
ADAL:(intercept)	27.624*			
	(14.226)			
LISI:(intercept)		32.064**		
		(12.986)		
PERI:(intercept)		−44.645***		
		(15.171)		
RAMI:(intercept)		15.357		
		(13.205)		
PRAV:(intercept)			38.500***	
			(11.545)	
SIMV:(intercept)			−1.176	
			(6.971)	
IRBE:(intercept)				33.930**
				(17.078)
LOSA:(intercept)				80.808***
				(18.448)
OLME:(intercept)				142.106***
				(30.070)
TELM:(intercept)				99.632***
				(24.455)
VALS:(intercept)				43.568**
				(19.539)
Detailing	0.498***	0.628***	0.020	0.361***
	(0.081)	(0.042)	(0.013)	(0.052)
Learning	0.566***	0.433***	0.349***	1.471***
	(0.019)	(0.010)	(0.009)	(0.054)
Popularity	4.113***	−1.444	0.189	−6.592***
	(1.041)	(0.976)	(0.664)	(1.604)
Detailing: Internet	−0.858***	−0.642***	−0.064***	−0.386***
	(0.123)	(0.064)	(0.023)	(0.087)
Learning: Internet	−0.703***	−0.545***	−0.518***	−2.122***
	(0.032)	(0.016)	(0.014)	(0.089)
Popularity: Internet	−4.522**	1.612	3.872***	19.154***
	(2.054)	(2.091)	(1.187)	(3.325)
Generic Availability	NA	NA	NA	6.254***
				(1.056)
Residuals	−0.089	−0.245***	−0.003	−0.114***
	(0.060)	(0.020)	(0.009)	(0.022)

Table A2. (Continued)

	Drug category			
	CCB	ACE	Statin	ARB
TILD:Internet	−0.351			
	(1.536)			
FELO: Internet	−0.589			
	(0.990)			
ADAL: Internet	−0.034			
	(1.107)			
TILD:Pat_Age	0.013***			
	(0.004)			
FELO:Pat_Age	0.010***			
	(0.003)			
ADALPat_Age	0.005			
	(0.003)			
TILDPr_Size	−0.034			
	(0.032)			
FELO:Pr_Size	−0.013			
	(0.039)			
ADAL:Pr_Size	0.020			
	(0.028)			
TILD:Qual_Date	−0.009			
	(0.008)			
FELO:Qual_Date	0.014*			
	(0.007)			
ADAL:Qual_Date	−0.013*			
	(0.007)			
TILD:Dr_SexM	−0.037			
	(0.152)			
FELO:Dr_SexM	0.290**			
	(0.117)			
ADAL:Dr_SexM	0.063			
	(0.127)			
TILD:week	−0.003**			
	(0.001)			
FELO:week	−0.002**			
	(0.001)			
ADAL:week	−0.002**			
	(0.001)			
TILD:quarter2	0.199			
	(0.145)			
FELO:quarter2	0.075			
	(0.102)			
ADAL:quarter2	0.090			
	(0.118)			
TILD:quarter3	0.321**			
	(0.150)			
FELO:quarter3	0.189*			
	(0.103)			

(Continues)

Table A2. (Continued)

	Drug category			
	CCB	ACE	Statin	ARB
ADAL:quarter3	−0.022			
	(0.120)			
TILD:quarter4	0.191			
	(0.149)			
FELO:quarter4	0.174*			
	(0.103)			
ADALquarter4	0.050			
	(0.118)			
LISI: Internet		0.162		
		(0.957)		
PERI: Internet		2.546**		
		(1.056)		
RAMI: Internet		1.822*		
		(1.008)		
LISI:Pat_Age		−0.003		
		(0.003)		
PERI:Pat_Age		0.003		
		(0.004)		
RAMI:Pat_Age		0.002		
		(0.003)		
LISI:Pr_Size		0.109***		
		(0.023)		
PERI:Pr_Size		0.049*		
		(0.029)		
RAMI:Pr_Size		0.082***		
		(0.025)		
LISI:Qual_Date		−0.018***		
		(0.007)		
PERI:Qual_Date		0.020***		
		(0.008)		
RAMI:Qual_Date		−0.010		
		(0.007)		
LISI:Dr_SexM		0.035		
		(0.100)		
PERI:Dr_SexM		−0.221*		
		(0.120)		
RAMI:Dr_SexM		0.123		
		(0.108)		
LISI:week		0.003***		
		(0.001)		
PERI:week		0.004***		
		(0.001)		
RAMI:week		0.003***		
		(0.001)		
LISI:quarter2		−0.092		
		(0.111)		

(Continues)

Table A2. (Continued)

	Drug category			
	CCB	ACE	Statin	ARB
PERI:quarter2		0.132		
		(0.128)		
RAMI:quarter2		0.073		
		(0.109)		
LISI:quarter3		0.013		
		(0.112)		
PERI:quarter3		0.042		
		(0.130)		
RAMI:quarter3		0.094		
		(0.111)		
LISI:quarter4		−0.165		
		(0.112)		
PERI:quarter4		−0.152		
		(0.129)		
RAMI:quarter4		0.012		
		(0.111)		
PRAV: Internet			−1.447	
			(0.897)	
SIMV: Internet			2.000***	
			(0.543)	
PRAV:Pat_Age			0.011***	
			(0.003)	
SIMV:Pat_Age			0.011***	
			(0.002)	
PRAV:Pr_Size			−0.072***	
			(0.023)	
SIMV:Pr_Size			−0.022	
			(0.014)	
PRAV:Qual_Date			−0.019***	
			(0.006)	
SIMV:Qual_Date			0.0001	
			(0.004)	
PRAV:Dr_SexM			0.153	
			(0.097)	
SIMV:Dr_SexM			0.077	
			(0.059)	
PRAV:week			−0.001	
			(0.001)	
SIMV:week			−0.001*	
			(0.001)	
PRAV:quarter2			−0.045	
			(0.096)	
SIMV:quarter2			−0.005	
			(0.059)	
PRAV:quarter3			0.015	
			(0.098)	

(Continues)

Table A2. (Continued)

	Drug category			
	CCB	ACE	Statin	ARB
SIMV:quarter3			0.214***	
			(0.059)	
PRAV:quarter4			−0.037	
			(0.098)	
SIMV:quarter4			0.088	
			(0.060)	
IRBE: Internet				1.854
				(1.302)
LOSA: Internet				−1.758
				(1.284)
OLME: Internet				−3.372
				(2.320)
TELM: Internet				−6.069***
				(1.908)
VALS: Internet				−3.145**
				(1.456)
IRBE:Pat_Age				−0.003
				(0.004)
LOSA:Pat_Age				0.014***
				(0.004)
OLME:Pat_Age				−0.002
				(0.007)
TELM:Pat_Age				−0.001
				(0.006)
VALS:Pat_Age				0.003
				(0.005)
IRBE:Pr_Size				0.103***
				(0.031)
LOSA:Pr_Size				0.050
				(0.031)
OLME:Pr_Size				−0.106*
				(0.057)
TELM:Pr_Size				−0.014
				(0.046)
VALS:Pr_Size				0.130***
				(0.035)
IRBE:Qual_Date				−0.017**
				(0.009)
LOSA:Qual_Date				−0.041***
				(0.009)
OLME:Qual_Date				−0.068***
				(0.016)
TELM:Qual_Date				−0.050***
				(0.012)
VALS:Qual_Date				−0.022**
				(0.010)

(Continues)

Table A2. (Continued)

	Drug category			
	CCB	ACE	Statin	ARB
IRBE:Dr_SexM				0.468***
				(0.163)
LOSA:Dr_SexM				0.050
				(0.157)
OLME:Dr_SexM				0.236
				(0.316)
TELM:Dr_SexM				0.177
				(0.224)
VALS:Dr_SexM				0.200
				(0.175)
IRBE:week				−0.002
				(0.001)
LOSA:week				−0.001
				(0.001)
OLME:week				−0.005*
				(0.003)
TELM:week				0.003
				(0.002)
VALS:week				0.001
				(0.001)
IRBE:quarter2				0.075
				(0.156)
LOSA:quarter2				0.162
				(0.159)
OLME:quarter2				−0.043
				(0.258)
TELM:quarter2				0.035
				(0.211)
VALS:quarter2				−0.229
				(0.173)
IRBE:quarter3				−0.079
				(0.157)
LOSA:quarter3				−0.072
				(0.163)
OLME:quarter3				−0.561**
				(0.269)
TELM:quarter3				−0.282
				(0.213)
VALS:quarter3				−0.464***
				(0.172)
IRBE:quarter4				−0.175
				(0.161)
LOSA:quarter4				−0.108
				(0.168)
OLME:quarter4				−0.506*
				(0.267)

(Continues)

Table A2. (Continued)

	Drug category			
	CCB	ACE	Statin	ARB
TELM:quarter4				–0.536**
				(0.221)
VALS:quarter4				–0.642***
				(0.177)
Observations	8,811	13,273	16,037	5,614
R^2	0.386	0.413	0.246	0.429
Log Likelihood	–6,381.922	–9,947.337	–11,209.430	–5,368.493
LR Test	8,008.791*** (df = 58)	13,996.270*** (df = 58)	7,315.430*** (df = 48)	8,058.030*** (df = 79)

*$P<0.1$,
**$P<0.05$,
***$P<0.01$.

A.3 RELATIONSHIP BETWEEN THE ARRIVAL OF NEW PATIENTS AND INTERNET DIFFUSION

Table A3 below shows the relationship between the internet diffusion and the weekly patient arrivals after controlling for various drug categories and time trend. The dependent variable in both model 1 and model 2 below is the number of patient visits in a week for a physician in the category. We observe that accounting for the weekly time trend diminishes the positive impact of the internet on the new patient arrivals. The reference drug category in both models is Statin.

Table A3. Relationship between patient arrival and internet diffusion

	Model 1			Model 2		
Variable	Estimate	Std. error	*P*-value	Estimate	Std. error	*P*-value
(Intercept)	2.969	0.105	0	1.982	0.499	0
Internet	2.012	0.253	0	–0.097	1.148	0.269
week				0.002	0.001	0.069
Calcium Channel Blockers (CCB)	0.93	0.092	0	0.941	0.091	0
ACE Inhibitor (ACE)	1.132	0.091	0	1.143	0.089	0
Angiotensin II receptor blockers (ARB)	3.28	0.176	0	3.277	0.178	0
Adj. R Squared	0.159			0.161		
Observations	35,015			35,015		