NUNO CAMACHO

Health and Marketing

Essays on Physician and Patient Decision-making

Health and Marketing:

Essays on physician and patient decision-making

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Essays on physician and patient decision-making

Gezondheid en marketing:
Essays over de besluitvorming van de arts en patiënt

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Para a Paula,
Para a minha família (Irene, Maria João, Margarida e Mário),
em memória dos meus avós, Emília, David e João.

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I started my Ph.D. in October 2005, one year after arriving in Rotterdam. I remember that for one of my first meetings with my supervisors, Stefan and Bas, I prepared a *PowerPoint* presentation with a picture illustrating how I perceived the path before me: a mountaineer preparing himself to climb a very high mountain. Since then, I have lived the most intense, but also the most rewarding, period of my adult life while attempting to reach the top of that mountain. As a real mountaineer, I lived moments of extreme excitement, active learning and never stopped being surprised and fascinated by the increasingly beautiful knowledge landscape that opened underneath my eyes. I learned immensely and, through this learning process, I discovered myself and grew. Honestly, as I suspect happens with almost all mountaineers, I also had a few moments of frustration. On those moments, one person was always by my side, remembering that it's in my nature to always keep fighting! Thank you Paula for understanding all the times I couldn't devote more time to you and always be by my side.

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No mountaineer climbs a large mountain all on its own. In the last five years I was extremely lucky to meet many other fellow mountaineers from whom I also learned

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The view from the top of this first mountain is already beautiful. Yet, from here I can also see many other mountains, some of which with peaks well above the peak I'm about to reach … I can only imagine the view one can get from those mountains… and I can't wait to start climbing them ;)!

Nuno Miguel Almeida Camacho

Rotterdam, 27th April 2011

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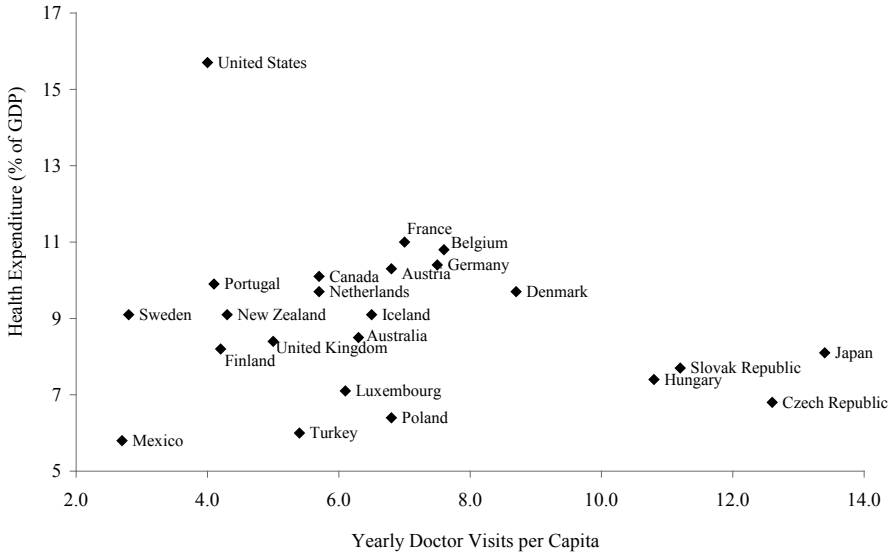
CHAPTER 1: INTRODUCTION

Healthcare, nowadays, represents 6.4% of American consumers' expenses, making it the 5th largest expenditure category for an average household (only surpassed by (i) housing, (ii) transportation, (iii) food and (iv) personal insurance and pensions). In 1989, healthcare represented 5.1% of the expenditures of an average American household, i.e. in 20 years this share grew by more than 25%. In addition, a large fraction of consumer spending in *personal insurance and pensions* represents expenditures in health insurance plans. In fact, according to data from the OECD, in 2010, each citizen in the United States spent, on average, 7,538 USD in health, resulting in a total expenditure of about 15.7% of the GDP of the United States of America (OECD Health Data 2010).

Figure 1.1 Expenditure on health (as % of GDP) vs. Doctor visits per capita



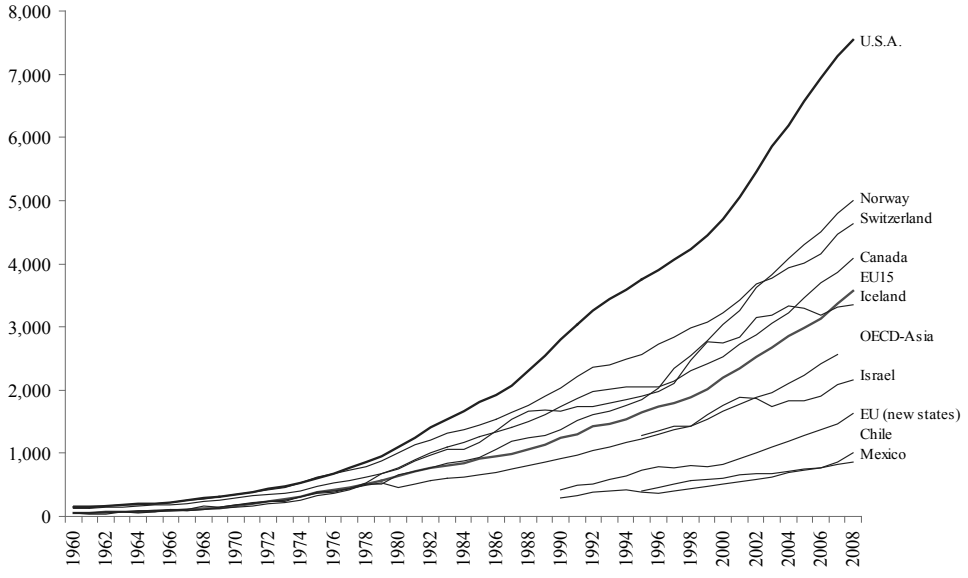
Source: OECD Health Data, 2010

Even though per capita health expenditures in the U.S. are significantly higher than in other developed economies, the fact that healthcare represents a large fraction of the GDP

is common across many countries. Figure 1.1, above, contrasts the number of yearly consumer visits to doctors with health expenditures as a percentage of the GDP. We can see that the vast majority of countries spend between 6% and 11% of their GDP in healthcare and the number of yearly doctor visits ranges from 2.7 in Mexico and 2.8 in Sweden to 11.2 in Slovak Republic, 12.6 in Czech Republic and 13.4 in Japan.

Moreover, consumer spending in healthcare has been rising steadily across the globe (see Figure 1.2), an effect that is expected to accelerate in developed economies, as healthcare expenditures tend to increase steadily as people age (see Figure 1.3).

Figure 1.2 Expenditure on health (per capita, US $ purchasing power parity)

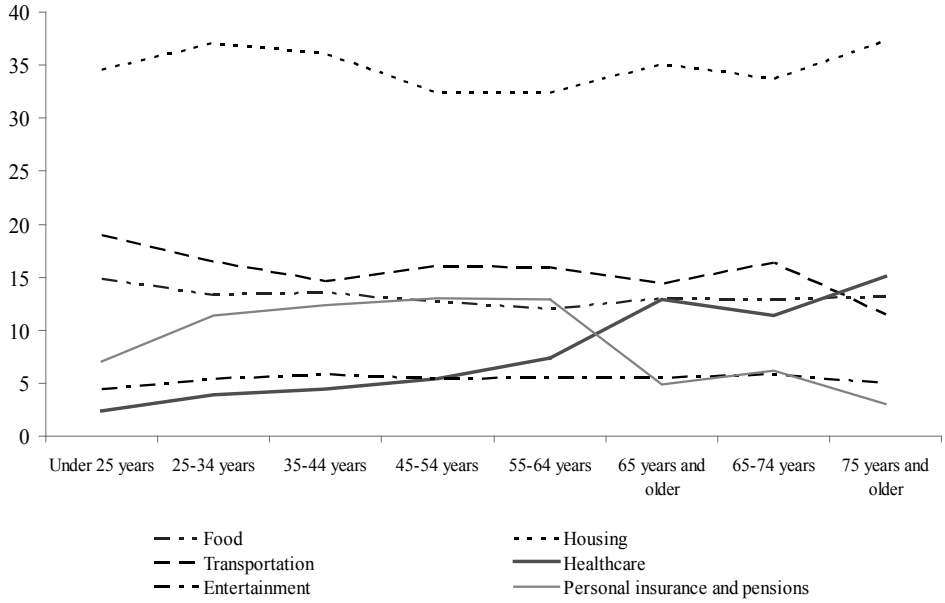


Source: OECD Health Data, 2010

Given the share of wallet of health-related expenditures for consumers, it was rather surprising that, when I started my Ph.D., health marketing was still far from being considered a mainstream research topic within marketing. The situation has meanwhile changed. Most major marketing science conferences and journals now devote considerable effort to improve our understanding of consumer choices and firm strategies in the healthcare industry. In 2008, in response to the crescent interest in health marketing, the

International Journal of Research in Marketing published a special issue on the topic which garnered significant interest and attention (Stremersch 2008).

Figure 1.3 Major expenditures of average American consumers by age of the reference person within a household (October 2010)



Source: Consumer Expenditure Survey, U.S. Bureau of Labor Statistics, October, 2010

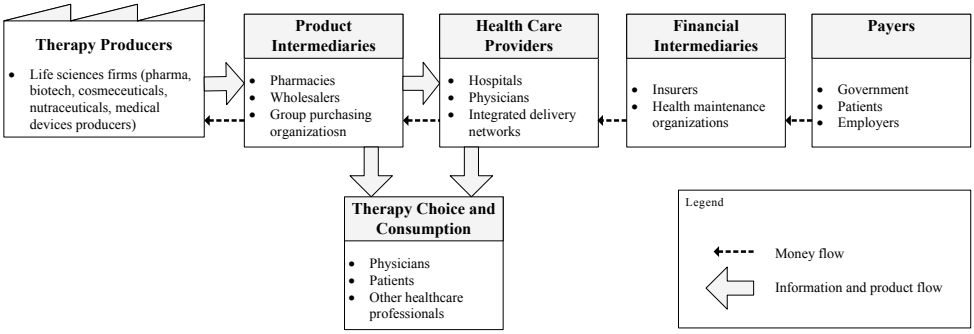
In July 2009, Stremersch and Van Dyck published an article in the *Journal of Marketing* with the goal of organizing the problems faced by pharmaceutical marketers and proposing a research agenda for the nascent field of *Life Sciences Marketing*. The most relevant research topics in life sciences marketing – identified both by academics and industry practitioners - revolved around therapy creation (e.g. innovation alliances, pipeline optimization), therapy launch (e.g. new drug adoption, key opinion leader selection) and therapy promotion (e.g. sales force management, communication management and stimulating patient adherence).

Figure 1.4 summarizes the healthcare value chain. In my dissertation I focus on the consumer side of the healthcare market. More specifically, my goal was to improve our

understanding of therapy choice and consumption, which differs from consumption of other goods in key aspects like consumer involvement in the decision process, a high-consequential consumption context (i.e. a bad choice can have serious psychological and physical consequences for consumer welfare) and the fact that consumption choice requires specialized knowledge often possessed by an expert – the physician – who needs to act in accordance with patient values and preferences. Many marketing scholars have called for research in this area in recent years (Manchanda et al. 2005).

A better understanding of the decision-making processes behind therapy consumption has the potential to generate valuable insights to academics, public health officials and policy makers, consumers and physicians. It can also provide key inputs for managerial decisions. In fact, trustees of the Marketing Science Institute have consistently rated *deeper understanding of consumption behavior* as a key research priority in marketing.

Figure 1.4 The Healthcare Value Chain



Source: Adapted from Stremersch and Van Dyck (2009) and Burns (2005).

Dissertation Outline: Exploring Patient and Physician Decision-Making

Current medical practice is influenced by two major paradigms: evidence-based medicine and the fast-growing paradigm of patient empowerment (Bensing 2000). Evidence-based medicine defends that physicians should make prescription choices based on sound scientific evidence, which need to be integrated with the physician's clinical expertise and intuition. Therefore, evidence-based medicine, which gained popularity among medical scholars during the 1990's (Sacket et al. 1996), has a strong focus on physician expertise

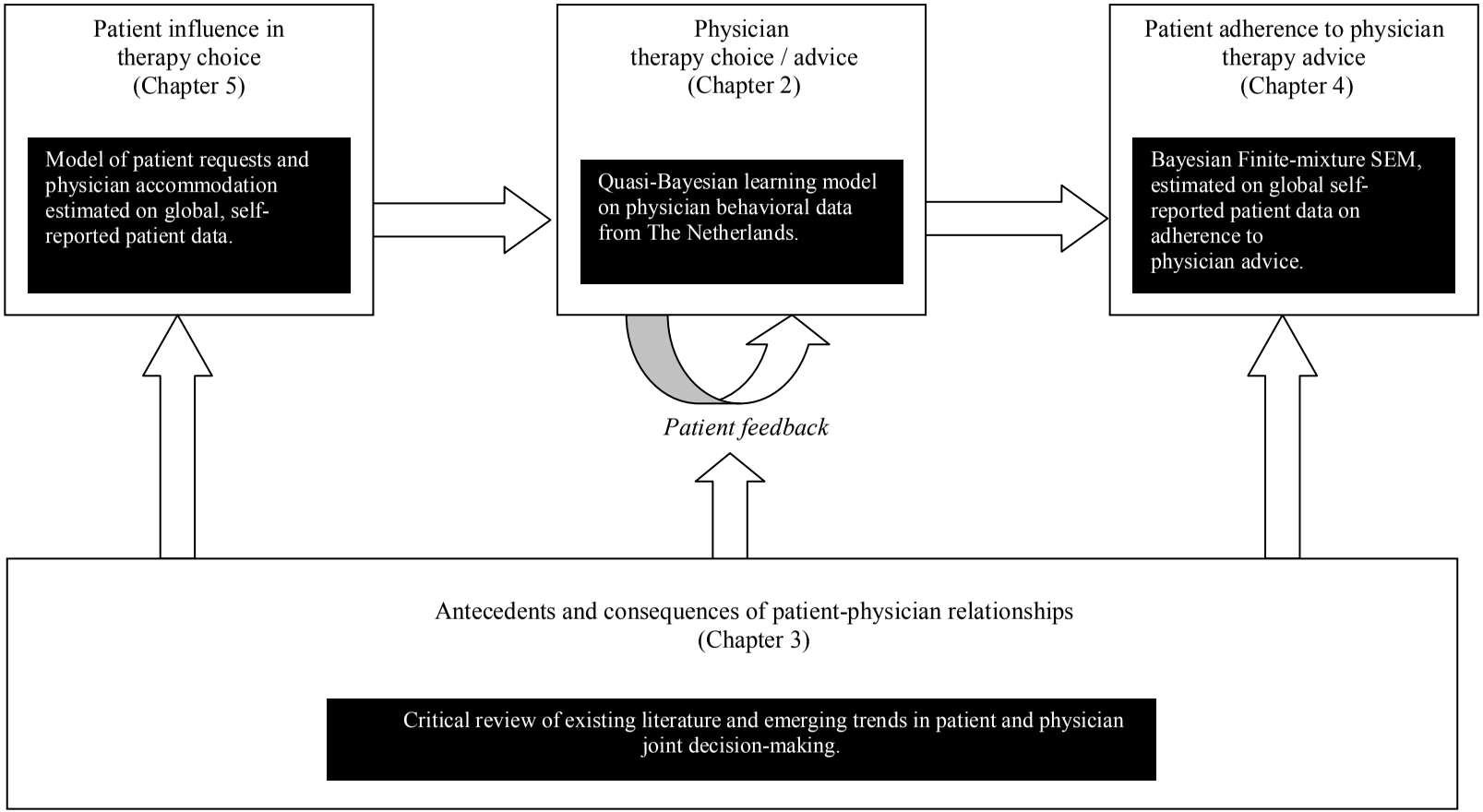
and on available scientific evidence. However, this focus on the physician and the scientific basis of medicine, led many scholars to criticize evidence-based medicine for not being sufficiently patient-centered (Bensing 2000).

The second major paradigm governing modern medical practice - *patient-empowerment* - defends that medical practice should increasingly focus on the patient as an active participant in treatment choice (Epstein, Alper and Quill 2004; Krahn and Naglie 2008). Although the roots of patient empowerment can be traced back to classical medicine (e.g. to the work of Plato, see Emanuel and Emanuel 1992), its popularity in modern medicine is more recent than evidence-based medicine (Bensing 2000). Closely related terms to patient empowerment are terms like patient-centered medicine, participatory medicine and shared decision-making, all of which suggest a more active role for the patient than traditionally found in the more paternalistic "white-coat" model, which assumes physicians choose a therapy on behalf of the patient[1]. The patient empowerment paradigm also fits a more general trend towards higher customer participation in the marketplace (Prahalad and Ramaswamy 2000; Vargo and Lusch 2004). Pharmaceutical industry, policy-makers, physicians and patients cannot afford to ignore this emerging trend as it has the potential to fundamentally change the patient-physician relationship, and consequently the way prescription drugs are chosen during medical encounters.

The different chapters in my dissertation all reflect upon the interaction between patients and physicians and how such interaction reflects on therapy-related decisions. Specifically, in Chapter 2, I focus on the physician and how she learns from patient feedbacks, in Chapter 3, I provide an overview of current trends in patient-physician joint decision-making, and in Chapters 4 and 5, I focus on the patient. Figure 1.5 summarizes the common framework behind my dissertation.

[1] In 2009, a group of medical scholars, concerned with the fact that patients are not sufficiently informed and active in therapy and health decisions, founded the Society for Participatory Medicine (http://participatorymedicine.org/), in order to promote *"a movement in which networked patients shift from being mere passengers to responsible drivers of their health, and in which providers encourage and value them as full partners."* The society has meanwhile launched the *Journal of Participatory Medicine* to promote active research on these topics.

Figure 1.5 Dissertation Outline



In Chapter 2, I explore the effect of *salience* in physician learning (through patient feedbacks) about the quality of a new drug. Salience is a memory-related process through which some pieces of information are easier to retrieve from memory than others. I capture salience effects in physician learning through a Quasi-Bayesian learning structure that extends existing Bayesian learning models. Theoretically, salience interferes with physician learning because physicians become overconfident about the informativeness of the quality feedback signals from switching patients (vis-à-vis other patients). Overconfidence regarding the informativeness of vivid information is a systematic human tendency (Griffin and Tversky 1992). Bayesian updating models are very flexible and, in this chapter, I show that with adequate modification, they can be used to capture these predictable deviations from normative weighting of evidence whereby evidence and prior beliefs are integrated using Bayes' rule. In the proposed quasi-Bayesian model, feedback from switching patients is allowed to receive extra weight. I calibrate this model in a Dutch patient and physician-level panel dataset (obtained through collaboration with the medical school at Erasmus University Rotterdam) with observed prescription choices and show that feedback from switching patients receives between 7 and 10 times more weight than feedback from other patients. I also show that salience results in slower physician learning and, consequently, in slower adoption of the newest treatment in the market I study: treatments for asthma and chronic obstructive pulmonary disease.

In Chapter 3, I discuss new trends in patient-physician relationships, namely the antecedents and consequences of the emergence of patient empowerment as a new paradigm in medical decision-making. I first discuss how (i) demographic and lifestyle changes, (ii) technological changes and (iii) regulatory changes have contributed to the emergence of this new medical decision-making model where patients assume a more active role in therapy choice. I critically review existing literature and discuss the clinical and relational consequences of more patient participation on trust, satisfaction, therapy adherence and patient health improvements. The existing literature suggests that patient empowerment has many positive consequences in these clinical and relational variables. However, such literature is mostly based on conceptual and theoretical arguments and empirical scrutiny is still relatively rare. Moreover, it is also not clear whether the scarce empirical evidence, which is almost exclusively based on the U.S. and a few Western

nations, is generalizable across countries and cultures, which is a serious limitation of the medical decision-making literature (Charles et al. 2006). Therefore, in the next two chapters I use self-reported data from 17 countries, chosen to guarantee a large cross-cultural variation, to empirically study drivers of key patient decisions: adherence to the physician's therapy advice (Chapter 4) and drug requests using brand name (Chapter 5).

In Chapter 4, I study whether patient empowerment leads to higher patient therapy adherence, a topic with high societal and economic relevance. Several scholars in medicine and public health, nowadays, claim that patients should be given power in treatment choices, with the main benefit accredited to patient empowerment being increased patient adherence. Using a novel and richer conceptualization of patient empowerment – one that distinguishes doctor-initiated and patient-initiated informational empowerment from decisional empowerment – I show that patient empowerment can backfire and result in lower therapy adherence[2]. Proponents of patient empowerment find theoretical support for their arguments on self-determination theory, which demonstrates that people tend to show more behavioral persistence and be more confident on their capacity to execute and maintain behavior that is intrinsically motivated (Ryan and Deci 2000). Thus, self-determination theory predicts that patient empowerment leads to higher therapy adherence.

However, self-determination theory ignores important human tendencies that can mitigate some of its beneficial effects, for instance the tendency for people to quickly start overestimating their skills and abilities, a phenomenon known as overconfidence (Daniel, Hirshleifer and Subrahmanyam 1998). In my theoretical framework I thus rely on theories form psychology and behavioral economics to make richer hypotheses for the effects of patient empowerment on therapy adherence. In particular, I rely on spreading activation theories to hypothesize effects of patient empowerment on the key drivers of both reasoned and unintentional non-adherence: comprehension (Mick 1992; Raaijmakers and Shiffrin 1992) and recall (Anderson 1983) of therapy advice, and patient overconfidence (DeBondt and Thaler 1995). These theories predict effects that contradict the predictions of self-determination theory. In short, because asking patients to make treatment choices is cognitively and emotionally taxing, patient comprehension and recall of therapy advice can

[2] Therapy adherence is defined as the extent to which a consumer follows a treatment plan - such as taking medication - in accordance with the recommendations from her medical care provider (World Health Organization 2003).

be hurt by patient empowerment, in contrast to the prediction of self-determination theory. Moreover, when patients choose their own treatment (decisional empowerment), they tend to become overconfident about their capacity to make future treatment decisions (not only therapy choice but also decisions like stopping or altering treatment…), which can lead to lower adherence (e.g. because patient simply stop taking their medication based on an erroneous belief that they do not need more therapy, contrary to the physician's advice). Empirically, I demonstrate that many of these effects indeed drive patient behavior leading to the conclusion that, contrary to current medical wisdom, doctors may be doing a disservice to patients when they ask them to make their own treatment choices.

Finally, in Chapter 5, I discuss the antecedents of patients' requests of drugs by brand name and its consequences on physician accommodation of such requests. I use data collected from the same 11,735 respondents in 17 countries used in Chapter 4. Yet, here I develop a model aimed at understanding the roles of (i) different sources of therapy and health information like word-of-mouth (among patients and between the patient and other healthcare professionals) and mass-media information, (ii) direct-to-physician marketing (samples and promotional materials in the physician's office) and (iv) patient values as antecedents of patient drug requests using brand name. I also study the drivers of physician accommodation of such patient requests and a possible feedback effect from physician accommodation on patients' intention to voice more requests in the future. Two important findings emerge from this chapter.

First, even though mass-media information indeed leads to more patient requests, word-of-mouth (from peers or experts) is a significantly stronger driver of patient requests than mass-media. Moreover, information patients gather through mass-media (or through any other source) doesn't influence physician accommodation of patient requests. Interestingly, we find that direct-to-physician marketing efforts (samples dispensed and promotion materials) do lead to more patient requests, but not to more physician accommodation of patient requests. These findings suggest that policy-makers may be looking at the wrong culprit when they concentrate their energies scrutinizing therapy and health information disseminated via mass-media channels.

Second, patient values – patient goals that serve as life guiding principles and which tend to be trans-situational and relatively homogenous among patients from the same

culture (Schwartz et al. 2001) - emerge as an important driver of patient requests and moderator of the relationship between physician accommodation of patient requests and patients' intention to request drugs by brand name in the future. In fact, patients who hold stronger values of openness to change (i.e. people who value self-direction and a higher level of stimulation) or self-enhancement (achievement and power) are more likely to request drugs by brand name from their physician than patients who hold stronger self-transcendence values (benevolence and universalism). Yet, when self-transcendent patients do make a request for a branded medication, physician accommodation of such request sends a strong signal and significantly increases the likelihood that these patients will make more requests for branded medications in the future.

In sum, my overarching goal, with this dissertation, is to study many important issues in the consumer side of healthcare industry and demonstrate that modeling consumer decision-making allows us to better understand key industry and market dynamics. I focus on decision-making models calibrated in real world individual data in order to obtain generalizable findings, an effort that is not only highly relevant for marketing scholars (Camerer, Ho and Lim 2006), it also allows us to bring novel insights for non-academic stakeholders like managers, policy-makers and consumers. While these models typically come at the cost of increased complexity (either mathematical, theoretical, or both) and more demanding data requirements, they allow us to better understand consumer decisions via the integration of robust insights from different behavioral sciences (e.g. economics, psychology and sociology) in our models.

CHAPTER 2: PREDICTABLY NON-BAYESIAN: QUANTIFYING SALIENCE EFFECTS IN PHYSICIAN LEARNING ABOUT DRUG QUALITY[3]

Scholars in marketing and economics have developed Bayesian updating models for consumer (e.g. Erdem and Keane 1996; Mehta et al. 2008; Roberts and Urban 1988) and physician learning (Coscelli and Shum 2004; Crawford and Shum 2005; Narayanan et al. 2005; Narayanan and Manchanda 2009). Bayesian learning enables researchers to structurally model the evolution of an agent's belief about any uncertain attribute, e.g. about the quality of a product, by integrating new information and prior beliefs using Bayes' rule. Bayes' rule is the normative way to update probabilistic beliefs, i.e. these models assume that decision-makers learn using an optimal rule. However, many scholars claim that the assumptions behind Bayesian learning are not psychologically or cognitively valid (see e.g. Camerer and Loewenstein 2004).

In particular, consumers often deviate from Bayes' rule by giving more weight to more easily accessible, i.e. more salient, pieces of information they retrieve from memory. To model salience effects we propose a quasi-Bayesian learning model. Quasi-Bayesian learning models apply Bayes' rule to subjectively revised evidence or prior beliefs (Epstein 2006; Rabin and Schrag 1999) and may *"become the standard way for translating the cognitive psychology of judgment into a tractable alternative to Bayes' rule"* (Camerer and Loewenstein 2004, p.13).

However, identification and estimation of quasi-Bayesian models is often difficult and empirical applications using revealed preference data are still rare (for notable exceptions, see Mehta et al. 2004 and Mehta et al. 2008). In this paper, we study physician learning about the quality of a new treatment, a context where consumers are particularly sophisticated and involved in the choice process, as the stakes are high. Our proposed model fits in the rapidly growing field of behavioral modeling, a field that seeks to enrich

[3] This chapter is based on Camacho, N., B. Donkers and S. Stremersch (2011), "Predictably Non-Bayesian: Quantifying Salience Effects in Physician Learning about Drug Quality," *Marketing Science*, 30(2), 305-320.

mathematical models of consumer behavior, which are typically normative models, with robust psychological regularities (Häubl et al. 2010; Ho et al. 2006; Narasimhan et al. 2005).

Despite their specialized training, physicians often rely on their intuition and are selective in the use of new information, deviating from normative rules in predictable ways, very much like humans in general (e.g. Croskerry 2002; Elstein and Schwartz 2002; Redelmeier 2005). However, the evidence accumulated about physicians' deviation from optimal reasoning and decision-making so far relies solely on experimental and survey research with physicians (Bornstein et al. 1999; Estrada et al. 1997; Poses and Anthony 1991) and participants role-playing as physicians (Medin et al. 1982) rather than research on actual physician decisions for real patients, as presented in the present paper.

We calibrate our model on a unique panel dataset of Dutch general practitioner prescription behavior in the obstructive airways diseases category (i.e. treatments for asthma and chronic obstructive pulmonary disease). The data was retrieved from the Integrated Primary Care Information database, which is maintained by the School of Medicine of the Erasmus University Rotterdam (for a detailed description see Vlug et al. 1999). This data is particularly well-suited to test whether salience interferes with physicians' formation of treatment quality beliefs and if yes, to what extent. First, physicians in our dataset use *paperless offices* guaranteeing that the full clinical history of their patients gets stored in the database, which allows us to model treatment[4] choices using both new prescriptions and repeat prescriptions. Second, at the start of our observation period, a new treatment - AstraZeneca's Symbicort - was introduced in the category we study, which facilitates identification of dynamics in physicians' quality beliefs.

Our central hypothesis is that patients who the physician switches away from a specific treatment to a clinically equivalent alternative[5] become salient in the physician's

[4] We use the term *treatment* instead of *drug* because our empirical application is focused on treatments with two molecules, a preventive (anti-inflammatory) and a reliever (bronchodilator) either prescribed in two distinct inhalers or combined in a single inhaler device.

[5] Clinically equivalent alternatives are those that can be considered as substitutes in terms of therapeutic indication. Clinical equivalence among the set of treatments we use in our

memory. Consider the case of Dr. Jones, an imaginary general practitioner who sees about five or six patients with asthma complaints per week. Dr. Jones decides to prescribe a new brand - Symbicort - to twenty patients, i.e. about half of the asthma patients he sees in the first eight weeks after the launch of Symbicort. Two of these patients, Mrs. Smith and Mr. Miller, later complain that Symbicort made them dizzy, nauseated and tired. In order to avoid future complaints, Dr. Jones switches Mrs. Smith and Mr. Miller to an older treatment alternative.

In the coming weeks, while meeting with other asthma patients, Dr. Jones recalls the experiences of patients who tried Symbicort and continuously updates his quality beliefs about the new brand. He recalls, from his medical training, that he should consider the experiences of all his patients with the new drug (as large a sample as possible). Yet, Dr. Jones seems to recall the complaints of Mrs. Smith and Mr. Miller much more readily than the feedbacks provided by other patients. The complaints of Mrs. Smith and Mr. Miller are, therefore, particularly influential in Dr. Jones' quality belief-formation about Symbicort and in his adoption decision.

The objective of our model is to extend the Bayesian learning framework to enable it to accommodate the type of salience effects that Dr. Jones experiences while he learns about the quality of Symbicort. We find that a salience effect is indeed present and it affects physician learning. As to its magnitude, we find that feedback from patients who are salient in the physician's mind receives between 7 and 10 times more weight than feedback from other patients**.** Physicians' choices also exhibit within-patient persistence, suggesting that physicians (and patients) perceive a cost to switching treatment.

Finally, our model brings valuable insights for firms launching new therapies, a high-research priority area according to life sciences managers and marketing scholars (Stremersch 2008; Stremersch and Van Dyck 2009). In particular, salience slows down the adoption of new treatments. Using counterfactual simulations, we show that AstraZeneca could have increase its market share by as much as8.5 percentage points by eliminating salience for its new brand (Symbicort). Furthermore, if a policy maker is able to reduce

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model was confirmed by two experts (a lung specialist and the head of the pharmacy department of the medical school at our University).

salience across all treatments, physicians adopt newer combination treatments significantly faster. We explore the managerial and policy implications of these findings.

2. Salience in Physician Learning

We now discuss the antecedents and consequences of salience of patients subject to treatment switching. We also discuss other drivers of prescription choices.

Antecedents of salience of patients subject to treatment switching

Salience may result from medical ethics, cognition and emotion, which we discuss next, each in turn. First, medical practice rests on strong ethical foundations. The motto *primum non nocere* (*first, do no harm*) is a central ethical principle that guides the practice of medicine (Brewin 1994). Thus, physicians are under ethical and legal pressure to avoid any (unnecessary) risk that could potentially harm patients. This pressure may enhance the salience of patients who did not react to a treatment as expected and, consequently, had to be switched to a substitute treatment (an experience the physician wants to minimize in the future).

Second, psychological and neurological research suggests that we react more strongly to undesirable outcomes than to desirable ones (for an overview, see Baumeister et al. 2001 and Rozin and Royzman 2001).During learning and information processing, negative information receives more attention and more elaboration than positive information (Baumeister et al. 2001). Switching a patient to a clinically equivalent treatment is an undesirable outcome for the physician, as it means the patient's reaction to the treatment was different from what the doctor had hoped. Thus, the salience of switching patients may have a cognitive rationale.

Third, treatment switching usually reveals disconfirmation of physician or patient expectations from a treatment. Along the reasoning of Oliver (1993), disconfirmation of expectations provokes not only a cognitive response but also a negative affective response. Moreover, treatment switching can be seen by some patients as a correction to a prior decision and, consequently, perceived by the physician as a threat to her reputation. The ensuing negative emotions alert the physician to the need to eliminate or reduce the trigger of such threats (Taylor 1991). Salience of switching patients will then emerge as a natural

consequence of these affective responses and of the human tendency to respond more strongly to negative than to positive emotions (Cacioppo and Gardner 1999).

Consequences of salience of patients subject to treatment switching

Salience interferes with belief formation through the dynamics of over- and under-confidence about different information signals. Griffin and Tversky (1992) show that when weighting evidence, humans tend to overreact to the extremeness and vividness of information (*strength*) irrespective of its predictive validity (*weight*). Compared with a normative statistical model- where evidence and prior beliefs are integrated using Bayes' rule -experimental subjects in their studies were overconfident about evidence when strength was high and weight was low, but under-confident when strength was low and weight was high.

According to Griffin and Tversky (1992) the overconfidence about salient information results from the combination of two cognitive shortcuts: anchoring and adjustment and representativeness (Tversky and Kahneman 1974). A third cognitive shortcut that can contribute to the influence of salience in belief formation is the availability heuristic (Tversky and Kahneman 1974). Experimental and survey-based research indeed suggests that these heuristics interfere with medical decisions (Klein 2005; Poses and Anthony 1991; Redelmeier 2005).

As a result, we hypothesize that physicians give extra weight to feedback provided by easier to recall patients, i.e. those who are switched to an alternative treatment. The influence of feedback provided by switching patients will thus be systematically stronger than what is predicted by a pure Bayesian learning model.

Other drivers of prescription choices

In addition to quality beliefs, other effects might also drive treatment choices. First, we expect patients to face a switch cost whenever they change treatment, a cost the physician takes into account in her treatment choices. This switch cost is estimated controlling for quality perceptions, so it captures a non-quality based persistence, e.g. the psychological impact of changing treatments or the time and effort associated with switching drugs (see also Chan et al. 2010). Second, treatments can have serious side effects, so physicians may

be risk averse in their treatment choices. Thus, we allow for risk-aversion in our model specification. Note that substantial debate exists on physicians' risk attitude, with some studies finding physicians to be risk neutral (Chintagunta et al. 2009; Narayanan et al. 2005; Narayanan and Manchanda 2009), while others find physicians to be risk averse (Ching and Ishihara 2010; Coscelli and Shum 2004; Crawford and Shum 2005). Third, we control for marketing effects using a reduced-form approach, i.e. by letting marketing expenditures shift the utility levels of each treatment alternative (for a similar approach see Chintagunta et al. 2009).

3. Model Specification

In this section, we first lay down the pure Bayesian learning component of our model. Next, we extend this specification by introducing salience in a quasi-Bayesian fashion. This structure clarifies that our quasi-Bayesian model nests its pure Bayesian counterpart. We close the section with the utility specification. Whenever we use mathematical symbols, i indexes physicians ($i=1,\ldots,N$), p indexes patients ($p=1,\ldots,P_i$ being the patients of physician i), k indexes encounters ($k=1,\ldots,K_i$ being the encounters of physician i)and j indexes treatments ($j=1,\ldots,J$).

Pure Bayesian learning framework

We define mean quality of treatment j for physician I (Q_{ij}) as a general attribute that summarizes how well, across all patients of physician i, the treatment provides symptomatic relief (i.e. relief during asthma attacks) and maintains patient health (i.e. avoids recurrence of such attacks),while avoiding severe side effects (for a similar definition see, e.g., Narayanan et al. 2005). However, a certain treatment j will not work equally well for every patient. Therefore, we explicitly model patient heterogeneity, i.e. the across-patient variability of treatment quality ($\sigma^2_{q,ipj}$), in line with the work of Chintagunta et al. (2009). Thus, we define the true quality of treatment j for patient p, visiting physician i, as the sum of the true mean quality of treatment j across all patients of physician i and a patient-specific deviation from this mean quality, i.e.:

$$Q_{ipj} = Q_{ij} + q_{ipj}\text{, with } q_{ipj} \sim N(0, \sigma^2_{q,ipj}) \tag{2.1}$$

Next, we assume that, at the start of our data, each physician has a prior (uncertain) belief about Q_{ij}, treatment j's mean quality and about q_{ipj}, the patient-treatment idiosyncratic deviation. We specify a normal distribution for these initial beliefs:

$$Q_{0,ij} \sim N(\overline{Q}_{0,ij}, \sigma^2_{Q0,ij}) \tag{2.2}$$

$$q_{0,ipj} \sim N(\overline{q}_{0,ipj}, \sigma^2_{q0,ipj}) \tag{2.3}$$

Here we assume that $\overline{q}_{0,ipj} = 0$, i.e. that when seeing a new patient, physician i believes that the quality of treatment j, for that particular patient, is equal to the population mean. We also assume rational expectations, a common practice in Bayesian learning models (e.g. Crawford and Shum 2005; Narayanan and Manchanda 2009). Under this assumption physicians have correct initial beliefs about mean quality and quality dispersion across patients, even though they do not know the quality of each treatment for a specific patient. In our model this assumption means that $\overline{Q}_{0,ij} = Q_{ij}$ and $\sigma^2_{q0,ipj} = \sigma^2_{q,ipj}$ .Starting from these prior beliefs, physicians learn about treatment quality in order to(i) reduce the uncertainty surrounding their mean quality belief and (ii) learn about each patient's idiosyncratic deviation from a treatment's mean quality.

We assume physicians learn from their clinical experience, i.e. from the feedback provided by their patients. At the start of each medical encounter, a patient provides a feedback signal about the treatment that was prescribed in her last encounter. These feedback signals are truthful but noisy. That is, if at encounter k physician i receives a feedback signal from patient p about treatment j, we assume this feedback signal to be normally distributed:

$$F_{ipj,k} \mid Q_{ipj} \sim N\left(Q_{ipj}, \sigma^2_{F,i}\right) \tag{2.4}$$

Note that Bayesian learning guarantees that, even though patients only provide feedback about the last treatment their physician prescribed them, physician *i*'s treatment choices are influenced by the feedbacks from all patients on all treatments. The information set of physician *i,* at encounter *k*, is then the clinical history of all her patients, which can be summarized by the average of each patient's feedback signals up to and including encounter *k* (denoted $\overline{F}_{ipj,k}$).

Our assumptions of normally distributed prior beliefs and feedback signals guarantees that physician *i*'s posterior beliefs are also normally distributed. Specifically, physician *i*'s posterior belief, at encounter *k*, about the mean (across-patient) quality of treatment *j* is:

$$\widetilde{Q}_{ij,k} \sim N(\overline{Q}_{ij,k}, \sigma^2_{Q,ij,k}) \tag{2.5}$$

The mean and the variance in Equation (2.5) result from the assumption that physician *i* integrates each patient's clinical history ($\overline{F}_{ipj,k}$) with her prior beliefs according to Bayes' rule (Chintagunta et al. 2009; DeGroot 1970; see online Appendix II.A for the derivation). That is, denoting the number of feedbacks provided by patient *p* to physician *i* about treatment *j* up to and including encounter *k* by $n^p_{ij,k}$ we can write:

$$\overline{Q}_{ij,k} = \frac{\sigma^2_{Q,ij,k}}{\sigma^2_{Q0,ij}} \cdot \overline{Q}_{0,ij} + \sum_p \frac{n^p_{ij,k} \cdot \sigma^2_{Q,ij,k}}{\sigma^2_{F,i} + n^p_{ij,k} \cdot \sigma^2_{q,ipj}} \cdot \overline{F}_{ipj,k} , \tag{2.6}$$

where

$$\sigma^2_{Q,ij,k} = \left[1 \big/ \sigma^2_{Q0,ij} + \sum_p n^p_{ij,k} \Big/ \left(\sigma^2_{F,i} + n^p_{ij,k} \cdot \sigma^2_{q,ipj} \right) \right]^{-1} . \tag{2.7}$$

Similarly, physician *i*'s posterior belief, at encounter *k*, about patient *p*'s idiosyncratic deviation from this mean quality is defined as:

$$\widetilde{q}_{ipj,k} \sim N(\overline{q}_{ipj,k}, \sigma^2_{q,ipj,k}) \tag{2.8}$$

The mean, in Equation (2.8), results from physician *i*'s Bayesian updating of her initial prior belief about this deviation ($\overline{q}_{ipj,0}$) with the observed difference between the mean of patient *p*'s feedback signals about treatment *j* up to and including encounter *k* ($\overline{F}_{ipj,k}$) and physician *i*'s belief, at encounter *k*, about the mean quality of treatment *j* across patients ($\overline{Q}_{ij,k}$), i.e.:

$$\overline{q}_{ipj,k} = \frac{\sigma^2_{q,ipj,k}}{\sigma^2_{q0,ipj}} \cdot \overline{q}_{0,ipj} + \frac{n^p_{ij,k} \cdot \sigma^2_{q,ipj,k}}{\sigma^2_{F,i}} \cdot \left(\overline{F}_{ipj,k} - \overline{Q}_{ij,k}\right), \tag{2.9}$$

where

$$\sigma^2_{q,ipj,k} = \left(1 \big/ \sigma^2_{q0,ipj} + n^p_{ij,k} \big/ \sigma^2_{F,i}\right)^{-1}. \tag{2.10}$$

The expected quality (i.e. the mean belief of physician *i*) of prescribing treatment *j* to the patient visiting at occasion *k* is obtained by adding Equations (2.6) and (2.9).We now introduce salience and, afterwards, discuss dynamics in physicians' uncertainty about the quality of each treatment.

Introducing salience

We modify Bayesian learning in order to incorporate the different roles of information weight and information salience, or strength as referred by Griffin and Tversky (1992). Specifically, *weight* depends on (i) the variance of patient feedback signals ($\sigma^2_{F,i}$), (ii) the variances of physician *i*'s prior quality beliefs ($\sigma^2_{Q0,ij}$ and $\sigma^2_{q0,ipj}$) and (iii) the number of feedback signals provided by each patient. We introduce a salience parameter, $\omega_{ipj,k}$, which quantifies the *extra* weight - when compared with the pure Bayesian learning weight – given by physician *i* to the feedbacks of a patient, *p*, who was subject to treatment switching. We define $SWITCH_{ipj,k}$ as a dummy variable that assumes the value one if, before encounter *k*, patient *p* has been switched away from treatment *j* and has not yet been prescribed treatment *j* again (until the start of encounter *k*). We then introduce the impact

of salience in physician i's posterior belief about the mean quality of treatment j as follows:

$$\overline{Q}_{ij,k}^{\omega} = \frac{\psi_{Q,\omega,ij,k}^{2}}{\sigma_{Q0,ij}^{2}} \cdot \overline{Q}_{0,ij} + \sum_{p} \frac{\psi_{Q,\omega,ij,k}^{2} \cdot n_{ij,k}^{p} \cdot (1+\omega_{ipj,k} \cdot SWITCH_{ipj,k})}{\sigma_{F,i}^{2} + n_{ij,k}^{p} \cdot \sigma_{q,ipj}^{2}} \cdot \overline{F}_{ipj,k} \qquad (2.11)$$

where

$$\psi_{Q,\omega,ij,k}^{2} = \left[1 \big/ \sigma_{Q0,ij}^{2} + \sum_{p} n_{ij,k}^{p} \cdot (1+\omega_{ipj,k} \cdot SWITCH_{ipj,k}) \big/ \left(\sigma_{F,i}^{2} + n_{ij,k}^{p} \cdot \sigma_{q,ipj}^{2} \right) \right]^{-1}. \qquad (2.12)$$

Please note that the expression in Equation (2.12) is not the variance of physician i's belief about the mean quality of j as would be the case in a pure Bayesian setting. This is because in our model physicians' beliefs are affected by salience and, hence, they learn in a quasi-Bayesian manner (see Boulding et al. 1999; Rabin and Schrag 1999). After a treatment switch, a physician changes the relative weight she gives to the feedbacks of the switching patient about the abandoned treatment vis-à-vis her prior belief and the feedback of other patients. The resulting posterior belief will, therefore, necessarily depart from a pure Bayesian belief. Given that Bayes' rule is the optimal way to learn, we expect this departure to be manifested in slower learning. In sum, we specify a quasi-Bayesian learning model which incorporates salience effects but is equivalent to a pure Bayesian learning model in case $\omega_{ipj,k}$= 0.

Note that salience predicts a systematic misinterpretation of patient feedbacks about the quality of abandoned treatments. In contrast, salience does not predict any systematic bias in physicians' belief-updating for any other treatment alternative. Therefore, physicians' choice of a new treatment will always reveal physician's preference for that treatment, irrespectively of whether the patient was switched from another treatment or is a new patient[6].

In order to test whether salience is a temporary or permanent phenomenon, and whether its magnitude changes with temporal distance from the focal switch, we operationalize salience using three parameters:

[6] We thank the Associate Editor and an anonymous reviewer for pointing out to us the need to clarify this issue.

$$\omega_{ipj,k} = \omega_{0,i} \cdot \lambda^{\omega}_{ipj,k} + \omega_{\infty,i} \cdot \left(1 - \lambda^{\omega}_{ipj,k}\right) \tag{2.13}$$

with the weight given to the immediate magnitude of salience ($\omega_{0,i}$), vis-à-vis the long-term magnitude of salience ($\omega_{\infty,i}$), decreasing over time as follows: $\lambda^{\omega}_{ipj,k} = 2 \Big/ \left\{1 + \exp\left[\lambda^{\omega}_{i} \cdot \left(\tau(k) - \tau(t^{sw}_{ipj})\right)\right]\right\}$. Here, *τ(k)* denotes the calendar date of encounter *k* and $\tau(t^{sw}_{ipj,k})$ the calendar date of the last occasion when patient *p* had to be switched away from treatment *j* in favor of one of the clinically equivalent treatments. The rate of decay is governed by the parameter λ^{ω}_{i}, which is assumed positive.

If salience interferes with the formation of mean quality beliefs, as specified in Equation (2.11), indirectly, it will also interfere with physicians' beliefs about patient-treatment idiosyncratic deviations, i.e.:

$$\overline{q}^{\omega}_{ipj,k} = \frac{\sigma^2_{q,ipj,k}}{\sigma^2_{q0,ipj}} \cdot \overline{q}_{0,ipj} + \frac{n^{p}_{ij,k} \cdot \sigma^2_{q,ipj,k}}{\sigma^2_{F,i}} \cdot \left(\overline{F}_{ipj,k} - \overline{Q}^{\omega}_{ij,k}\right), \tag{2.14}$$

The posterior belief of a quasi-Bayesian physician about the quality of treatment *j* for patient *p*, visiting at encounter *k* is then again the sum of her posterior belief about the mean quality of treatment *j* ($\widetilde{Q}^{\omega}_{ij,k}$) and her posterior belief about patient *p*'s idiosyncratic deviation from this mean ($\widetilde{q}^{\omega}_{ipj,k}$), i.e.:

$$\widetilde{Q}^{\omega}_{ipj,k} \sim N\left(\overline{Q}^{\omega}_{ij,k} + \overline{q}^{\omega}_{ipj,k}, \sigma^2_{Q,\omega,ipj,k}\right) \tag{2.15}$$

The posterior variance in Equation (2.15) describes how the uncertainty about the quality of treatment *j* for patient *p,* for a quasi-Bayesian physician, evolves over time, i.e.:

$$\begin{aligned}\sigma^2_{Q,\omega,ipj,k} &= \text{var}(\widetilde{Q}^{\omega}_{ipj,k}) \\ &= \text{var}(\widetilde{Q}^{\omega}_{ij,k}) + \text{var}(\widetilde{q}^{\omega}_{ipj,k}) + 2\cdot\text{cov}(\widetilde{Q}^{\omega}_{ij,k}, \widetilde{q}^{\omega}_{ipj,k})\end{aligned} \tag{2.16}$$

We provide the derivation of $\sigma^2_{Q,\omega,ipj,k}$ in online Appendix II.B. If the estimated salience ($\omega_{ipj,k}$) is different from zero, it provides evidence in favor of our hypothesized deviation from Bayesian updating. As a final note, the distribution of physician *i*'s beliefs, across all patients at encounter *k,* results in a structure like the one derived in Chintagunta et al. (2009).

Utility specification

In line with previous research (e.g. Erdem and Keane 1996; Narayanan and Manchanda 2009), we assume that, at each encounter *k*, physician *i* chooses the treatment *j* that, according to her beliefs, maximizes the expected utility of patient *p,* which is given by:

$$U_{ipj,k} = \overline{Q}^{\omega}_{ij,k} + \overline{q}^{\omega}_{ipj,k} - \frac{1}{2}\cdot r_i \cdot \sigma^2_{Q,\omega,ipj,k} + \delta_i \cdot LASTCHOICE_{ipj,k} + MARKETING_{ij,k} + \varepsilon_{ipj,k} \tag{2.17}$$

In this specification r_i is the absolute risk aversion coefficient, which measures each physician's risk attitude. A positive r_i indicates that physicians are risk averse, i.e. less inclined to prescribe a treatment when quality uncertainty is larger. Quality uncertainty enters the utility function via $\sigma^2_{Q,\omega,ipj,k}$, the posterior variance of $\widetilde{Q}^{\omega}_{ipj,k}$, as defined in Equation (2.16). $LASTCHOICE_{ipj,k}$ is a dummy variable assuming the value one if the physician prescribed treatment *j* to patient *p* in their last encounter and δ_i is a parameter capturing switch costs, i.e. a propensity of physician *i* to prescribe to patient *p* the same treatment *j* that had been prescribed in their last encounter. To control for the impact of marketing efforts we use $MARKETING_{ij,k}$, which is a flexible function of the market-level

marketing expenditures[7]. Finally, $\varepsilon_{ipj,k}$ is an error term capturing unobserved drivers of utility at encounter *k*. We assume these errors to be normally distributed and allow for between-treatment co-variation, i.e. $\boldsymbol{\varepsilon}_{\mathbf{ip,k}[\mathrm{Jx1}]} \sim \mathrm{N}(\mathbf{0},\boldsymbol{\Sigma})$. Our data provides a natural structure for the correlations across treatments[8].

4. Data

The market we study is the obstructive airways diseases category (i.e. asthma and chronic obstructive pulmonary disease or COPD), more in particular the class of inhaled corticosteroids (ICS) plus long-acting β_2-agonist (LABA) combinations, in the Netherlands. By 2017, global sales of medications for asthma and COPD are expected to reach $25 billion with ICS plus LABA combinations becoming the leading class in value (Datamonitor 2008). ICS plus LABA combinations are recommended for patients with moderately severe asthma (GINA - Global Initiative for Asthma 2006) and chronic obstructive pulmonary disease (Calverley et al. 2007).

We model treatment choice among eight clinically equivalent treatments. These include six two-inhaler combinations of the three ICS's (Beclomethasone, Budesonide, Fluticasone) and two LABA's (Formoterol and Salmeterol) recommended by clinical guidelines (GINA 2006), and two newer single-inhaler brands – GlaxoSmithKline's Seretide (Fluticasone + Salmeterol; approved in 1999; branded as Advair in the U.S.) and AstraZeneca's Symbicort (Budesonide + Formoterol; approved in 2001). Our data contains the introduction of Symbicort and covers a period of growing popularity, among physicians, of ICS plus LABA combinations, which is an ideal setting to model physician learning about the quality of different treatment alternatives within this category.

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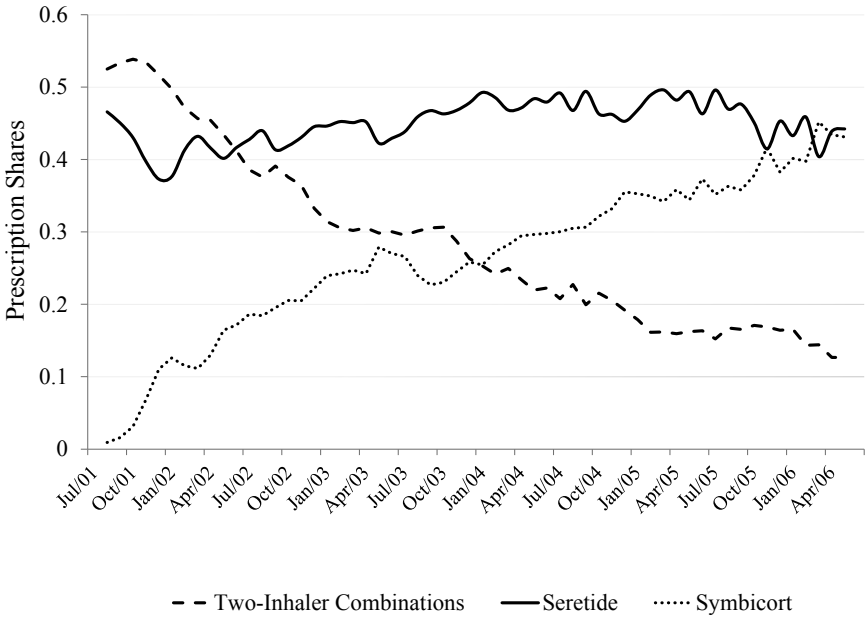
[7] In short, in $MARKETING_{ij,k}$ we integrate two components: (i) temporal responsiveness to marketing actions, assumed equal across physicians and molecules but changing over time and (ii) physician-specific marketing responsiveness, which is assumed constant over time. We will discuss in greater detail our specification of marketing after we have introduced our data.

[8] We distinguish between (i) treatment- and encounter-specific shocks which are independent across treatments and (ii) ingredient- or administration-specific shocks which can affect all treatments which share a certain molecular ingredient or route of administration.

Figure 2.1 depicts the evolution of prescription shares over time, in our sample, of the older two-inhaler treatments and the two newer combination brands. Roughly one year after the start of the observation period, Seretide had a higher prescription share than all the two-inhaler treatments together. Symbicort eventually reached a prescription share similar to Seretide, but only five years after its entry.

Figure 2.1 Prescription shares (three month moving average)



We obtained electronic patient records from July 2001 to June 2006, from the IPCI (Integrated Primary Care Information) database[9], a panel of General Practitioners, maintained by the School of Medicine at our university (for a detailed description see Vlug et al. 1999). These physicians use *paperless offices*, meaning that the system records the full prescription history of each patient, including all refills. The data from this panel is often used for research publications in medicine and pharmaco-epidemiology. Usage of the

[9] In fact, we have access to prescription data before July 2001 but we were only able to gather marketing data, which we will describe shortly, from July 2001 onwards. Still, we used data before July 2001 to initiate the switch cost variable. Moreover, although the formal approval of Symbicort was in January 2001, in our data only two prescriptions are recorded before July 2001.

data is supervised by a board of medical professionals and linking the data to other sources at the individual physician level, is prohibited.

The panel contains both single- and multi-physician practices. To ensure that we model belief-formation using all the relevant clinical experience for each physician, we only use data on single-physician practices. The data contains 2,398 patients across 22 physicians, and 12,186 prescription choices (of ICS plus LABA treatments)[10]. We obtained data on monthly expenditures on marketing (including detailing, journal advertising and conferences), for the respective treatments and time period from IMS Health. We use this data to construct, for each treatment and occasion the marketing variable introduced in Equation (2.17) as follows:

$$MARKETING_{ij,k} = \sum_{l=0}^{L} \left\{ \beta_{1,l}^{Mkt} \cdot \begin{bmatrix} I(two-inhalers) \cdot \left(\beta_{2,i}^{ICS} \cdot \ln(MKT_{j,m(k)-l}^{ICS} + 1) + \beta_{2,i}^{LABA} \cdot \ln(MKT_{j,m(k)-l}^{LABA} + 1)\right) \\ + \left(1 - I(two-inhalers)\right) \cdot \beta_{2,i}^{Comb.} \cdot \ln(MKT_{j,m(k)-l}^{Comb.} + 1) \end{bmatrix} \right\} \quad (2.18)$$

Here, *L=6* represents the number of lagged monthly marketing expenditures that, in our model, affect a treatment's utility, *I(two-inhalers)* is an indicator function assuming the value one if treatment *j* combines the preventive (ICS) and reliever (LABA) molecules in two distinct inhalers, and zero if these two molecules are combined in the same inhaler and *m(k)* indicates the calendar month of encounter *k* (contemporaneous marketing expenditures, i.e. when *l=0,* are adjusted for the timing of the encounter within a given month).

Table 2.1 presents a switching matrix among two-inhaler treatments, Seretide and Symbicort. It shows that physicians tend to switch patients away from two-inhaler treatments to Seretide (140 switches, i.e. 30.1% of the 458 switches) or to Symbicort (84 switches, i.e. 18.3% of the 458 switches). Yet, we also observe 43 switches from Seretide and 35 from Symbicort to two-inhaler treatments (i.e. 78 switches in total, or 17% of the 458 switches) as well as between the Seretide and Symbicort. Column five shows the

[10] In order to avoid concerns with patient drop-out in our data, we have compared the prescription shares in the full sample with the shares among patients who have dropped of the panel and found no significant differences.

switching rate as a percentage of the total number of prescriptions (which are, in turn, displayed in column six).

Table 2.1 Switching matrix

From \ To	Two-inhaler treatments	Seretide	Symbicort	Switch rate	Total number of prescrs.
Two-inhaler treatments	67	140	84	6.24%	3,592
Seretide	43	0	50	1.69%	5,506
Symbicort	35	39	0	2.40%	3,088

Let us now define a spell as a sequence of consecutive prescriptions of the *same treatment* (Crawford and Shum 2005). Table 2.2 shows descriptive statistics for our data. On average, a patient receives five prescriptions. The average number of spells per patient is 1.22 (we observe a total of 2,926 spells across the 2,398 patients) and, on average, each spell consists of 4.16 prescriptions. The average number of spells is very close to previous studies (Chintagunta et al. 2009; Crawford and Shum 2005). The mean length of each spell is larger than prior studies because we deal with patients having a moderate to severe chronic disease.

Table 2.2 Descriptive statistics – Patient visits

Measure	Mean	SD	Min.	Max.
Number of prescription occasions per patient	5.08	5.85	1	50
Number of spells per patient	1.22	0.68	1	10
Spell length	4.16	4.84	1	41

5. Estimation and Identification

Estimation

We estimate our model in a Bayesian fashion, using a Markov Chain Monte Carlo (MCMC) approach. We sample the parameters from their posterior distributions using a Gibbs sampler (see Casella and George 1992 for a review) together with data augmentation that allows us to sample the latent utilities and patient feedbacks alongside the model parameters (Tanner and Wong 1987). In addition, in line with Narayanan and Manchanda (2009), we use a hierarchical Bayes structure to model unobserved physician heterogeneity. We adapt McCulloch and Rossi's (1994) Gibbs sampler for hierarchical multinomial Probit models to account for Bayesian or quasi-Bayesian learning. The main difference, besides having to use data augmentation to sample patient feedbacks, is that we do not have a closed form solution for the posterior distributions of (i) the variances characterizing physicians' initial uncertainty and patient heterogeneity ($\{\sigma^2_{Q0,ij}\}$ and $\{\sigma^2_{q0,ipj}\}$), (ii) the variance of patients' feedbacks ($\sigma^2_{F,i}$) and (iii) the salience parameters ($\omega_{0,i}$, $\omega_{\infty,i}$ and λ^{ω}_{i}). To sample these parameters, we apply a Metropolis-Hastings step (Chib and Greenberg 1995) within our Gibbs-sampler. We specify proper but diffuse priors for all parameters. The exact implementation of our Gibbs sampler is given in online Appendix II.C. We let all chains converge and use 5,000 subsequent draws to obtain parameter estimates.

Identification

The structure of Bayesian learning and the dynamics in prescription shares– including the introduction of a new treatment (Symbicort) – help us in identification of the learning parameters. When Symbicort is introduced, physicians are uncertain about its quality and learning helps them reduce such uncertainty over time. The velocity of this reduction depends on the noise in feedback signals ($\sigma^2_{F,i}$) and on the variances characterizing prior quality uncertainty and patient heterogeneity ($\sigma^2_{Q0,ij}$ and $\sigma^2_{q,ipj}$).

To identify $\sigma^2_{Q0,ij}$ and $\sigma^2_{q,ipj}$, we rely on the attractiveness of a treatment for new versus old patients. Bayesian updating guarantees that the uncertainty surrounding the mean quality of a treatment ($\sigma^2_{Q0,ij}$) tends to zero after a large enough number of signals. At this point, the reluctance of a physician to prescribe that treatment to a new patient (which also does not depend on switch costs) enables identification of $\sigma^2_{q,ipj}$.

The assumption that physicians have rational expectations enables the dynamics in the choices of treatments with higher versus lower quality uncertainty to identify risk-aversion (r_i) and switch costs (δ_i). If quality expectations are on average correct, relative sluggishness in prescribing treatments with higher associated uncertainty to new patients is driven by risk aversion (r_i>0). Sluggishness in switching revisiting patients to treatments that the physician has already adopted for new patients enables identification of the switch cost parameter (δ_i). Thus, an overall unwillingness to try more uncertain treatments identifies risk-aversion while an unwillingness to switch revisiting patients away from a certain treatment identifies switch costs.

The salience parameters ($\omega_{0,i}$, $\omega_{\infty,i}$ and λ_i^{ω}) are identified by systematic changes in behavior triggered by the decision to switch a patient to a clinically equivalent alternative. For instance, if a physician starts adopting Symbicort to several patients at a certain pace but, after switching a patient away from Symbicort, slows down this adoption process more than what Bayes' rule would predict, this reduction in the speed of adoption is captured by $\omega_{0,i}$. If the strength of this effect changes over time, our model will capture such dynamics through λ_i^{ω} and $\omega_{\infty,i}$. Please note that it is not possible to identify the sign of the decay parameter separately from the levels of the two salience parameters. We avoid this identification issue by restricting λ_i^{ω} to be positive.

For the marketing parameters ($\boldsymbol{\beta}_1^{\mathbf{Mkt}}$ and $\boldsymbol{\beta}_{2,\mathbf{i}}^{\mathbf{Mkt}}$) identification is straightforward. Controlling for learning and switch costs, the effect of marketing efforts on the attractiveness of alternative treatments is identified by the responsiveness, in terms of prescription choices, of physicians to variations in the marketing effort variables. For

identification purposes, we assume that the temporal marketing responsiveness parameters add up to one.

Unrestricted multinomial Probit models suffer from additional identification issues as choice probabilities are invariant to location or scale transformations of the latent utilities (Rossi et al. 2005). Hence, we normalize the scale and location of the utility levels by restricting the quality of a reference alternative - the two-inhaler combination of Fluticasone and Salmeterol – to zero and the variance of the error term of the reference alternative to 1. Note that especially the latter has implications for comparability of estimation results across models (c.f. Swait and Louviere 1993). Estimates of the utility levels, variances, marketing effects, but also risk aversion and switch costs, will be affected by the restriction in the variance of the error terms and by the amount of unexplained variation actually present in the behavior under consideration.

As a final note, this type of models is demanding in terms of identification. To guarantee that our results are robust, we have run our focal models using a different set of priors. Even though we made priors much more diffuse, by increasing prior variances by a factor of 10, results were largely unchanged which suggests that identification of our model is achieved without relying on information contained in the priors. Furthermore, we have also simulated data according to our model and were able to recover the parameters very well.

6. Results

Posterior estimates of the relevant parameters are obtained directly from the sample of MCMC draws. In order to isolate the contribution of salience, we compare the following models: (M0) a pure Bayesian learning model,(M1) a quasi-Bayesian learning model with static salience (i.e. $\omega_i = \omega_{\infty,i} = \omega_{0,i}$) and (M2) a quasi-Bayesian learning model with dynamic salience. Following the suggestion of Rossi et al. (2005, p.168) to focus on the log-likelihood to verify convergence, we apply Raftery and Lewis's (1992) *I-stat* and Geweke's (1992) convergence tests on the log-likelihood for all three models, which confirmed that the chains have converged.

Next, we compare the fit of the models using log-marginal densities (LMDs) and log-Bayes factors (Kass and Raftery 1995). The two quasi-Bayesian learning models (LMD_{M1}=

-19,518and LMD_{M2} = -19,509) clearly outperformed the pure Bayesian learning benchmark (LMD_{M0} = -27,845). This provides strong evidence that any of the quasi-Bayesian learning models is a posteriori more likely than the pure Bayesian learning model, assuming equal prior probabilities for all models. The log-Bayes Factor of the model with dynamic salience (M2) with respect to the model with non-dynamic salience (M1) is also above 5, the threshold suggested by Kass and Raftery (1995, p.777) for strong evidence in favor of the best fitting model, which supports dynamics in salience effects. Lastly, including two different patient feedback signal variances (one for the first encounter and another for subsequent encounters) in order to accommodate experience effects in the patient-physician relationship, did not improve the quasi-Bayesian learning models (M1 and M2) based on log-Bayes factors. We now turn to the parameter estimates and their interpretation.

Parameter estimates: Salience

A key finding from our model is the strong salience effect triggered by the decision to switch a patient to an alternative treatment option (see first three rows of Table 2.3). When learning about the quality of a treatment, feedback from patients subject to treatment switching receives between 7 and 10times more weight ($\overline{\omega_{0,i}} = 9.05$ with *SD* = 0.432, $\overline{\omega_{\infty,i}} = 6.31$ with *SD* = 0.435, and $\overline{\lambda_i^{\omega}} = 1.27$ with *SD* = 0.566)[11] than a pure Bayesian learning model would predict.

We now turn to the dynamics in salience effects. We fix $\overline{\lambda_i^{\omega}}$ at its mean and compute the magnitude of salience since the time of a switch until one year after the switch based on the medians of $\overline{\omega_{0,i}}$ and $\overline{\omega_{\infty,i}}$. We find that 56% of the total decay from the immediate level of salience ($\overline{\omega_{0,i}}$) to its steady state level ($\overline{\omega_{\infty,i}}$) occurs in one year time. Thus, we find evidence for a significant but slow decay in salience.

[11] The values of 7 and 10 are obtained by adding one to our estimates of $\overline{\omega_{\infty,i}}$ and $\overline{\omega_{0,i}}$, as the impact of salience in the utility is determined by $(1+\omega_{ipj,k} \cdot SWITCH_{ipj,k})$. We use SD to denote the standard deviation across all the MCMC draws used for posterior inference.

We also find significant physician heterogeneity in salience effects. In order to determine whether physician heterogeneity is significant, we follow Narayanan and Manchanda's (2009) approach of contrasting each parameter's across-physician standard deviations with the within-physician standard deviations. If the physician-specific 95% credible intervals for a certain parameter do not overlap, then the across-physician standard deviation of that parameter needs to be larger than the corresponding within-physician standard deviation. From the last two columns of Table 2.3, we can see that the across-physician variation is substantially larger than the within-physician variation, suggesting significant heterogeneity in salience effects.

Table 2.3 Parameter estimates (salience, switch costs, risk aversion and feedback error)

Parameter	**Posterior median [95% credible intervals]**	**Across-physician standard deviation**	**Within-physician standard deviation**
Immediate salience effect ($\overline{\omega_{0,i}}$)	9.05	1.21	1.04
	[8.18; 9.89]		
Long-run salience effect ($\overline{\omega_{\infty,i}}$)	6.31	1.56	1.05
	[5.43; 7.11]		
Salience decay ($\overline{\lambda_i^{\omega}}$)	1.27	2.18	1.32
	[0.14; 2.28]		
Switch costs ($\overline{\delta_i}$)	2.78	0.18	0.16
	[2.57; 3.03]		
Absolute risk aversion ($\overline{r_i}$)	0.60	0.86	0.60
	[-0.53; 1.76]		
Patient feedback error ($\overline{\sigma_{F,i}^2}$)	0.66	0.39	0.14
	[0.53; 0.81]		

Notes. The estimates reported in the second column are the medians, across all MCMC draws, of the population mean parameter in the second level of our hierarchical model (i.e. the mean in the random coefficients distribution). In parentheses, we report the 2.5th and the 97.5th percentiles of the distribution of these MCMC draws. In the last two columns we report the across-physician standard deviations (the standard deviation of the physician-specific means of each parameter) and within-physician standard deviations (the mean of the physician-specific standard deviations of each parameter), in line with Narayanan and Manchanda (2009).

Salience has two major effects on prescription behavior. First, because it represents a departure from optimal Bayesian learning, it tends to slow down physician learning about the quality of new treatments, which delays its adoption by physicians. Second, in the long run, it benefits treatments that generate fewer switches (i.e. that have higher quality, lower treatment heterogeneity or that are targeted to patients that will benefit the most from them). In the next section, we will quantify the overall impact of the salience effect on the market.

Parameter estimates: Switch costs

The parameter measuring patient switch costs ($\overline{\delta_i}$ =2.78 with *SD* =0.121) suggests that, on top of uncertainty-driven persistence, physicians exhibit a strong tendency to prescribe the same treatment for a certain patient even when they believe that an alternative treatment could perform better for this specific patient. This finding is in line with the findings of Chan et al. (2010) and Coscelli (2000). Physician heterogeneity in these switch costs seems only marginally significant, as the across-physician and the within-physician standard deviations are close to each other.

Parameter estimates: Absolute risk aversion

The mean risk-aversion parameter is positive and the standard deviation of the draws is of similar magnitude ($\overline{r_i}$ = 0.60, *SD* = 0.584). We computed the percentage of draws indicating risk aversion (i.e. $r_i > 0$) for each of the physicians in our sample and found that all except one physician have the majority of the MCMC draws with positive risk aversion and, for more than half of the physicians, at least 90% of the draws indicate risk aversion. Finally, we find that physicians show significant heterogeneity in their risk attitudes, with the across-physician standard deviation being much larger than the within-physician standard deviation (0.86 vs. 0.60), a finding in line with evidence from medicine (Fiscella et al. 2000).

Parameter estimates: Patient feedback error

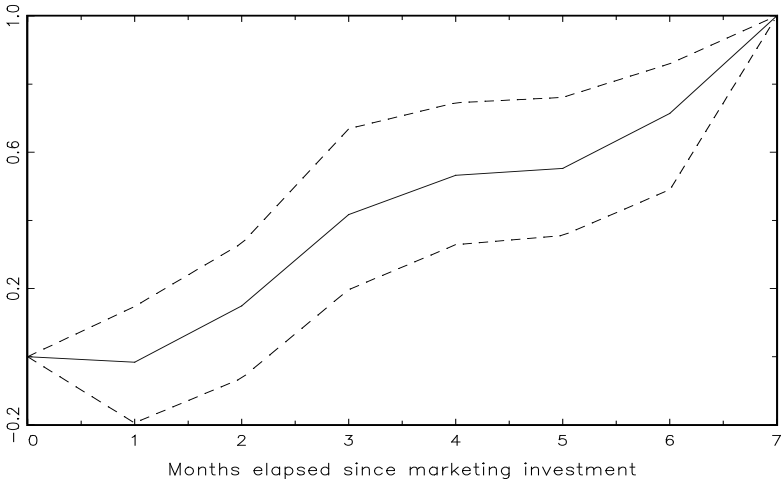
To understand the magnitude of patients' feedback errors ($\overline{\sigma^2_{F,i}}$ =0.66 with *SD*= 0.07) we simulated physician uncertainty about the mean quality of Symbicort and analyzed how long it takes a physician to reduce such uncertainty. On average, a pure Bayesian physician needs to receive 26 patient feedback signals (each patient providing a single feedback) to reduce her uncertainty by 90%. If the same physician learns in a quasi-Bayesian fashion, i.e. giving more weight to the feedbacks of salient patients, then she needs 38 signals, all from salient patients, to obtain the same reduction in uncertainty. Thus, as we would expect from the fact that salience represents a deviation from optimal Bayesian learning, salience reduces physicians' speed of learning, which, everything else constant, results in slower adoption. We explore managerial and patient welfare implications of salience in the next two sections.

Parameter estimates: Marketing efforts

We now discuss the impact of marketing efforts on treatment utility and choice. We divide marketing responsiveness in two effects: (i) temporal marketing responsiveness, which we use to describe how the effect of pharmaceutical companies' marketing efforts builds up over time (an effect we assume common across physicians and treatments) and (ii) molecule- and physician-specific marketing responsiveness, which is assumed constant over time.

In order to describe temporal marketing responsiveness, in Figure 2.2 we depict the cumulative temporal marketing responsiveness effect since the period a marketing investment is effected until *L* months have passed since such investment (i.e. $CTMR_L = \sum_{l=0}^{L-1} \beta_{1,l}^{Mkt}$ with *L*=1,…,7). For identification, the sum of the temporal marketing responsiveness parameters is restricted to one. Hence, the curves in Figure 2.2, represent the fraction of the total marketing responsiveness that has already affected physician *i*'s prescription behavior when *L* months have passed since marketing was expended. We can conclude that marketing effects gradually build up from the first to the seventh month after the investment is made.

Figure 2.2 Cumulative temporal marketing responsiveness



Notes. In the horizontal axis we depict the number of months elapsed since the focal marketing investment. For illustrative purposes we start the graph from zero, hence '1' in the horizontal axis refers to the contemporaneous marketing and '7' refers to the 6th lag of temporal marketing responsiveness. In the vertical-axis, we depict the sum of the temporal marketing responsiveness parameters up to and including the lag indicated in the horizontal axis. The lines depict the 2.5th (lower dashed line), the median (solid line) and the 97.5th (upper dashed line) percentiles, across all MCMC draws, of $CTMR_L$ (for L = *1,…,7*).

In terms of the molecule- and physician-specific marketing responsiveness, our estimates show that marketing efforts to promote Seretide and Symbicort ($\overline{\beta_{2,i}^{Comb.}} = 0.12$, *SD* = 0.05 and 95% *Cred. Int.* = [0.03; 0.22]) significantly drive prescription choices. In contrast, marketing expenditures for ICS's ($\overline{\beta_{2,i}^{ICS}} = -0.01$, *SD* = 0.05 and 95% *Cred. Int.* = [-0.11; 0.08]) and for LABA's ($\overline{\beta_{2,i}^{LABA}} = 0.06$, *SD* = 0.05 and 95% *Cred. Int.* = [-0.03; 0.16]) do not significantly affect prescription behavior, in line with prior research showing effectiveness of pharmaceutical marketing to be higher for new than for mature treatments (Narayanan et al. 2005; Neslin 2001).

Parameter estimates: Treatment characteristics

Table 2.4, below, summarizes the posterior medians (and 95% credible intervals) for each treatment's true mean quality ($\overline{Q_{ij}}$), initial physician uncertainty about the mean quality belief ($\overline{\sigma_{Q0,ij}^2}$) and patient heterogeneity ($\overline{\sigma_{q,ipj}^2}$).

Table 2.4 Parameter estimates: Treatment quality perceptions

Treatment Alternative	$\overline{Q_{ij}}$	$\overline{\sigma^2_{Q0,ij}}$	$\overline{\sigma^2_{q,ipj}}$
1 – Fluticasone + Salmeterol		0.87	0.80
		[0.68; 1.09]	[0.60; 0.97]
2 – Fluticasone + Formoterol	-0.06	0.69	1.34
	[-0.30; 0.22]	[0.57; 0.85]	[1.10; 1.67]
3 – Beclomethasone + Salmeterol	-0.04	1.06	0.76
	[-0.30; 0.17]	[0.81; 1.41]	[0.61; 0.90]
4 – Beclomethasone + Formoterol	-0.24	0.68	1.09
	[-0.46; 0.00]	[0.56; 0.88]	[0.91; 1.29]
5 – Budesonide + Salmeterol	-0.02	0.92	0.98
	[-0.24; 0.18]	[0.79; 1.07]	[0.81; 1.16]
6 – Budesonide + Formoterol	0.14	0.67	1.04
	[-0.10; 0.38]	[0.57; 0.80]	[0.88; 1.23]
7 - Seretide	0.25	0.74	0.80
	[0.04; 0.46]	[0.60; 0.94]	[0.65; 0.93]
8 - Symbicort	0.10	1.30	0.89
	[-0.12; 0.33]	[1.05; 1.61]	[0.74; 1.03]

Notes. Fluticasone + Salmeterol, is the reference treatment alternative; Seretide contains Fluticasone and Salmeterol and Symbicort contains Budesonide and Formoterol.

In terms of true mean qualities, we find that the fourth treatment alternative (two-inhalers combining Beclomethasone and Formoterol) is the one with lowest quality while Seretide is perceived as the best treatment, on average. This finding is consistent with the results from a pure Bayesian learning model. In fact, the only relevant difference between the two models is that, in the quasi-Bayesian learning model, Seretide's quality is significantly higher than the remaining alternatives. In contrast, in the pure Bayesian learning model, the estimate for the mean quality of Seretide was very close to zero.

In terms of face validity, the results from our quasi-Bayesian learning model (M2) are consistent with medical studies, which show that the different treatment alternatives in this category are equivalent in terms of efficacy and side effects (Marks and Ind 2005). The fact that Seretide seems to be perceived, by the physicians in our sample, as having higher mean quality than the remaining treatments is also consistent with evidence from the industry indicating that AstraZeneca's initial differentiation strategy – which was to allow patients to adjust the dosing of the ICS's component - may have been received with skepticism by many physicians, who believed that a fixed dosing of ICS was actually one

of the advantages of combination treatments[12]. These differences indicate that treatments are also characterized by other dimensions such as dosage, administration method and convenience (Venkataraman and Stremersch 2007).

The estimates for initial uncertainty about the mean quality of each treatment also have high face validity in our model. Symbicort, the newest treatment, shows the highest mean quality uncertainty ($\overline{\sigma^2_{Q0,iSYMBI}} = 1.30$, SD = 0.142), while Seretide, which had been introduced two years before the start of our data and was, at the time, already the most prescribed treatment shows significantly lower prior mean quality uncertainty ($\overline{\sigma^2_{Q0,iSERE}} = 0.74$, SD = 0.089, with all draws having $\overline{\sigma^2_{Q0,iSYMBI}} > \overline{\sigma^2_{Q0,iSERE}}$). Finally, physicians perceive patient heterogeneity ($\overline{\sigma^2_{q,ipj}}$) as similar across all treatments.

7. Effects of Salience on Market Shares

Having established the presence of strong salience effects in physician learning, we now quantify the consequences of this behavioral regularity at the market level. We use the posterior draws from the quasi-Bayesian learning model with dynamic salience (M2) to simulate market shares under two counterfactual experiments: (i) our model with salience set to zero only for Symbicort and (ii) our model with salience set to zero for all treatments. The first counterfactual experiment tests whether reducing salience can be a useful objective for firms to pursue while the second tests whether salience produces significant deviations from normative prescription behavior (a potential welfare concern).

Figure 2.3 depicts the results of our counterfactual experiments. Each bar represents the mean predicted market share for two-inhaler treatments, Seretide and Symbicort. Each of the three blocks represents one of the scenarios we compare. The first thing to note is that, if AstraZeneca would have been able to eliminate salience for Symbicort (second block in Figure 2.3), it would have significantly increased its market share. The share of

[12] See for example Datamonitor's report named "Symbicort and Seretide's battle for the respiratory market": http://www.datamonitor.com/store/News/symbicort_and_seretides_battle_for_the_respiratory_market?productid=489DA887-A5B9-4660-B285-29D22EC64F6A, last accessed April 2010.

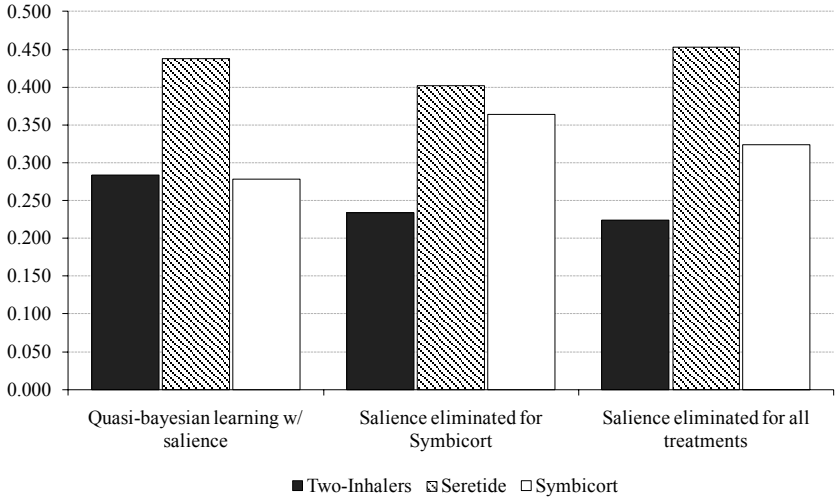
Symbicort increased, on average, by 8.5 percentage points (from 0.279 to 0.364) with 99.6% of the simulations showing an increase in market share[13].This significant increase in Symbicort's share was mainly achieved at the expense of older two-inhaler alternatives, which lost an average of 5 percentage points (from 0.284 to 0.234) with more than 98% of the simulations resulting in a decrease of these treatments' share. Hence, if a company alone is able to eliminate, or at least reduce, salience effects, it can reap significant market benefits. Moreover, with an additional counterfactual experiment we find that a reduction of 50% in salience achieved about one third of the total market share effect of a full elimination of salience. Thus, in the managerial implications section we discuss possible salience-reducing strategies to achieve such goal.

Finally, the shares predicted by a model with salience set to zero for all brands shows that, in general, newer treatments benefit from salience elimination. The share of two-inhaler treatments decreased, on average, by 6 percentage points (from 0.284 to 0.224), with 99% of the simulations resulting in a decrease for these older treatment alternatives. In contrast, Seretide's share increased on average, by 1.5 percentage points (from 0.437 to 0.453). We observed increases in 74% of the simulations. The prescription share of the newest entrant – Symbicort – increased 4.5 percentage points (from 0.279 to 0.324), with 89% of the simulations showing an increase.

These results indicate that, in the market we study, the prevalence of salience effects in physician learning resulted in systematic changes in prescription shares, potentially with an associated welfare loss: salience (of the feedbacks) of switching patients slows physician learning and significantly delays the adoption of newer treatments in favor of older treatments.

[13] Note that we compare the realizations of the market shares for the two models that are based on the same set of realizations for the patient quality matches, feedback signals, etc.

Figure 2.3 Mean predicted market shares with and without salience



8. Additional Analyses on Salience

Realizing that some concerns may persist regarding the psychological process behind the treatment switching effect we document, we conducted additional analyses to test the robustness of our salience interpretation. We have run a survey among 156 GPs and asked these physicians to rate the importance of different drivers of their decision to prescribe an older or a newer treatment. Specifically, we compared our salience explanation with competing psychological explanations (fear about the new treatment's side effects, need to justify the decision, or potential regret). Salience was rated as significantly higher, confirming our expectations.

Another possible concern is that, in addition to salience, the treatment switching effect may be driven by a correlated unobservable like detailing. If a physician's decision to switch patients away from a certain treatment and the choice of the new treatment are driven by detailing, and if detailing also alters long-term market shares, our salience estimate could be inflated. We used two strategies to alleviate this concern[14]. First, in the physician survey we conducted, we also included detailing as a possible driver of

[14] We thank the review team for bringing this issue to our attention and suggesting strategies to deal with this problem.

prescription choices. Detailing was rated as significantly less important than salience by the 156 physicians. Second, please note that – if we consider a switch from treatment *A* to treatment *B* - salience predicts a penalty effect in the utility of treatment *A* while detailing predicts a bonus effect in the utility of treatment *B*. Hence, we estimated a pure Bayesian learning model where we allow the number of switch-outs and the number of switch-ins to affect each treatment's utility. We find that in more than 95% of the draws the (negative) effect of switch-outs is substantially stronger than the (positive) effect of switch-ins. This implies that switches affect the treatment that was abandoned most, in line with our salience interpretation.

9. Managerial and Public Policy Implications

Two major findings emerged from our counterfactual experiments. First, a firm that is able to eliminate or reduce salience for its treatment can gain an important competitive advantage. Considering that Symbicort had global sales, in the period 2001-2006, of $3,918 million, the significant increase of 8.5 percentage points in its prescription share when its salience was set to zero would have represented a gain of $333 million in sales. Second, setting salience to zero for all treatments confirmed that salience delays physician adoption of new treatments, suggesting a potential patient welfare loss. But what can one do to reduce salience effects?

Prior research has demonstrated that several cognitive debiasing strategies can effectively reduce biases like salience (Arkes 1991; Bradley 2005; Croskerry 2003). In the case of salience there are at least three possible debiasing strategies we can think of. First, psychological effects, like salience, often exert their influence on judgment because people are unaware of their impact on judgments and decisions. Thus, increasing physician awareness about salience effects should help reducing its impact (Croskerry 2003). Second, prescription support systems that decrease physicians' reliance on memory in their decisions should help reducing salience effects (e.g. Bradley 2005; Croskerry 2003). Third, refreshing physicians' knowledge about the use of Bayes rule should also help reducing salience effects (Hall 2002; Nisbett et al. 1983).

A second type of salience-reducing strategies involves streamlining marketing actions, early in a treatment's life cycle. For example, firms could invest in innovations aimed at

reducing patient heterogeneity in a new treatment's quality. If a firm is able to reduce patient heterogeneity for a new treatment -for instance through new product development efforts aimed at reducing quality dispersion - it benefits both from a direct and from an indirect increase in the new treatment's utility. The former effect occurs because treatment heterogeneity increases the uncertainty about the quality of the new treatment, while the latter effect occurs because lower treatment heterogeneity reduces switching which, in turn, reduces salience effects.

Finally, our model also suggests that a controlled roll-out of a new drug may help speed-up its adoption. Instead of aggressively targeting all patients simultaneously, firms may be better off by helping physicians to more accurately target new therapies to the patients who will most likely benefit from them. Such a strategy would represent a win-win situation whereby physicians avoid prescribing the new therapy to patients that lie on the lower tail of the quality distribution and, as a consequence, avoid undesirable switches, reducing salience effects.

10. Alternative Applications of our Model in Marketing Science

Beyond the phenomenon studied in this paper, it is possible to adapt the model we specify to study other behavioral regularities that can be of interest to marketing scientists. First, our model can be adapted to test - using scanner panel data - whether there is empirical evidence for positive (or negative) spillovers among different elements of a new brand's marketing mix. For instance, one could expect advertising messages to become more influential in consumer learning when the product is also featured or on display. Re-specifying our salience dummy to account for these interactions would allow a researcher to quantify such spillover effects.

Second, our model can also be used to quantify the disproportionate weight given to word of mouth by dissatisfied versus satisfied consumers (e.g. Goldenberg et al. 2007). Following this route would require data on consumers' (i) purchase histories, (ii) social network and (iii) satisfaction. Our salience parameter could then be used to quantify the extra weight given to feedback signals from dissatisfied peers in consumer learning, a metric for the disproportionate influence of unfavorable information (Mizerski 1982).

Third, our model can also be used to model confirmatory bias, i.e. consumers' tendency to pay more attention and weight more heavily information that confirms their prior beliefs (see also Boulding et al. 1999 and Mehta et al. 2008). Our specification allows a researcher to model confirmatory bias directly through the weight they give to different consumption signals. For example, if we re-specify the switch dummy, in our model, as a dummy indicating whether a certain signal confirms a consumer's prior expectation, then positive estimates for $\omega_{0,i}$ and $\omega_{\infty,i}$ can be used to directly quantify the magnitude of confirmatory bias.

11. Conclusion

In this paper, we show that salience interferes with physician learning. Patients that switch to alternative treatments are more influential during physician's quality belief formation than patients that continue their therapy. We extend the Bayesian learning model to account for these salience effects. To the best of our knowledge, this is the first paper to uncover salience effects in physician learning using actual data on physicians' prescription choices for real patients. We find that feedback from switching patients receives between 7 and 10 times more weight, in physician learning, than feedback from other patients. Our finding is in line with experimental evidence that suggests that physicians are prone to use cognitive shortcuts like availability, representativeness and anchoring and adjustment. Salience results in slower physician learning about the quality of new treatments, delaying adoption. Consequently, reducing salience effects ahead of or to a greater extent than competition, all else equal, may be very beneficial for firms that market new treatments (in our case, AstraZeneca with Symbicort). Also public policy officials may find reduction of salience effects a worthwhile goal, as it represents a welfare loss. We have discussed how cognitive debiasing strategies and marketing actions may reduce salience.

Limitations and directions for future research

A first limitation is our interpretation of the treatment switching effect we quantify as a salience effect. The data we use allows us to establish that the feedback of patients who switch treatments receives significantly more weight, in physicians' belief-formation about the quality of a new treatment, than Bayesian updating predicts. We used robust findings

from psychology and medical decision-making theory and discussed additional self-reported data and analyses that reinforced our confidence that salience effects drive this treatment switching effect. Nevertheless, it would be interesting if future research, possibly using laboratory experiments, could establish that the psychological process that underlies the treatment switching effect we document is indeed the salience of the feedbacks from switching patients.

Second, we model learning solely through patient feedbacks. The context we have chosen (single-physician practices in a geographical market that has strict regulations on pharmaceutical marketing) limits the impact of alternative sources of information (like word of mouth and direct-to-consumer advertising). Still, if physicians' decisions to switch a patient away from a certain treatment and the choice of the new treatment are driven by unobserved detailing or advertising, and if detailing also alters long-term market shares, our salience estimate could be inflated due to the well-known issue of correlated unobservables. In order to alleviate these concerns, we have conducted additional analyses showing that salience is significantly more likely to be the driver of the treatment switching effect we document. It would be valuable if future studies would examine the potential for informative marketing to reduce salience effects.

Third, we assume that, at each encounter, the visiting patient only provides feedback about the last treatment she or he has been prescribed. We don't expect this assumption to introduce bias in our estimates. Still, modeling physician learning from multivariate patient feedbacks could allow researchers to better understand how patient and physician perceptions about different treatment alternatives interact with each other. Operationalization of such a model would require either additional data (e.g. survey data on which treatments, and what aspects of the treatment, were discussed in a certain encounter) or additional assumptions (e.g. structurally model the amount of feedback allocated to each of the treatments a patient has previously tried). This is a very promising area for future research on consumer learning.

Finally, although we control for unobserved heterogeneity both at the patient and physician level, observed heterogeneity could also be explored by introducing patient and physician characteristics explicitly in the model specification. Modeling across-consumer

learning effects, and quantifying which consumers are more influential, is another area that deserves future study.

Overall, this study confirms the usefulness of quasi-Bayesian learning models. While such models come at the cost of increased complexity, they allow for the integration of the robust insight that human decision-makers often deviate from normative rules in predictable ways into the well-established normative Bayesian learning framework.

Appendix II.A – Derivation of Mean Quality Learning Weights

We first derive the variance of patient feedback signals for a physician learning about the quality of treatment *j*. Let us write patient *p*'s feedback signal about treatment *j* provided at encounter *k* as follows:

$$F_{ipj,k} = Q_{ij} + q_{ipj} + \varepsilon_{F,ipj,k}$$
$$\text{With } \varepsilon_{F,ipj,k} \sim N\left(0, \sigma^2_{F,i}\right) \text{ and } q_{ipj} \sim N(0, \sigma^2_{q,ipj}) \tag{A.2.1}$$

The sequence of unobserved feedback signals provided by patient *p* to physician *i* about treatment *j* up to and including encounter *k* can be summarized by its sample mean ($\overline{F}_{ipj,k}$). Conditional on the mean quality of treatment *j* (Q_{ij}), the variance of this sample mean depends on patient feedback noise and patient quality heterogeneity, i.e.:

$$\overline{F}_{ipj,k} = \frac{\sum_{t=1}^{k} F_{ipj,t}}{n^p_{ij,k}} \mid Q_{ij} \sim N\left(Q_{ij}, \frac{n^p_{ij,k} \cdot \sigma^2_{q,ipj} + \sigma^2_{F,i}}{n^p_{ij,k}}\right) \tag{A.2.2}$$

Integrating $\overline{F}_{ipj,k}$ for all patients and $\overline{Q}_{0,ij}$, with precisions $\frac{n^p_{ij,k}}{n^p_{ij,k} \cdot \sigma^2_{q,ipj} + \sigma^2_{F,i}}$ and $\frac{1}{\sigma^2_{Q0,ij}}$, in a Bayesian way (in line with DeGroot 1970), results in Equations (2.6) and (2.7) in the main paper.

Appendix II.B – Derivation of the posterior variance of a physician's patient level quality beliefs

Please recall that the posterior belief of physician *i* about the quality of treatment *j* for patient *p*, visiting at encounter *k* ($\widetilde{Q}^{\omega}_{ipj,k}$), specified in Equation (2.15) in the main paper, is normally distributed with posterior mean $\overline{Q}^{\omega}_{ij,k} + \overline{q}^{\omega}_{ipj,k}$ and posterior variance $\sigma^2_{Q,\omega,ipj,k}$. It is straightforward to see, from the structure of our model, that this posterior belief can be divided into (i) a posterior belief about treatment *j*'s mean quality ($\widetilde{Q}^{\omega}_{ij,k}$) and a posterior belief about the patient-treatment idiosyncratic deviation ($\widetilde{q}^{\omega}_{ipj,k}$). The posterior variance of physician *i*'s belief about the quality of *j* for patient *p*, visiting at *k*, is then simply obtained from:

$$\sigma^2_{Q,\omega,ipj,k} = \mathrm{var}\left(\widetilde{Q}^{\omega}_{ij,k}\right) + \mathrm{var}\left(\widetilde{q}^{\omega}_{ipj,k}\right) + 2 \cdot \mathrm{cov}\left(\widetilde{Q}^{\omega}_{ij,k}, \widetilde{q}^{\omega}_{ipj,k}\right) \qquad \text{(A.2.3)}$$

The posterior variance in Equation (A.2.3) is therefore driven by physician *i*'s initial beliefs ($\overline{Q}_{0,ij}$ and $\overline{q}_{0,ipj}$) and all patients' feedback signals about *j*. Consequently we can determine the posterior variance in terms of the variances of each of these components.

First, we collect the updating weights, defined in Equation (2.11) in the main paper, in:

- $\alpha^{\omega}_{0,ij,k} = \dfrac{\psi^2_{Q,\omega,ij,k}}{\sigma^2_{Q0,ij}}$, the weight given by physician *i* to her initial mean quality belief, and
- $\alpha^{\omega}_{F,ipj,k} = \dfrac{\psi^2_{Q,\omega,ij,k} \cdot n^p_{ij,k} \cdot (1 + \omega_{ipj,k} \cdot SWITCH_{ipj,k})}{\sigma^2_{F,i} + n^p_{ij,k} \cdot \sigma^2_{q,ipj}}$, the weight given by physician *i* to each patient's average feedback about treatment *j,* with $\psi^2_{Q,\omega,ij,k}$ defined in Equation (2.12).

Second, we collect the updating weights, defined in Equation (2.14) in the main paper, in:

- $\beta_{0,ipj,k} = \dfrac{\sigma^2_{q,ipj,k}}{\sigma^2_{q0,ipj}}$, the weight given by physician i to her initial belief about each patient's idiosyncratic deviation from the mean quality, and
- $\beta_{F,ipj,k} = \dfrac{n^p_{ij,k} \cdot \sigma^2_{q,ipj,k}}{\sigma^2_{F,i}}$, with $\sigma^2_{q,ipj,k} = \left(1/\sigma^2_{q0,ipj} + n^p_{ij,k}/\sigma^2_{F,i}\right)^{-1}$.

Introducing the weights just defined ($\alpha^{\omega}_{0,ij,k}$, $\alpha^{\omega}_{F,ipj,k}$, $\beta_{0,ipj,k}$ and $\beta_{F,ipj,k}$) in Equations (2.11) and (2.14) in the main text, together with the assumption of prior independence and the assumption of independence between the priors and patient feedback signals, clarifies that we can write each of the three components of $\sigma^2_{Q,\omega,ipj,k}$ as follows:

$$\begin{aligned}\mathrm{var}\left(\widetilde{Q}^{\omega}_{ij,k}\right) &= \mathrm{var}\left(\alpha^{\omega}_{0,ij,k} \cdot Q_{0,ij} + \sum_p \alpha^{\omega}_{F,ipj,k} \cdot \overline{F}_{ipj,k}\right) \\ &= (\alpha^{\omega}_{0,ij,k})^2 \cdot \sigma^2_{Q0,ij} + \sum_p \left\{(\alpha^{\omega}_{F,ipj,k})^2 \cdot \left[\frac{n^p_{ij,k} \cdot \sigma^2_{q,ipj} + \sigma^2_{F,i}}{n^p_{ij,k}}\right]\right\}\end{aligned} \tag{A.2.4}$$

$$\begin{aligned}\mathrm{var}\left(\widetilde{q}^{\omega}_{ipj,k}\right) &= \mathrm{var}\left[\beta_{0,ipj,k} \cdot q_{0,ipj} + \beta_{F,ipj,k} \cdot \left(\overline{F}_{ipj,k} - \widetilde{Q}^{\omega}_{ij,k}\right)\right] \\ &= \beta^2_{0,ipj,k} \cdot \sigma^2_{q0,ipj} + \beta^2_{F,ipj,k} \cdot \left[\left(\sigma^2_{F,i}/n^p_{ij,k}\right) + \mathrm{var}\left(\widetilde{Q}^{\omega}_{ij,k}\right) - 2 \cdot \left(\sigma^2_{F,i}/n^p_{ij,k}\right) \cdot \alpha^{\omega}_{F,ipj,k}\right]\end{aligned} \tag{A.2.5}$$

$$\begin{aligned}\mathrm{cov}\left(\widetilde{Q}^{\omega}_{ij,k}, \widetilde{q}^{\omega}_{ipj,k}\right) &= \mathrm{cov}\left[\alpha^{\omega}_{0,ij,k} \cdot Q_{0,ij} + \sum_p \alpha^{\omega}_{F,ipj,k} \cdot \overline{F}_{ipj,k}, \beta_{0,ipj,k} \cdot q_{0,ipj} + \beta_{F,ipj,k} \cdot \left(\overline{F}_{ipj,k} - \widetilde{Q}^{\omega}_{ij,k}\right)\right] \\ &= \beta_{F,ipj,k} \cdot \left[\alpha^{\omega}_{F,ipj,k} \cdot \left(\sigma^2_{F,i}/n^p_{ij,k}\right) - \mathrm{var}\left(\widetilde{Q}^{\omega}_{ij,k}\right)\right]\end{aligned} \tag{A.2.6}$$

Appendix II.C – Model Estimation

In order to facilitate exposition of our estimation scheme, we first define the symbols we will be using in this Appendix in Table A.2.1.

Table A.2.1 – Variable definitions

$\mathbf{U}_{\mathbf{i}[(K_i \cdot J)\times 1]}$	- a vector stacking the utilities of each treatment alternative at each of the K_i encounters of physician i;
$\mathbf{y}_{\mathbf{i}[(K_i \cdot J)\times 1]}$	- a vector of dummy variables indicating which alternative is prescribed at each of the K_i encounters of physician i;
$\mathbf{Q}_{\mathbf{ipj}[P_i\times 1]}$	- a vector stacking the true quality of treatment j for each of the P_i patients of physician i (Q_{ipj}'s);
$\boldsymbol{\beta}_{\mathbf{1}}^{\mathbf{Mkt}}{}_{[7\times 1]}$	- a vector stacking the temporal marketing response parameters $\left\{\beta_{1,m(k)-l}^{Mkt}\right\}$, $l=0,\ldots,6$, where $\beta_{1,m(k)-l}^{Mkt}$ captures the impact that marketing expenditures in month $m(k)-l$ in any of the molecules of treatment j have on this treatment's utility;
$\boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}}{}_{[3\times 1]}$	- a vector stacking the physician-specific marketing responsiveness parameters, which we also allow to differ across molecule types, i.e. $\boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}} = \left(\beta_{2,i}^{ICS} \quad \beta_{2,i}^{LABA} \quad \beta_{2,i}^{Comb.}\right)^T$;
$\mathbf{M}_{\mathbf{i}[(K_i \cdot J)\times((nlags+1)\cdot 3)]}$	- matrix with the log of contemporaneous plus six lags of monthly marketing expenditures for ICS, LABA and Combination treatments, mapped to each treatment at each of physician i's K_i encounters. Contemporaneous marketing expenditures are adjusted for the timing of the encounter within a given month[15].
$\mathbf{LC}_{\mathbf{i}[(K_i \cdot J)\times 1]}$	- a vector stacking, for each treatment and encounter of physician i, the $LASTCHOICE_{ipj,k}$ dummies;

We refer to a subset of the vectors in table A.2.1 by adding the relevant subscripts. For instance, $\mathbf{F}_{\mathbf{ij}[NF_{ij}\times 1]}$ refers to the feedbacks about treatment j received by physician i.

Before providing details on the implementation of our Gibbs sampler, we clarify the structure of our errors, introduce our joint posterior distribution, detail the specification of marketing and discuss the priors we used. Recall that we index physicians by $i=1,\ldots,N$, treatments by $j=1,\ldots,J$ (we consider eight possible alternative ICS plus LABA combination

[15] For instance, contemporaneous marketing for an encounter in the first day of the month equals the log of one plus 1/30 of that month's marketing expenditure for all molecules contained in the treatment.

treatments) and that each physician sees P_i patients in a total of K_i encounters. Moreover, we define *ningrs = 5,* as the number of molecular ingredients that are used in the composition of the treatment alternatives in our model: three ICS's (Fluticasone, Beclomethasone and Budesonide) and two LABA's (Formoterol and Salmeterol). Each treatment alternative is a combination of one out of three ICS's and one out of two LABA's. The first six alternatives combine these ingredients in two separate inhaling devices (two-inhalers) while the last two alternatives are the newer single-inhaler, or combination, brands (Seretide and Symbicort).

(I) Structure of the Errors

We now clarify the structure we use for the errors. First, we introduce **TC**, a Jx($ningrs$+1) treatment composition matrix which maps ingredient-specific unobserved shocks (first five columns of **TC**) and unobserved shocks specific to Seretide and Symbicort (last column of **TC**), into the utility of each treatment alternative based on their composition, i.e.,

TC =

	Inhaled Corticosteroids (ICS)			**Long-Acting β2-Agonists (LABA)**		
Alternative	**Fluticasone**	**Beclomethasone**	**Budesonide**	**Salmeterol**	**Formoterol**	**Combination**
1	1	0	0	1	0	0
2	1	0	0	0	1	0
3	0	1	0	1	0	0
4	0	1	0	0	1	0
5	0	0	1	1	0	0
6	0	0	1	0	1	0
7	1	0	0	1	0	1
8	0	0	1	0	1	1

Next, we assume that, in Equations (2.17) in the main paper, $\varepsilon_{ipj,k}$ can be separated into an unobserved shock that independently affects the utility of each treatment alternative ($\varepsilon_{ipj,k}^{iid}$) and unobserved shocks $\tilde{\boldsymbol{\eta}}_{\mathbf{i,k}}$ that independently affect (i) the utility of treatments sharing the same molecular ingredients or (ii) the utility of the combination treatments. The structure of the treatments then implies that $\boldsymbol{\varepsilon}_{\mathbf{ip,k}} = \boldsymbol{\varepsilon}_{\mathbf{ip,k}}^{\mathbf{iid}} + \mathbf{TC} \cdot \tilde{\boldsymbol{\eta}}_{\mathbf{i,k}}$. For both $\boldsymbol{\varepsilon}_{\mathbf{ip,k}}^{\mathbf{iid}}$ and $\tilde{\boldsymbol{\eta}}_{\mathbf{i,k}}$ we assume a mean zero normal distribution with diagonal covariance matrices $\boldsymbol{\Sigma}_{\mathbf{iid}}$ and $\boldsymbol{\Sigma}_{\boldsymbol{\eta}}$, respectively, i.e. at each choice occasion we have:

$$\boldsymbol{\varepsilon}_{\mathbf{ip,k}_{[J\times 1]}} \sim MVN(\mathbf{0}, \boldsymbol{\Sigma}) \tag{A.2.7}$$

where

$$\boldsymbol{\Sigma} = \boldsymbol{\Sigma}_{\mathbf{iid}} + \mathbf{TC} \cdot \boldsymbol{\Sigma}_{\boldsymbol{\eta}} \cdot \mathbf{TC}^{\mathbf{T}}, \tag{A.2.8}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{\eta}} = \mathrm{diag}(\sigma^2_{Fluticasone}, \sigma^2_{Beclomethasone}, \sigma^2_{Budesonide}, \sigma^2_{Salmeterol}, \sigma^2_{Formoterol}, \sigma^2_{Combination}), \tag{A.2.9}$$

and

$$\boldsymbol{\Sigma}_{\mathbf{iid}} = \mathrm{diag}(\sigma_1^2, \ldots, \sigma_J^2). \tag{A.2.10}$$

The separation of the two types of unobserved shocks allows us to circumvent some of the computational difficulties associated with the estimation of off-diagonal elements in error covariance matrices, which are known to be difficult to estimate in Multinomial Probit models (e.g. Rossi et al. 2005, p. 173).

(II) Physician heterogeneity and joint posterior distributions

We follow Narayanan and Manchanda's (2009) approach and add a hierarchical Bayesian structure to our model in order to model physician heterogeneity. For each physician, we collect her individual-level parameters, so:

$$\boldsymbol{\theta}_{\mathbf{i}} = \left\{\left\{\ln(\sigma^2_{Q0,ij}), \ln(\sigma^2_{q0,ipj})\right\}_{j=1,\ldots,J}, \omega_{0,i}, \omega_{\infty,i}, \lambda_i^{\omega}, \ln(\sigma^2_{F,i}), \left\{Q_{ij}\right\}_{j=1,\ldots,J}, r_i, \beta_{2,i}^{ICS}, \beta_{2,i}^{LABA}, \beta_{2,i}^{Comb.}\right. \tag{A.2.11}$$

Next, we model physician heterogeneity by assuming that these individual-level parameters are distributed as:

$$\boldsymbol{\theta}_{\mathbf{i}} \sim N(\overline{\boldsymbol{\theta}}, \mathbf{V}_{\boldsymbol{\theta}}) \tag{A.2.12}$$

Given this assumption for the specification of the physician-specific parameters and our model specification, we now introduce the joint posterior distribution of the model parameters conditional on our data:

$$\begin{aligned}
p(\boldsymbol{\theta} \mid \mathbf{y}) &\propto L(\boldsymbol{\theta}) \times p(\boldsymbol{\theta}) \\
&= p(\mathbf{y} \mid \boldsymbol{\theta}) \times p(\boldsymbol{\theta}) \\
&= \prod_{i=1}^{N} \left\{ \begin{array}{l} \prod_{k=1}^{K_i} \left(\prod_{j=1}^{J} \left(\begin{array}{l} f_N(U_{ipj,k} \mid y_{ipj,k}, MARKETING_{ij,k}, LASTCHOICE_{ipj,k}, F_{ipj,k}, \boldsymbol{\theta}_{\mathbf{i}}, \boldsymbol{\beta}_{\mathbf{1}}^{\mathbf{Mkt}}, \eta_{ipj,k}, \boldsymbol{\Sigma}_{\mathbf{iid}}) \\ \cdot f_N(F_{ipj,k} \mid Q_{ipj}, \sigma_{F,i}^2)^{LASTCHOICE_{ipj,k}} \end{array} \right) \cdot f_N(\boldsymbol{\eta}_{\mathbf{ip,k}} \mid \boldsymbol{\Sigma}_{\boldsymbol{\eta}}) \right) \\ \cdot \prod_{j=1}^{J} \left(\prod_{p=1}^{P_i} f_N(Q_{ipj} \mid Q_{ij}, \sigma_{q,ipj}^2) \right) \cdot f_N(\boldsymbol{\theta}_{\mathbf{i}} \mid \overline{\boldsymbol{\theta}}, \mathbf{V}_{\boldsymbol{\theta}}) \end{array} \right\} \\
&\cdot \pi(\boldsymbol{\beta}_{\mathbf{1}}^{\mathbf{Mkt}}) \cdot \prod_{j=2}^{J} \left[\pi(\sigma_{\varepsilon,j}^2) \right] \cdot \prod_{u=1}^{ningr+1} \left[\pi(\sigma_{\eta,u}^2) \right] \cdot \pi(\overline{\boldsymbol{\theta}}) \cdot \pi(\mathbf{V}_{\boldsymbol{\theta}})
\end{aligned} \tag{A.2.13}$$

(III) Marketing specification

We have data on monthly expenditures on marketing (i.e. detailing, journal advertising and conferences) at the molecule level and for the period 2001-2006, which we obtained from IMS Health. $MARKETING_{ij,k}$, introduced in Equations (2.17) and (2.18) in the main paper, captures both temporal marketing responsiveness, which we assume equal across physicians but varying over time, and molecule-type-specific marketing responsiveness, which we assume constant over time but varying across physicians. The construction of this marketing variable deserves some more explanation. In particular, we compute the log of contemporaneous monthly marketing expenditures or any of the 6 lags of these monthly marketing expenditures at the molecule level. For instance, $MKT_{j,m(k)-l}^{ICS}$, in Equation (2.18), refers to the actual amount, in Euros, spent to promote the ICS molecule contained in treatment *j,* in The Netherlands, *l* months before the month when encounter *k* occurred (*m(k)*). If *l=0*, $MKT_{j,m(k)-l}^{ICS}$ represents contemporaneous marketing, which we adjust for the day, within month *m(k)*, where encounter *k* occurred. For two-inhalers, we consider the

marketing expenditures associated with each of the molecules used in each treatment alternative. For single-inhalers, we use the brand-level expenditures (i.e. the marketing support for Seretide or Symbicort).

Thus we use L+1 parameters to capture temporal marketing effects ($\left\{\beta_{1,l}^{Mkt}\right\} l=0,\ldots,L$). Recall that, for identification we assume that $\sum_{l=0}^{L}\beta_{1,l}^{Mkt}=1$, so we only sample six temporal marketing responsiveness parameters. Molecule- and physician-specific marketing responsiveness parameters, in turn, are gathered in $\boldsymbol{\beta}_{2,\mathbf{i}}^{\mathbf{Mkt}}=\left(\beta_{2,i}^{ICS}\quad \beta_{2,i}^{LABA}\quad \beta_{2,i}^{Comb.}\right)$.

(IV) Prior distributions

We have five sets of priors for our hierarchical model: (i) a prior on $\boldsymbol{\Sigma}_{\boldsymbol{\eta}}$ (the variance-covariance matrix of ingredient errors), (ii) a prior on $\boldsymbol{\Sigma}_{\mathbf{iid}}$ (the variance-covariance matrix of the treatment-specific errors), (iii) a prior on $\overline{\boldsymbol{\theta}}$ (the mean vector characterizing the heterogeneity distribution of the $\boldsymbol{\theta}_{\mathbf{i}}$'s ($i=1,\ldots,N$)), (iv) a prior on $\mathbf{V}_{\boldsymbol{\theta}}$ (the covariance matrix of the heterogeneity distribution), and (v) a prior on $\boldsymbol{\beta}_{\mathbf{1}}^{\mathbf{Mkt}}$, the vector of temporal marketing response parameters.

1. Prior on $\boldsymbol{\Sigma}_{\boldsymbol{\eta}}$ = diag($\sigma^2_{Fluticasone}, \sigma^2_{Beclomethasone}, \sigma^2_{Budesonide}, \sigma^2_{Salmeterol}, \sigma^2_{Formoterol}, \sigma^2_{Combination}$):

For each of the ($ningrs$+1) variances in the diagonal of $\boldsymbol{\Sigma}_{\boldsymbol{\eta}}$ we define an inverse-gamma prior:

$$\sigma_u^2 \sim Inverse\ Gamma(\upsilon_0^{\eta}, s_0^{2,\eta}) \qquad \text{(A.2.14)}$$

with

$u \in \{Fluticasone, Beclomethasone, Budesonide, Salmeterol, Formoterol, Combination\}$ and where we set $\upsilon_0^{\eta}=ningrs+3$ and $s_0^{2,\eta}=1$, which makes these priors quite diffuse.

2. Prior on $\mathbf{\Sigma_{iid}} = diag(\sigma_1^2,...,\sigma_J^2)$:

$$\sigma_j^2 \sim Inverse\ Gamma(\upsilon_0^{\varepsilon}, s_0^{2,\varepsilon}) \tag{A.2.15}$$

with *j=2,...,J* ($\sigma_1^2 = 1$, for identification) and where we set $\upsilon_0^{\varepsilon} = J + 2$ and $s_0^{2,\varepsilon} = 1$.

3. Prior on $\overline{\boldsymbol{\theta}}$:

$$\overline{\boldsymbol{\theta}} \sim N(\underline{\boldsymbol{\Delta}_{\mathbf{0,\overline{\theta}}}}, \underline{\mathbf{V}_{\mathbf{0,\theta}}}) \tag{A.2.16}$$

where $\underline{\boldsymbol{\Delta}_{\mathbf{0,\overline{\theta}}}} = \mathbf{0}$ is a vector of zeros with dimension equal to the number of physician-specific parameters and $\underline{\mathbf{V}_{\mathbf{0,\theta}}} = diag\left(\mathbf{s}^2_{\mathbf{0,Q0,ij}}, \mathbf{s}^2_{\mathbf{0,q0,ipj}}, \mathbf{s}^2_{\mathbf{0,\omega,i}}, s^2_{0,F,i}, \mathbf{s}^2_{\mathbf{Q,ij}}, s^2_{0,r,i}, \mathbf{s}^2_{\boldsymbol{\beta}\mathbf{,2Mkt,i}}, s^2_{0,\delta,i}\right)$. For parameters following a lognormal distribution (i.e. $\sigma^2_{Q0,ij}, \sigma^2_{q0,ipj}$ and $\sigma^2_{F,i}$ in Equation (A.2.11)) we set the prior variance to 5 and for parameters following a normal distribution (i.e. $\omega_{0,i}, \omega_{\infty,i}, \lambda_i^{\omega}, Q_{ij}, r_i, \beta_{2,i}^{ICS}, \beta_{2,i}^{LABA}, \beta_{2,i}^{Comb.}$ and δ_i) we set the prior variance to 50. Both result in diffuse priors for the parameters of interest.

4. Prior on $\mathbf{V_\theta}$:

$$\mathbf{V_\theta} \sim \text{Inverted-Wishart}(g_0, G_0) \tag{A.2.17}$$

where, defining the number of parameters in $\boldsymbol{\theta}_\mathbf{i}$ as *NPAR*, we set g_0 = *NPAR*+3 and $G_\mathbf{0}$ = $g_0 * \mathbf{I_{NPAR}}$.

5. Prior on $\boldsymbol{\beta}_\mathbf{1}^{\mathbf{Mkt}}$:

We define a normal prior for contemporaneous and the first five lags of the temporal marketing responsiveness parameters, so:

$$\beta_{1,l}^{Mkt} \sim N(0,50) \text{ for } l=0,...,L-1 \tag{A.2.18}$$

where $L=6$ represents the number of lagged monthly marketing expenditures that, in our model, affect a treatment's utility. For $\beta_{1,L}^{Mkt}$, the last element of $\boldsymbol{\beta}_1^{\mathbf{Mkt}}$, the prior is implied by the identification restriction (the sum of all the elements in $\boldsymbol{\beta}_1^{\mathbf{Mkt}}$ adds up to one).

(V) Full-conditional distributions and the Gibbs Sampler

First, we use using the updating weights introduced in online Appendix II.B ($\alpha_{0,ij,k}^{\omega}$, $\alpha_{F,ipj,k}^{\omega}$, $\beta_{0,ipj,k}$ and $\beta_{F,ipj,k}$) to write the mean beliefs ($\overline{Q}_{ij,k}^{\omega}$ and $\overline{q}_{ipj,k}^{\omega}$), used in the utility specification introduced in Equation (2.17), as follows:

$$\overline{Q}_{ij,k}^{\omega} = \alpha_{0,ij,k}^{\omega} \cdot \overline{Q}_{0,ij} + \sum_{p} \alpha_{F,ipj,k}^{\omega} \cdot \overline{F}_{ipj,k} \tag{A.2.19}$$

$$\overline{q}_{ipj,k}^{\omega} = \beta_{0,ipj,k} \cdot \overline{q}_{0,ipj} + \beta_{F,ipj,k} \cdot \left(\overline{F}_{ipj,k} - \overline{Q}_{ij,k}^{\omega}\right) \tag{A.2.20}$$

Introducing the expressions in Equations (A.2.19) and (A.2.20) in Equation (2.17) in the main paper, and replacing $\varepsilon_{ipj,k}$ by the sum of the ingredient-specific and the treatment-specific errors ($\eta_{ipj,k} + \varepsilon_{ipj,k}^{iid}$ for $j=1,\ldots,J$), we obtain:

$$\begin{aligned} U_{ipj,k} = {} & \delta_{0,ij,k}^{\omega} \cdot \overline{Q}_{0,ij} + \beta_{0,ipj,k} \cdot \overline{q}_{0,ipj} + \sum_{p} \delta_{F,ipj,k}^{\omega} \cdot \overline{F}_{ipj,k} - \frac{1}{2} \cdot r_i \cdot \sigma_{Q,\omega,ipj,k}^{2} \\ & + \delta_i \cdot LASTCHOICE_{ipj,k} + MARKETING_{ij,k} + \eta_{ipj,k} + \varepsilon_{ipj,k}^{iid} \end{aligned} \tag{A.2.21}$$

Here, $\delta_{0,ij,k}^{\omega} = \alpha_{0,ij,k}^{\omega} \cdot (1 - \beta_{F,ipj,k})$ and $\delta_{F,ipj,k}^{\omega} = \alpha_{F,ipj,k}^{\omega} \cdot (1 - \beta_{F,ipj,k}) + I(p = p(k)) \cdot \beta_{F,ipj,k}$, where $I(p = p(k))$ is an indicator function assuming the value one for *p(k)*, the patient visiting at encounter *k*.

For certain sets of parameters, we obtain closed form solutions for the full-conditional posterior distributions by rearranging the utility specification in order to isolate, in the

right-hand side, the focal elements of utility and the treatment-specific error term, and, in the left-hand side, the remaining utility components, including the ingredient-specific errors. We then combine the rearranged terms with the natural conjugate prior for each parameter being sampled and use least squares to determine the mean and variance of the full-conditional posterior distribution of interest, in line with standard results from Bayesian linear regression (c.f. Rossi et al. 2005, sections 2.8 and 2.12).

Estimation proceeds by selecting a set of starting values and subsequently drawing the model parameters by iterating over their full-conditional posterior distributions (specified below). Thus, indexing each draw by *m,* our Gibbs sampler proceeds by cycling through the following steps:

1. Sampling of $U_{ipj,k}$

We draw the utilities of the different treatment alternatives, for each physician-patient-encounter combination, from a truncated multivariate normal distribution. We use the property of conditional independence and data augmentation to draw the utilities conditional on the data and the last available draw of the remaining parameters. So, for each physician we sample:

$$U_{ipj,k}^{(m)} \mid \begin{bmatrix} y_{ipj,k}, MARKETING_{ij,k}, LASTCHOICE_{ipj,k}, \mathbf{F_{ij}}^{(m-1)}, Q_{ij}^{(m-1)}, \sigma_{Q0,ij}^{2,(m-1)}, \sigma_{q,ipj}^{2,(m-1)}, \\ \omega_{0,i}^{(m-1)}, \omega_{\infty,i}^{(m-1)}, \lambda_i^{\omega(m-1)}, \sigma_{Fi}^{2(m-1)}, r_i^{(m-1)}, \boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}(m-1)}, \delta_i^{(m-1)}, \boldsymbol{\beta}_{\mathbf{1}}^{\mathbf{Mkt}(m-1)}, \boldsymbol{\eta}^{(m-1)}, \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}^{(m-1)} \end{bmatrix} \sim truncatedMVN(\mu_{ipj,k}, \boldsymbol{\Sigma}_{\mathbf{iid}}) \qquad \text{(A.2.22)}$$

with $\mu_{ipj,k}$ being the expression introduced in Equation (A.2.21) conditional on the latest available draws of all parameters of interest. Recall as well that we assume $\overline{q}_{0,ipj} = 0$ and rational expectations entails $\overline{Q}_{0,ij} = Q_{ij}$ and $\sigma_{q0,ipj}^2 = \sigma_{q,ipj}^2$.

The truncation indicated in Equation (A.2.22) guarantees that $y_{ipk} = j \Rightarrow U_{ipj,k} > U_{ipl,k,\forall l \neq j}$. Finally, to draw the choice-specific latent utilities

from truncated univariate normal distributions, we use the approach proposed by McCulloch and Rossi (1994) and detailed in Rossi et al. (2005, p.108).

2. Sampling of $F_{ipj,k}$

Define $\mathbf{F_{ij}}_{[NF_{ij}\times 1]}$ as a vector containing all the feedbacks provided, across all encounters, by the patients of physician *i* about treatment *j*. We then collect the belief-updating weights given by physician *i*, at each encounter, to each of the NF_{ij} feedback signals she receives about treatment *j* in a K_i x NF_{ij} matrix $\boldsymbol{\delta}^{\boldsymbol{\omega}}_{\mathbf{F,ij}}$, such that the kth element in $\boldsymbol{\delta}^{\boldsymbol{\omega}}_{\mathbf{F,ij}} \cdot \mathbf{F_{ij}}$ equals $\sum_p \delta^{\omega}_{F,ipj,k} \cdot \overline{F}_{ipj,k}$. Next, we rearrange terms in Equation (A.2.21) in order to isolate in the right-hand side $\boldsymbol{\delta}^{\boldsymbol{\omega}}_{\mathbf{F,ij}} \cdot \mathbf{F_{ij}}$. Combining this with Equation (2.4) in the main paper – which we use as our normal conjugate prior for the feedbacks – we apply standard results from Bayesian linear regression and reach a closed form solution for the full-conditional distribution of the patient feedback signals. That is, for each treatment alternative we sample:

$$\mathbf{F_{ij}}^{(m)} \Big| \begin{matrix} \mathbf{y_{ij}}, \mathbf{M_{ij}}, \mathbf{LC_{ij}}, \mathbf{U_{ij}}^{(m)}, \mathbf{Q_{ipj}}^{(m-1)}, Q_{ij}^{(m-1)}, \sigma^{2,(m-1)}_{Q0,ij}, \sigma^{2,(m-1)}_{q,ipj}, \omega_{0,i}^{(m-1)}, \omega_{\infty,i}^{(m-1)}, \\ \lambda_i^{\omega(m-1)}, \sigma^{2\,(m-1)}_{Fi}, r_i^{(m-1)}, \boldsymbol{\beta}^{\mathbf{Mkt}(m-1)}_{\mathbf{2,i}}, \delta_i^{(m-1)}, \boldsymbol{\beta}^{\mathbf{Mkt}(m-1)}_{\mathbf{1}}, \boldsymbol{\eta}_{\mathbf{ij}}^{(m-1)}, \boldsymbol{\Sigma}_{\mathbf{iid}}^{(m-1)} \end{matrix} \sim N(\hat{\boldsymbol{\mu}}_{\mathbf{Fij}}, \hat{\boldsymbol{\Sigma}}_{\mathbf{Fij}}) \qquad \text{(A.2.23)}$$

We repeat this process for all physicians (*i=1,…,N*) and treatment options (*j=1,…,J*).

3. Sampling of Q_{ipj} and Q_{ij}

We start by sampling the true quality of each treatment for each of the P_i patients of physician *i* (Q_{ipj}) and, on a second level we sample the mean quality of each treatment

across physicians and patients (Q_{ij}), using the fact that $Q_{ipj} \sim N(Q_{ij}, \sigma^2_{q,ipj})$. We are thus using a hierarchical approach to draw both the patient-specific treatment qualities and the mean qualities themselves, in two levels of the hierarchical model. In other words, the true quality of treatment *j* for all patients of physician *i,* according to Equation (2.1) in the main paper can be defined as:

$$Q_{ipj} = Q_{ij} + \varepsilon_{q,ipj} \text{ , with } \varepsilon_{q,ipj} \sim N(0, \sigma^2_{q,ipj}) \tag{A.2.24}$$

From Equation (2.4), in the paper, we also know that patient feedbacks about the quality of treatment *j* are normally distributed around Q_{ipj}, i.e.:

$$F_{ipj,k} = Q_{ipj} + \varepsilon_{F,ipj,k} \text{ , with } \varepsilon_{F,ipj,k} \sim N(0, \sigma^2_{F,i}) \tag{A.2.25}$$

Using Equations (A.2.24), (A.2.25) we apply Bayesian linear regression to obtain a closed form solution for the full-conditional distribution of Q_{ipj}:

$$\mathbf{Q_{ipj}}^{(m)} \mid \mathbf{F_{ij}}^{(m)}, Q_{ij}^{(m-1)}, \sigma^{2,(m-1)}_{q,ipj}, \sigma^{2\ (m-1)}_{Fi} \sim N(\hat{\boldsymbol{\mu}}_{\mathbf{Qipj}}, \hat{\boldsymbol{\Sigma}}_{\mathbf{Qipj}}) \tag{A.2.26}$$

Next, we sample the true mean quality of treatment *j* (Q_{ij}). First, please note that the rational expectations assumption (which implies $\overline{Q}_{0,ij} = Q_{ij}$) requires us to also consider the information contained in physicians' choices about their prior mean beliefs. Therefore, we rearrange the utility components in Equation (A.2.21) to isolate in its right-hand side $\boldsymbol{\delta}^{\boldsymbol{\omega}}_{\mathbf{Q_0,ij}} \cdot \overline{Q}_{0,ij}$, combine this expression with Equation (A.2.24) and define, as our normal conjugate prior:

$$Q_{ij} \sim N(\boldsymbol{\theta}_{\mathbf{Qij|\theta}}, \mathbf{V}_{\mathbf{Qij|\theta}}) \tag{A.2.27}$$

where $\boldsymbol{\theta}_{\mathbf{Qij|\theta}}$ and $\mathbf{V}_{\mathbf{Qij|\theta}}$ are, respectively, the mean and variance of Q_{ij} conditional on all the remaining physician-level parameters in the physician heterogeneity distribution introduced in Equation (A.2.12), using the last available draws for its mean and variance (i.e. $\overline{\boldsymbol{\theta}}^{(m-1)}$ and $\mathbf{V}_{\boldsymbol{\theta}}^{(m-1)}$ and other parameters in $\boldsymbol{\theta}_{\mathbf{i}}$). We then apply standard Bayesian linear regression and reach a closed form solution for the full-conditional distribution of Q_{ij}:

$$Q_{ij}^{(m)} \mid \begin{matrix} \mathbf{M_{ij}}, \mathbf{LC_{ij}}, \mathbf{U_{ij}}^{(m)}, \mathbf{Q_{ipj}}^{(m)}, \mathbf{F_{ij}}^{(m)}, \sigma_{Q0,ij}^{2,(m-1)}, \sigma_{q,ipj}^{2,(m-1)}, \omega_{0,i}^{(m-1)}, \omega_{\infty,i}^{(m-1)}, \\ \lambda_i^{\omega(m-1)}, \sigma_{Fi}^{2\,(m-1)}, r_i^{(m-1)}, \boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}(m-1)}, \delta_i^{(m-1)}, \boldsymbol{\eta}_{\mathbf{ij}}^{(m-1)}, \boldsymbol{\Sigma}_{\mathbf{iid}}^{(m-1)}, \overline{\boldsymbol{\theta}}^{(m-1)}, \mathbf{V}_{\boldsymbol{\theta}}^{(m-1)} \end{matrix} \sim N(\hat{\boldsymbol{\mu}}_{\mathbf{Qij}}, \hat{\boldsymbol{\Sigma}}_{\mathbf{Qij}}) \qquad \text{(A.2.28)}$$

4. Sampling of $\sigma_{Q0,ij}^2$, $\sigma_{q0,ipj}^2$, $\omega_{0,i}$, $\omega_{\infty,i}$, λ_i^{ω} and $\sigma_{F,i}^2$

In this step we sample the variances that govern learning and the salience parameters (please recall also that rational expectations implies $\sigma_{q0,ipj}^2 = \sigma_{q,ipj}^2$). For these parameters we use a random-walk Metropolis-Hastings step (Chib and Greenberg 1995). First, we define $\boldsymbol{\theta}_{\mathbf{i}}^{\mathbf{NON-LEARNING}} = \boldsymbol{\theta}_{\mathbf{i}} \setminus \boldsymbol{\theta}_{\mathbf{i}}^{\mathbf{LEARNING}} = \{Q_{i1},\ldots,Q_{iJ}, r_i, \beta_{2,i}^{ICS}, \beta_{2,i}^{LABA}, \beta_{2,i}^{Comb.}, \delta_i\}$. Next, we specify the following physician-specific posterior likelihood function:

$$L(\boldsymbol{\theta}_{\mathbf{i}}^{\mathbf{LEARNING}}) = \left\{ \begin{matrix} f(\mathbf{y_i} \mid \boldsymbol{\theta}_{\mathbf{i}}^{\mathbf{LEARNING}}, \bullet) \cdot \prod_{j=1}^{J} \left[f(\mathbf{F_{ij}}^{(m)} \mid \mathbf{Q_{ipj}}^{(m)}, Q_{ij}^{(m)}, \sigma_{F,i}^{2\,(m-1)}) \cdot f(\mathbf{Q_{ipj}}^{(m)} \mid Q_{ij}^{(m)}, \sigma_{q,ipj}^{2\,(m-1)}) \right] \\ \cdot f(\boldsymbol{\theta}_{\mathbf{i}}^{\mathbf{LEARNING}} \mid \boldsymbol{\theta}_{\mathbf{i}}^{\mathbf{NON-LEARNING}}, \overline{\boldsymbol{\theta}}^{(m-1)}, \mathbf{V}_{\boldsymbol{\theta}}^{(m-1)}) \end{matrix} \right\} \qquad \text{(A.2.29)}$$

where $\bullet$ refers to all remaining drivers of the utility of the different treatments excluding the $\varepsilon_{ipj,k}^{iid}$'s. Next, we propose candidate parameters using:

$$\boldsymbol{\theta}_{\mathbf{i}}^{\mathbf{LEARNING}(cand.)} = \boldsymbol{\theta}_{\mathbf{i}}^{\mathbf{LEARNING}(m-1)} + \boldsymbol{\varepsilon}_{\mathbf{RW}}, \boldsymbol{\varepsilon}_{\mathbf{RW}} \sim N(\mathbf{O}, \gamma_{RW\,i} \cdot \boldsymbol{\Sigma}_{\mathbf{RW}})^{16} \qquad \text{(A.2.30)}$$

[16] Where for simplicity $\boldsymbol{\Sigma}_{\mathbf{RW}}$ = diag($\mathbf{S}_{\mathbf{[(2J+5)x1]}}$) is a matrix of parameter-specific scaling constants and γ_{RWi} is a physician-specific scaling parameter. These parameters are fine-tuned during the burn-in phase to ensure good navigation of the sampler through the posterior distribution (Rossi et al. 2005).

Finally, we accept or reject the proposed candidate parameters with probability α, which is computed using the ratio of the posterior likelihood at the candidate and current parameter values, as standard in random-walk Metropolis-Hastings algorithms (see Rossi et al. 2005).

5. Sampling of r_i, $\boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}}$ and δ_i

Rearranging our original expression, in Equation (A.2.21), to isolate the risk-aversion, marketing responsiveness and switch costs parameters in its right-hand side, and using, as a natural conjugate prior:

$$r_i, \boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}}, \delta_i \sim N\left(\overline{\boldsymbol{\theta}}_{\mathbf{r,\beta,\delta}}, \mathbf{V}_{\mathbf{r,\beta,\delta}}\right) \tag{A.2.31}$$

where $\boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}(m)} = \left\{\beta_{2,i}^{ICS(m)}, \beta_{2,i}^{LABA(m)}, \beta_{2,i}^{Comb.(m)}\right\}$, and where $\overline{\boldsymbol{\theta}}_{\mathbf{r,\beta,\delta}}$ and $\mathbf{V}_{\mathbf{r,\beta,\delta}}$ are, respectively, the mean and variance of $r_i, \boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}}, \delta_i$ conditional on all the remaining physician-level parameters in the physician heterogeneity distribution introduced in Equation (A.2.12), using the last available draws for its mean and variance. We again apply standard Bayesian linear regression in order to reach a closed form solution for the full-conditional distribution of $r_i, \boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}}, \delta_i$:

$$r_i^{(m)}, \boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}(m)}, \delta_i^{(m)} \mid \begin{matrix} \mathbf{U}_{\mathbf{i}}^{(m)}, \mathbf{M}_{\mathbf{i}}, \mathbf{LC}_{\mathbf{i}}, \mathbf{F}_{\mathbf{ij}}^{(m)}, \left\{Q_{ij}^{(m)}, \sigma_{Q0,ij}^{2,(m)}, \sigma_{q,ipj}^{2,(m)}\right\}_{j=1,\ldots,J}, \omega_{0,i}^{(m)}, \\ \omega_{\infty,i}^{(m)}, \lambda_i^{\omega(m)}, \sigma_{Fi}^{2\,(m)}, \boldsymbol{\beta}_{\mathbf{1}}^{\mathbf{Mkt}(m-1)}, \boldsymbol{\eta}^{(m-1)}, \boldsymbol{\Sigma}_{\mathbf{iid}}^{(m-1)}, \overline{\boldsymbol{\theta}}^{(m-1)}, \mathbf{V}_{\boldsymbol{\theta}}^{(m-1)} \end{matrix} \sim N(\hat{\boldsymbol{\mu}}_{\mathbf{ri}}, \hat{\boldsymbol{\Sigma}}_{\mathbf{ri}}) \tag{A.2.32}$$

6. Sampling of $\boldsymbol{\beta}_{\mathbf{1}}^{\mathbf{Mkt}}$

First, we substitute the last element in $\boldsymbol{\beta}_{\mathbf{1}}^{\mathbf{Mkt}}$ using the fact that $\beta_{1,L}^{Mkt} = 1 - \sum_{l=0}^{L-1} \beta_{1,l}^{Mkt}$ and rearrange Equation (A.2.21) in order to isolate, in its right-hand side, the temporal marketing responsiveness parameters. We then combine this expression with its natural conjugate prior, defined in Equation (A.2.18), and apply standard Bayesian linear

regression in order to reach a closed form solution for the full-conditional distribution of $\boldsymbol{\beta}_1^{\mathbf{Mkt}}$:

$$\boldsymbol{\beta}_1^{\mathbf{Mkt}(m)} \mid \left\{ \begin{matrix} \mathbf{U_i}^{(m)}, \mathbf{M_i}, \mathbf{LC_i}, \mathbf{F_{ij}}^{(m)}, Q_{ij}^{(m)}, \sigma_{Q0,ij}^{2,(m)}, \sigma_{q,ipj}^{2,(m)}, \\ \sigma_{Fi}^{2\,(m)}, \omega_{0,i}^{(m)}, \omega_{\infty,i}^{(m)}, \lambda_i^{\omega(m)}, r_i^{(m)}, \boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}(m)}, \delta_i^{(m)} \end{matrix} \right\}_{i=1,\ldots,N}, \boldsymbol{\eta}^{(m-1)}, \boldsymbol{\Sigma}_{\mathbf{iid}}^{(m-1)} \sim N(\hat{\boldsymbol{\mu}}_{\boldsymbol{\beta}}, \hat{\boldsymbol{\Sigma}}_{\boldsymbol{\beta}}) \quad \text{(A.2.33)}$$

7. Sampling of $\eta_{ij,k}$ and $\boldsymbol{\Sigma}_{\boldsymbol{\eta}}$

First we define $\tilde{\boldsymbol{\eta}}_{\mathbf{i,k}}$, a (*ningrs*+1) vector collecting the ingredient-specific unobserved shocks (first *ningrs* elements) plus the unobserved shocks specific to Seretide and Symbicort. We have, conditional on $\boldsymbol{\Sigma}_{\boldsymbol{\eta}}$, the following normal prior for $\tilde{\boldsymbol{\eta}}_{\mathbf{i,k}}$:

$$\tilde{\boldsymbol{\eta}}_{\mathbf{i,k}} \sim N\left(0, \boldsymbol{\Sigma}_{\boldsymbol{\eta}}\right) \quad \text{(A.2.34)}$$

Substituting, in Equation (A.2.21), $\eta_{ij,k} = \mathbf{TC_j} \cdot \tilde{\boldsymbol{\eta}}_{\mathbf{i,k}}$ (where $\mathbf{TC_j}$ denotes the jth row of the treatment-composition matrix), we can rearrange Equation (A.2.21) in order to isolate the realizations of the ingredient-specific errors for each treatment in the right-hand side ($\mathbf{TC_j} \cdot \tilde{\boldsymbol{\eta}}_{\mathbf{i,k}}$) and use Equation (A.2.34) as our natural conjugate prior in order to reach, using standard Bayesian linear regression, a closed form solution for the full-conditional distribution of $\tilde{\boldsymbol{\eta}}_{\mathbf{i,k}}$, which we sample across physicians:

$$\tilde{\boldsymbol{\eta}}_{\mathbf{i,k}}^{(m)} \mid \left\{ \begin{matrix} \mathbf{U_i}^{(m)}, \mathbf{M_i}, \mathbf{LC_i}, \mathbf{F_{ij}}^{(m)}, \left\{ Q_{ij}^{(m)}, \sigma_{Q0,ij}^{2,(m)}, \sigma_{q,ipj}^{2,(m)} \right\}_{j=1,\ldots,J}, \\ \omega_{0,i}^{(m)}, \omega_{\infty,i}^{(m)}, \lambda_i^{\omega(m)}, \sigma_{Fi}^{2\,(m)}, r_i^{(m)}, \boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}(m)}, \delta_i^{(m)} \end{matrix} \right\}_{i=1,\ldots,N}, \boldsymbol{\beta}_1^{\mathbf{Mkt}(m)}, \boldsymbol{\Sigma}_{\boldsymbol{\eta}}^{(m-1)}, \boldsymbol{\Sigma}_{\mathbf{iid}}^{(m-1)} \sim N(\boldsymbol{\mu}_{\tilde{\boldsymbol{\eta}}}, \boldsymbol{\Sigma}_{\tilde{\boldsymbol{\eta}}}) \quad \text{(A.2.35)}$$

Next, for $u \in \{Fluticasone, Beclomethasone, Budesonide, Salmeterol, Formoterol, Combination\}$, we collect in $\tilde{\boldsymbol{\eta}}_{\mathbf{u}}$ all sampled errors for *u*. We then sample the ingredient-specific error variances from:

$$\sigma_u^{2(m)} \mid \left[\tilde{\boldsymbol{\eta}}^{(m)}, \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}^{(m-1)}\right] \sim Inverse\ Gamma(\upsilon_1^{\eta}, s_{1u}^{2,\eta}), \tag{A.2.36}$$

where the posterior degrees of freedom is defined as $\upsilon_1^{\eta} = \upsilon_0^{\eta} + n$, and the posterior sum of squared errors as $s_{1u}^{2,\eta} = \upsilon_0^{\eta} \cdot s_0^{2,\eta} + \tilde{\boldsymbol{\eta}}_{\mathbf{u}}^{T} \tilde{\boldsymbol{\eta}}_{\mathbf{u}}$. Having sampled the ingredient-specific error variances, we use Equation (A.2.9) to obtain $\boldsymbol{\Sigma}_{\boldsymbol{\eta}}$.

8. Sampling of Σiid

Rearranging Equation (A.2.21) to obtain the value of $\varepsilon_{ipj,k}^{iid}$ and stacking these across encounters and physicians in a *NT*-dimensional vector $\boldsymbol{\varepsilon}_{\mathbf{j}}$, we sample each of the *J* diagonal elements of $\boldsymbol{\Sigma}_{\mathbf{iid}}$ from:

$$\sigma_j^{2(m)} \mid \left[\begin{array}{l} \left\{\begin{array}{l} \mathbf{U_i}^{(m)}, \mathbf{M_i}, \mathbf{LC_i}, \mathbf{F_{ij}}^{(m)}, \left\{Q_{ij}^{(m)}, \sigma_{Q0,ij}^{2,(m)}, \sigma_{q,ipj}^{2,(m)}\right\}_{j=1,\ldots,J}, \\ \omega_{0,i}^{(m)}, \omega_{\infty,i}^{(m)}, \lambda_i^{\omega(m)}, \sigma_{Fi}^{2(m)}, r_i^{(m)}, \boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}(m)}, \delta_i^{(m)} \end{array}\right\}_{i=1,\ldots,N}, \\ \boldsymbol{\beta}_{\mathbf{1}}^{\mathbf{Mkt}(m)}, \boldsymbol{\eta}^{(m)} \end{array}\right] \sim Inverse\ Gamma(\upsilon_1^{\varepsilon}, s_{1j}^{2,\varepsilon}) \tag{A.2.37}$$

where the posterior degrees of freedom is defined as $\upsilon_1^{\varepsilon} = \upsilon_0^{\varepsilon} + n$, and the posterior sum of squared errors as $s_{1j}^{2,\varepsilon} = \upsilon_0^{\varepsilon} \cdot s_0^{2,\varepsilon} + \boldsymbol{\varepsilon}_{\mathbf{j}}^{T} \boldsymbol{\varepsilon}_{\mathbf{j}}$.

9. Sampling of $\overline{\boldsymbol{\theta}}$ and $\mathbf{V}_{\boldsymbol{\theta}}$

To sample the mean and variance of the physician heterogeneity distribution we apply standard results for Hierarchical Bayesian linear models (see Rossi et al. 2005, section 3.7), which allows us to obtain closed form solutions for the two full-conditional distributions for $\overline{\boldsymbol{\theta}}$ and $\mathbf{V}_{\boldsymbol{\theta}}$:

$$\overline{\boldsymbol{\theta}}^{(m)} \mid \left\{\boldsymbol{\theta}_{\mathbf{i}}^{\mathbf{LEARNING},(m)}, \left\{Q_{ij}^{(m)}\right\}_{j=1,\ldots,J}, r_i^{(m)}, \boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}(m)}, \delta_i^{(m)}\right\}_{i=1,\ldots,N}, \mathbf{V}_{\boldsymbol{\theta}}^{(m-1)} \sim N(\boldsymbol{\mu}_{\boldsymbol{\theta}}, \boldsymbol{\Sigma}_{\boldsymbol{\theta}}) \tag{A.2.38}$$

$$\mathbf{V}_{\boldsymbol{\theta}}^{(m)} \mid \left\{\boldsymbol{\theta}_{\mathbf{i}}^{\mathbf{LEARNING},(m)}, \left\{Q_{ij}^{(m)}\right\}_{j=1,\ldots,J}, r_i^{(m)}, \boldsymbol{\beta}_{\mathbf{2,i}}^{\mathbf{Mkt}(m)}, \delta_i^{(m)}\right\}_{i=1,\ldots,N}, \overline{\boldsymbol{\theta}}^{(m)} \sim IW(g_0 + N, g_0 \cdot G_0 + \mathbf{S}_{\theta}) \tag{A.2.39}$$

Finally, we set m = m+1 and iterate until convergence.

CHAPTER 3: ANTECEDENTS AND CONSEQUENCES OF PATIENT EMPOWERMENT AND ITS IMPLICATIONS FOR PHARMACEUTICAL MARKETING[17]

When in 1992 Laura Landro, a journalist at *The Wall Street Journal,* was diagnosed with chronic myelogenous leukemia she decided to gather as much information as possible about her disease and to become an *informed patient*. At this time, the use of the Internet was still not sufficiently widespread, and physicians were not accustomed to patients bringing documents and medical data to the medical encounter. As a result, challenging doctors "was no picnic" and, in order to find the "accessible, wonderful, caring doctors" she deserved, Laura had to sever ties with a few more "impersonal physicians and medical workers who were simply annoyed at a patient who was trying to be her own best advocate" (Landro 1999, p.56).

At the same time pharmaceutical companies, perceiving changes in the role of patients in medical decision-making, initiated a trend that would soon become controversial. The amount invested in direct-to-consumer advertising (DTCA) by the American pharmaceutical industry rose steadily from the mid-1990's onwards. Indicative of recent changes in the healthcare systems, DTCA expenditures reached, in 2006, $4.8 billion (Pharmaceutical Research and Manufacturers of America 2008).

In this chapter, we review evidence supporting the claim that a fundamental shift in the role of the patient (and, consequently, of the physician) in medical decision-making is taking place. There is a trend toward more participatory decision-making in which doctors and patients *together* bear responsibility for medical decisions. This change has implications for patient welfare and for firms operating in the life sciences industry[18].

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[17] This chapter is based on Camacho, N., V. Landsman and S. Stremersch (2010), "The Connected Patient," in *The Connected Customer: The Changing Nature of Consumer and Business Markets*, S.H.K. Wuyts, M.G. Dekimpe, E. Gijsbrechts, F.G.M.(Rik) Pieters, eds. London, UK: Routledge Academic.

[18] Throughout the chapter we adopt Stremersch and Van Dyck's (2009) definition of the life sciences industry as an industry that develops science-based knowledge and improves consumers' quality of life. When we refer to life sciences firms we refer to pharmaceutical, biotechnology and therapeutic medical devices companies.

In this new paradigm, physicians are expected to establish a dialogue with their patients and apply their medical knowledge in order to connect scientific evidence to patient needs and preferences (Emanuel and Emanuel 1992; Epstein, Alper, and Quill 2004; Morgan 2003). Despite its renewed appeal, this idea of reaping benefits from a strong collaboration between patient and physician has a very long tradition in medicine. For example, in an influential paper about patient-physician relationships, Emanuel and Emanuel (1992) quoted Plato who, more than 2,000 years ago, wrote:

> *The free practitioner, who, for the most part, attends free men, treats their diseases by going into things thoroughly from the beginning in a scientific way… He does not give his prescriptions until he has won the patient's support, and when he has done so, he steadily aims at producing complete restoration to health by persuading the sufferer into compliance.*

Until recently, however, the relationship between patients and doctors could still, by and large, be characterized by a *white-coat model*, according to which the physician uses her or his knowledge to prescribe treatments in a paternalistic way (Charles, Gafni, and Whelan 1999). Limited patient participation in medical decisions was generally accepted because (i) the utility of different health outcomes was considered objective and independent of the subjective thoughts of doctors and/or patients, and (ii) society at large empowered physicians to use their knowledge to decide, on behalf of the patient, what treatment and tests were the most appropriate given her or his condition (Emanuel and Emanuel 1992).

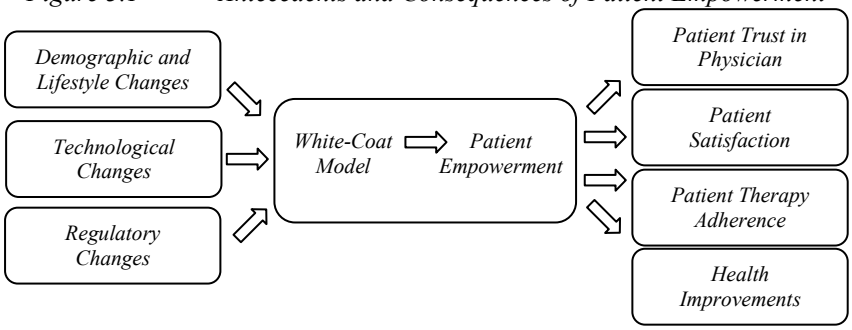
Today, the expectations and views of both physicians and patients regarding medical encounters are changing, and a trend toward *patient empowerment* is emerging. These changes are occurring based on a commonly held belief that patient participation in medical decisions has many desirable health consequences. For instance, scholars in medicine have argued that patient participation in medical decisions leads to improvements in adherence to treatment plans (Golin, DiMatteo, and Gelberg 1996; Horne 2006), and they have shown that empowered patients are more satisfied and have better perceived

improvement in symptoms than patients who are treated according to a white-coat model (Brody et al. 1989; Lerman et al. 1990; Little et al. 2001).

Yet, the transition toward a more active participation of patients is not free of controversy. First, many scholars in medicine claim that the empirical evidence to support patient empowerment is still too scarce to warrant an evidence-based change in medical decision-making paradigm (Bensing 2000). Second, the transition toward patient empowerment requires a transformation of the tie between patient and doctor, which may entail changes in the amount, content and directionality of information flow and in the level of reciprocity in the relationship. Neither all doctors nor all patients are equally prepared or motivated for this change.

In this chapter, we review antecedents and consequences of the trend toward increased patient participation in medical decisions. A better understanding of patient needs and preferences will help us uncover how patient satisfaction, health outcomes, effective healthcare delivery and life sciences firms' marketing strategies can be improved. This understanding will also provide insights on several open research topics. Figure 3.1 illustrates a conceptual overview of this chapter.

Figure 3.1 Antecedents and Consequences of Patient Empowerment



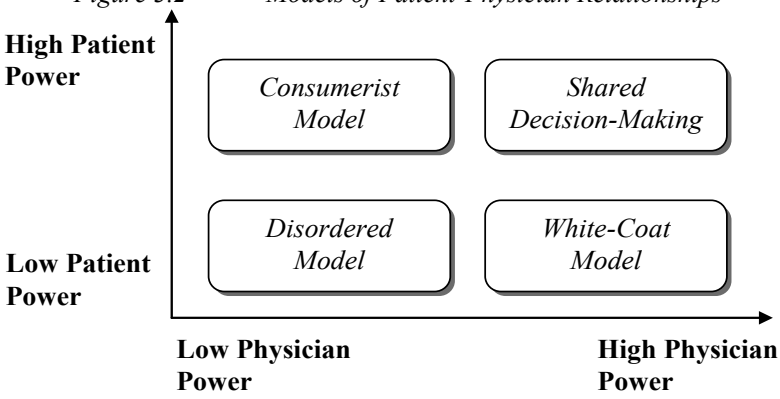
As can be seen from Figure 3.1, the primary focus in this chapter is the dyadic connectivity between patients and their physicians. However, in order to develop a more comprehensive understanding of the underlying processes in these relations, we consider – in an admittedly cursory manner – the broader context of these relations and investigate other types of ties in medical decision-making. Such "surrounding connections" may be

among patients, among physicians, or between heath-related entities (e.g., pharmaceutical companies, health insurance companies, pharmacists, nurses) and patients or physicians.

2. From a White-Coat Model to Shared Decision-Making

Figure 3.2 presents a typology for possible models for the patient-physician relationship according to the dual power structure within this relationship. The **white-coat model** on the lower right part of Figure 3.2 was the mainstream approach until the 1980's and is characterized by a relationship in which the physician takes a paternalistic role and acts as a guardian of the patient and his or her health. Under the white-coat model, the final goal of improving the patient's health status is treated as an objective goal that has priority over both patients' autonomy and personal choices (Emanuel and Emanuel 1992). In such a model, the patient is expected to cooperate and *comply* with the physicians' orders and recommendations. The relationship usually assumes a biomedical tone, with the emotional and psychosocial components of medical care garnering relatively less importance (Morgan 2003).

Figure 3.2 Models of Patient-Physician Relationships



Adapted from Roter (2000), © 2000, with permission from Elsevier.

Moving away from the white-coat model, however, is neither easy nor consensual. Different physicians react differently to patient participation in medical decisions. Some

argue that there is a lack of practical guidelines to guide physicians in the process of adapting their behavior to the new reality of patient empowerment (Taylor 2007). Others fear that physicians might start interpreting their role solely as providers of important information to the patient rather than as influencers of patient decisions. In such cases, a **consumerist model** would be established and patients would turn to physicians for medical information but assume the control of their medical decisions (upper left part of Figure 3.2). Many physicians feel uncomfortable with these challenges, which might explain why today, despite the increasing agreement on the need for more patient participation, many physicians still adopt a white-coat approach to medical care (Young et al. 2008).

In fact, a risk entailed in the process of empowering patients is that physicians might practice reactive, rather than proactive, medicine. Reactive medical care - a tendency to offer only the advice and information requested by patients - can be particularly undesirable when patients are not able or willing to take the lead in making medical decisions. In effect, if the physician assumes erroneously that the patient wants to make his or her own decisions and prematurely hands over relational power and control to the patient, the patient-physician relationship can suffer from lack of direction. We labeled such situations as a **disordered model**[19].

This discussion suggests that it is important (i) to distinguish shared decision-making from other alternative models of the patient-physician relationship (a topic explored in detail in Chapter 4), (ii) to better understand whether and how shared decision-making can be promoted (a topic explored both in Chapter 4, which studies the link between patient empowerment and therapy adherence, and Chapter 5, which studies the relationship between patient requests for medications using brand name and physician accommodation of such requests) and (iii) to understand the role of patient expectations in shaping patient-physician relationships. In essence, the medical literature tends to rely on self-determination theory – which predicts that self-motivated behavior leads to better performance and higher persistence (Ryan and Deci 2000) - to argue that patient empowerment is a desirable goal for XXI century medicine. Patient empowerment should,

[19]Roter (2000) suggested that in such cases, the relationship can be transformed into a *dysfunctional standstill* in which misunderstandings and frustrations can be frequent and often lead to a breach in the relationship.

according to this literature, ideally lead to a **shared decision-making model**, which entails a *mutual* involvement of patients and physicians in clinical decisions. According to Charles, Gafni, and Whelan (1999; 1997), four necessary conditions must be met in order for a relationship to be classified as *shared decision-making*:

(1) *Mutual participation* - both the physician and the patient participate in the decision-making process[20];

(2) *Mutual sharing of information* – the physician shares information about existing treatment alternatives and listens to information the patient might have gathered from other sources;

(3) *Value-sharing* - the patient expresses his or her preferences, and the physician shares his or her knowledge-based values about the best course of action;

(4) *Mutual agreement* – this last condition, which focuses on the decision outcome rather than the decision process, claims that more than mutual participation, the physician and the patient need to reach mutual agreement about the best course of action.

In sum, there is an increasing number of proponents of the shared decision-making. This paradigm change entails opportunities and challenges for all stakeholders involved in healthcare. In particular, for life sciences firms, this new model suggests the need to invest in marketing strategies that address the increasingly active role of patients in treatment decisions. For policy-makers and physicians, the biggest challenge at the moment is the lack of empirical evidence to support the benefits and best practices that should guide patient empowerment.

3. Antecedents of Patient Empowerment

Now we turn to the antecedents of the trend from a white-coat model toward a shared decision-making model, i.e. the antecedents of *patient empowerment*, and address the magnitude of this trend. Patient-physician ties are based on the flow of information between these two actors and are, therefore, directional. That is, one can ask whether the information flows from Actor A to Actor B, or vice versa. This directionality allows us to

[20] In some cases, other participants, such as relatives, might also play an important role in a medical encounter. These triadic relationships are frequent in the case of elderly and adolescent patients (Charles, Gafni, and Whelan 1997).

look at levels of *reciprocity* or *symmetry* in the patient-physician relationship[21]. Reciprocity can serve as a 'starting mechanism' in early relational phases to induce higher levels of cooperation (Gouldner 1960). For example, many scholars in medicine defend that patient empowerment needs to be initiated by the physician. That is, according to these scholars, physicians have to take the first step by taking the initiative to share non-biomedical information (e.g. regarding the fit of therapy with the patient lifestyle or family obligations, meaning of the illness for the patient, and so on…) with their patients, in order to create, during medical encounters, a more participatory atmosphere (Charles, Gafni and Wheelan 1999; Epstein, Alper and Quill 2004; Lerman 1990).

Symmetry refers to the degree of power-sharing in the dyad and, therefore, can also be used to capture the trend towards patient empowerment, that is, the extent to which one observes a shift away from a sole focus on the "voice of medicine" to an increasing emphasis on the "voice of the patient" (Morgan 2003, p.55).

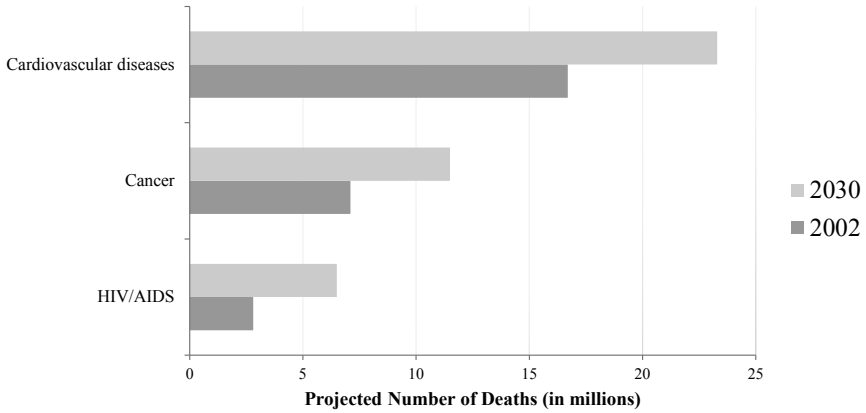
We can identify three major drivers triggering the move toward more patient autonomy and participation in medical care: (i) demographic changes, (ii) technological advances, and (iii) changes in the regulatory environment.

Demographic and lifestyle changes

Demographic and lifestyle changes are important contributors to the trend toward more patient participation in medical decisions. Ongoing shifts in demography (for example, an aging population) and lifestyle (such as increased urbanization, exposure to pollutants, or stress) contribute to an increased focus on chronic conditions worldwide (Murray and Lopez 1996). Leading public health concerns include ischemic heart disease, the continued spread of HIV/AIDS, and several forms of cancer (see Figure 3.3, adapted from Mathers and Loncar 2006).

[21] In our context, reciprocity or symmetry refer to a directed and bi-directional tie between a physician and a patient, i.e. a tie that is directed and flows from the physician to the patient as well as from the patient to the physician (Van den Bulte and Wuyts 2007).

Figure 3.3 Projections for Major Causes of Death Globally 2002-2030



Source: Mathers and Loncar (2006)

The increase in the prevalence and importance of chronic diseases creates two forces that encourage more informed and more connected patients, that is, shared decision-making. First, chronic patients have a strong incentive to collect information and discuss their health with friends or through patient support groups; hence, they will typically be more knowledgeable about their diseases than patients suffering from acute diseases. The increased knowledge possessed by chronically ill patients equips such patients with a greater ability to participate in their own medical care. Second, public health initiatives increasingly promote the need for lifestyle changes like smoking prevention and cessation (Pauwels et al. 2001) and eating a well-balanced diet (Grundy et al. 2004). This need to persuade healthy consumers to make lifestyle changes (with the objective of avoiding future health hazards) is facilitated by more patient involvement, and thus by a shared decision-making approach (Roter and Hall 2006; Sheridan, Harris, and Woolf 2004).

Technological changes

Technological advances also contribute to the obsolescence of the white-coat model. Specifically, two major technological shifts have facilitated the transition toward shared decision-making: (i) the advent of the Internet and the consequent democratization of

access to medical information, and (ii) the sequencing of the human genome, which triggered the emergence of personalized medicine.

The Rise of the Internet and E-health. The first important technological development that impacts patient-physician relationships involves the advent of the Internet and the consequent consumer access to health information. A recent survey conducted by iCrossing (2008), which is a research firm specialized in digital marketing, found that 59% of all American adults look for health information on the Internet. This makes the Internet the most popular source of health information, as 55% stated that they look for health information by visiting their physicians and only 29% acknowledged looking for such information by talking with friends, relatives or co-workers. Scholars in medicine indeed recognize that the massive accessibility of online health information has contributed to the "most important techno-cultural medical revolution of the past century" (Ferguson and Frydman 2004, p.1149).

In fact, the Internet affects the structure of the patient-physician network in two ways: it lowers the access barriers to medical information, and it facilitates the connection and sharing of information among actors (i.e. among patients, among physicians, between physicians and patients and between firms and the other stakeholders). The first effect – easier access to medical information – directly facilitates patient empowerment, because patients can now easily collect information that they can later discuss with their physicians. The second effect – increased connection among actors – also operates by increasing patients' knowledge but it typically interferes with the patient-physician relationship in an indirect manner. Virtual networking among patients, for example, facilitates the patient-to-patient word-of-mouth, i.e. sharing of experiences, information and support that can help patients understand and participate in therapy choice (Mukherjee and McGinnis 2007). On the physician side, the advent of e-healthcare is also strengthening social networks by facilitating the establishment of new ties among physicians and health professionals, allowing for more information to flow directly in the system. The increased importance of such virtual communities of physicians has the potential to improve the lives of many patients (Mukherjee and McGinnis 2007). Moreover, patients also have easier access to the

opinions of healthcare professionals other than their doctor via blogs and health-related webpages like WebMD.com.

It is important for all stakeholders in the healthcare industry to understand the implications of these changes and to learn how to leverage the potential of the Internet in general, and social media in particular. Marketers, for example, can serve an important role in convincing both patients and physicians to use these new tools to improve the quality of their mutual relationship and promote shared decision-making.

Genomics and Personalized Medicine. A second critical technological development in the life sciences has been the sequencing of the human genome and the ensuing rise of *genomics* as a revolution in medicine and drug discovery (Zerhouni 2003). Genomics is the study of the genetic material of an organism. Launched in 1990 by the U.S. government, the *Human Genome Project* (HGP) was a large research project involving more than 350 laboratories from several countries in order to study human genetic material (Enriquez and Goldberg 2000). In 2003, the HGP completed the mapping of the human genome, which opened a vast array of new possibilities in tailoring medicine to the needs of individual patients.

A good example of the impact of genomics on the prescription drug market is the growth of the biotechnology sector as compared to the pharmaceutical industry overall. Table 3.1 shows the largest 25 companies in the world in terms of sales of human prescription drugs and vaccines. The table shows that companies like *Amgen* and *Genentech* have grown faster than the market and thus have climbed up in ranking. Between 2005 and 2006, for example, the biologics sector grew 17.1% and reached sales figures above $52 billion, while the pharmaceutical market as a whole only grew 7% (Pharmaceutical Executive 2006).

Although the rise of personalized medicine cannot be considered an antecedent of the recent trend toward patient empowerment, we can certainly expect it to reinforce such a trend. Developments in genetics and biotechnology will boost personalized medicine, which requires detailed information flows between patients and their physicians for both diagnosis and treatment decisions. Therefore, we expect the rise of personalized medicine

to accelerate the trend toward shared decision-making by enhancing the volume and frequency of information flow between patients and physicians.

Table 3.1 Top 25 Companies in Terms of Prescription Drug Sales

Rank	2001	2002	2003	2004	2005	2006	2007
1	Pfizer	Pfizer	Pfizer	Pfizer	Pfizer	Pfizer	Pfizer
2	GlaxoSmithKline	GlaxoSmithKline	GlaxoSmithKline	GlaxoSmithKline	GlaxoSmithKline	GlaxoSmithKline	GlaxoSmithKline
3	Merck	Merck	Merck	Sanofi-Aventis	Sanofi-Aventis	Sanofi-Aventis	Sanofi-Aventis
4	AstraZenca	AstraZeneca	Johnson & Johnson	Johnson & Johnson	Novartis	Novartis	Novartis
5	Bristol-Myers Squibb	Aventis	Aventis	Merck	AstraZeneca	AstraZeneca	AstraZeneca
6	Aventis	Johnson & Johnson	AstraZeneca	AstraZeneca	Johnson & Johnson	Johnson & Johnson	Johnson & Johnson
7	Johnson & Johnson	Novartis	Novartis	Novartis	Merck	Merck	Merck
8	Novartis	Bristol-Myers Squibb	Bristol-MyersSquibb	Bristol-Myers Squibb	Wyeth	Roche	Roche
9	Pharmacia	Pharmacia	Wyeth	Wyeth	Bristol-Myers Squibb	Eli Lilly	Wyeth
10	Lilly	Wyeth	EliLilly	Abbott Labs	Eli Lilly	Wyeth	Eli Lilly
11	Wyeth	Eli Lilly	AbbottLabs	Eli Lilly	Abbott Labs	Bristol-Myers Squibb	Bristol-Myers Squibb
12	Roche	Roche	Roche	Roche	Roche	**Amgen**	Bayer
13	Schering-Plough	Abbott Labs	Sanofi-Synthlabo	**Amgen**	**Amgen**	Abbott	Abbott
14	Abbott Laboratories	Schering-Plough	Boehringer-Ingelheim	Boehringer-Ingelheim	Boehringer-Ingelheim	Boehringer-Ingelheim	**Amgen**
15	Takeda	Sanofi-Synthelabo	**Amgen**	Takeda	Takeda	Bayer	Boehringer-Ingelheim
16	Sanofi-Synthelabo	Boehringer Ingelheim	Takeda	Schering Plough	Astellas	Takeda	Schering-Plough
17	Boehringer Ingelheim	Takeda	Schering-Plough	Schering AG	Schering-Plough	Schering-Plough	Takeda
18	Bayer	Schering AG	ScheringAG	Bayer	Bayer	Teva	**Genentech**
19	Schering AG	Bayer	Bayer	Eisai	Schering AG	**Genentech**	Teva
20	Akzo Nobel	**Amgen**	Sankyo	Teva	**Genentech**	Schering AG	Novo Nordisk
21	**Amgen**	Sankyo	Eisai	Merck KGaA	Novo Nordisk	Astellas Pharma	Astellas
22	Sankyo	Akzo Nobel	Yamanouchi	**Genentech**	Eisai	Novo Nordisk	Daiichi Sankyo
23	Merck KGaA	Eisai	NovoNordisk	Yamanouchi	Teva	Merck KGaA	Merck KGaA
24	Novo Nordisk	Yamanouchi	MerckKGaA	Otsuka	Merck KGaA	Eisai	Eisai
25	Shionogi	Merck KGaA	Teva	Novo Nordisk	Sankyo	Otsuka	Otsuka

Source: Pharm Exec 50 - http://www.pharmexec.com/

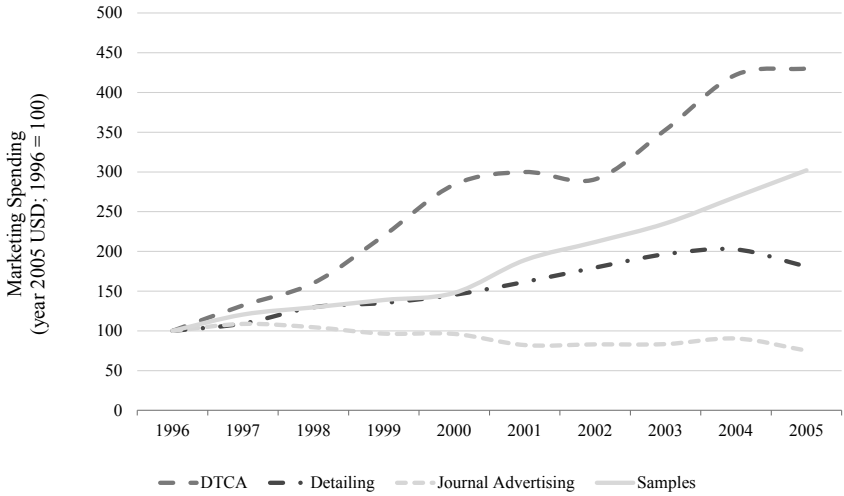
Regulatory changes

Increases in patient-physician connectedness have also been triggered by changes in existing regulations. Examples of such changes include greater flexibility in DTCA regulation, especially in the United States and New Zealand, and the increased use of malpractice suits by patients against physicians. Together with health and therapy information distributed via mass-media in general, and the Internet in particular (which is often seen with suspicion by doctors and policy-makers), DTCA is perhaps the most controversial topic in the pharmaceutical industry, thus triggering strong regulatory reactions in many countries around the Globe.

Regulation of Direct-to-Consumer Advertising. There is a generalized belief that direct-to-consumer health and therapy information distributed via mass-media contributes to an increase in patient requests for certain medication brands, eventually leading to overprescription and unnecessary healthcare costs. DTCA, in particular, has been pointed as the culprit of the current rise in costs with prescription drugs in the U.S. where, from the mid-1990s, the increase in DTCA expenditures became quite evident (see Figure 3.4).

There exists strong controversy about DTCA and the need for stricter regulation. On the one hand, some authors defend DTCA as a means to educate and empower patients to take a more active role in their treatment (Holmer 1999). On the other hand, other authors suggest that such efforts mainly boost consumer demand and distort the role of patients in the (traditional) relationship with their physicians (Hollon 1999; Moynihan, Heath, and Henry 2002), which may result in a consumerist or, even worse, a disordered model (see Figure 3.2).

Figure 3.4 *Growth in Annual Spending per type of Marketing (1996-2005)*



Source: Donohue, Cevasco and Rosenthal (2007)

Still, almost everyone agrees that the main effects of DTCA are to prompt patients to visit their physicians, possibly in order to request a specific drug (Bell, Wilkes, and Kravitz 1999). Venkataraman and Stremersch (2007), for example, have found that patient requests for a certain drug increases physicians' prescriptions of that drug. Moreover, physicians' refusals to accommodate such requests have been associated with patient dissatisfaction and even with intentions of switching physicians (Bell, Wilkes, and Kravitz 1999). Thus, DTCA might contribute to an increase in patient power in medical decisions, leading some scholars to recognize that "DTC advertising has the potential to fundamentally alter the roles of doctor and patient" (Wilkes, Bell, and Kravitz 2000, p.122).

A network perspective can help uncover important consequences of DTCA. For instance, social network theory suggests that different network properties, and different positions in a network, can make some actors more or less influential in marketing events (Van den Bulte and Wuyts 2007). Physician and patient beliefs can be influenced by the decisions of (i) those who are close to them (that is, contagion by direct contact, which is promoted by cohesion), (ii) those who are similar to them (that is, contagion by structural equivalence) or (iii) those who are particularly respected by them (Burt 1987; Nair, Manchanda, and Bhatia 2010). Both the Internet and DTCA can contribute to changes in

these properties. In particular, from a social network perspective, we can see the entities behind both DTCA and Internet websites targeting patients as additional "actors" who provide patients with information regarding their health conditions.

Thus, DTCA can influence patient power in medical decisions by increasing their *degree centrality* and *closeness centrality* in the social network and, consequently, lowering the informational advantages of physicians[22]. In fact, on top of their specialized training and knowledge, physicians used to monopolize the brokering of information across patients. That is, their contact with many patients gave them yet another informational advantage, that of building knowledge from learning about the experiences of different patients. These bridge positions – that is, network locations that span structural holes in the network – are a typical source of informational advantages (Burt 1992). However, DTCA (and the Internet) contributes to a new network structure that has fewer structural holes and, as a result, fewer actors occupying bridge positions in the network.

Previous literature has connected informational advantages with power (Brass et al. 2004; Podolny, Stuart, and Hannan 1996). In the patient-physician context, this implies that physicians in the new network structure have less 'power' in their relationship with patients than before. This leads us back to Figure 3.2 and to the general trend toward relationships that are characterized by shared decision-making (see also Figure 3.1). Nonetheless, physicians are still expected to keep their role as major players in patient-physician relationships. Their specialized training is not replaceable by either DTCA or by health information available on the Internet. In fact, it is well-accepted that patients, even though more knowledgeable about their own values and preferences, should not simply takeover the power over physicians, who are still experts on diagnoses and treatments (Roter and Hall 2006). Thus, we anticipate a trend toward shared decision-making involving the mutual participation of more informed patients with more facilitative, less authoritative physicians, rather than a shift toward a consumerist model. Moreover, more evidence is needed to support this shift, and inform physicians, marketers and policy-makers about the desirable degree of patient empowerment.

[22] Degree centrality reflects the number of ties an actor has in the system. Closeness centrality measures how close the actor is to each of the other actors in the social system (Van Den Bulte and Wuyts 2007).

Frequency and Severity of Malpractice Suits against physicians. Another regulatory factor that may promote patient involvement in medical decisions involves the climate created by increases in the frequency and severity of malpractice claims. In the U.S., there are on average 15 claims per 100 physicians per year (Danzon 2000). Physicians practicing in high-risk specialties, such as surgery or obstetrics, can expect to be sued once every six years, and although the vast majority of suits are either dropped or won by physicians, legal defense is still very expensive (Danzon 2000; Gawande 2005). This liability climate impacts patient-physician relationships.

First, appropriate involvement of a patient in medical decisions might help the physician share the responsibility of the decisions made with patients and, thus, reduce the likelihood of being sued. Failure to obtain *informed consent*[23] from patients, for example, is treated as medical negligence and can be used in court as equivalent to careless medical practice (Faden and Beauchamp 1986). Second, a way to reduce the threat of litigation is to promote open communication between the patient and the physician. In fact, when they proposed the National Medical Error Disclosure and Compensation Bill, Senators Hillary Clinton and Barack Obama believed in open communication within the patient-physician relationship as a way to reduce litigation (Clinton and Obama 2006).

In sum, technological, demographic and regulatory changes affect the structure of the social system of patients and physicians and contribute to increased connectedness in this network. We now turn to the consequences of shared decision-making.

4. Clinical and Relational Consequences

Increased patient connectedness entails structural changes in patient-physician relationships and in the health system that are capable of affecting the performance, productivity or innovativeness of existing ties. Cohesion in social networks, for instance, can be translated into performance improvements because of the increased capacity of such a network to encourage knowledge transfer, enhanced collaboration and learning. In a study of the performance of corporate R&D teams, Reagans and Zuckerman (2001) show

[23] Informed consent implies that the physician has a duty to provide information to his or her patients. If harm results from a certain medical treatment, and the patient is able to show in court that he or she would have opposed that medical decision, then the doctor runs a high risk of being found negligent (Faden and Beauchamp 1986).

that both cohesion and diversity among actors contribute to team productivity. We expect stronger ties between physicians and patients to contribute to improvements in clinical and relational outcomes, including patient trust in physicians, patient satisfaction, adherence to physician recommendations and general health outcomes.

Trust

In medicine, trust is typically considered to be the cornerstone of the patient-physician relationship (Kao et al. 1998). It is also a core construct in relationship marketing, and it can be defined as "a willingness to rely on an exchange partner in whom one has confidence" (Moorman, Zaltman, and Deshpande 1992, p.315). The current trend toward more patient involvement has consequences for patient trust in physicians. Partnership-building efforts from physicians, for instance, facilitate the transfer of important information between the patient and the physician, reinforcing the patient's trust in his or her physician (Epstein, Alper, and Quill 2004). Patients also are more likely to trust physicians who explore their disease and illness experience and provide longer consultations (Fiscella et al. 2004). Thus, we expect the trend toward shared decision-making to foster patients' trust in their physicians.

Trust has important health, social and economic consequences. In Kao et al.'s (1998) study, patients with lower trust levels are more than twice as likely to have considered changing physicians. This may have direct implications for managers in the healthcare industry looking to foster patient loyalty. Patients with a low level of trust are also more likely to report a lower satisfaction with care, weaker intentions to adhere to their physician's recommendations and lower improvements in health (Thom et al. 2002). Finally, patient trust in physicians promotes the spread of positive word-of-mouth, reduces conflicts between patient and physician and encourages perceived effectiveness of care (Hall et al. 2001).

Patient Satisfaction

Increased patient connectedness can also affect a second important health-related outcome, patient satisfaction. Research in medicine suggests a clear link between a physician's practice style and patient satisfaction. Flocke, Miller and Crabtree (2002) conducted a

study based on 2,881 patients and 138 family physicians to quantify the extent to which the style of interaction between patients and physicians influences patient satisfaction. They classified physicians into four mutually exclusive categories: (i) *person-focused* physicians (49%) were personable, friendly and more focused on the patient than on the disease; (ii) *biomedical* physicians (20%) focused on the disease and were unlikely to invest time exploring bio-psychosocial information; (iii) *bio-psychosocial* physicians (16%) elicited some psychosocial clinical information, such as information on social and psychological issues, but overall were more focused on the disease; and (iv) *high-physician-control* physicians (15%) dominated the clinical encounter and disregarded the patient's agenda. They found that patients visiting person-focused physicians were significantly more satisfied with the care they received (Flocke, Miller and Crabtree 2002). Therefore, in general, we expect the trend toward shared decision-making to lead to higher levels of patient satisfaction.

Adherence to Treatment Plan and Preventive Behaviors

Adherence to treatment plans is a very important health issue for all stakeholders in the medical care system. We adopt the definition of adherence provided by the World Health Organization: "the extent to which a person's behavior – taking medication, following a diet, and/or executing lifestyle changes, corresponds with agreed recommendations from a healthcare provider" (2003, p.3). Scholars in medicine have suggested that adherence might be a key mediator between medical practice and health outcomes (Kravitz and Melnikow 2004). Increased adherence, besides being a very important health outcome on its own, has also been linked to higher patient satisfaction (Dellande, Gilly, and Graham 2004) and to lower healthcare costs. Hence, improving patient adherence has the potential to improve societal welfare.

A better understanding of patients, physicians and the relationships they establish should help in designing better, perhaps branded adherence programs for patients. Facilitating shared decision-making could be an important step in this direction. For example, some authors defend the need to replace terms like *compliance*, which suggests a passive role for the patient, with the term *adherence*, which implies patient involvement and mutual decision-making (Osterberg and Blaschke 2005).

Furthermore, the economic costs of *non-adherence* are very high. In the United States alone, non-adherence causes 33 to 69 percent of all medication-related hospital admissions and an overall economic burden in excess of $100 billion a year (Dunbar-Jacob and Mortimer-Stephens 2001). Moreover, lost sales due to non-adherence cost the pharmaceutical between 15 and 20 billion annually (Wosinska 2005). Thus, adherence is an important topic for many stakeholders in the health system, like pharmaceutical firms and insurance companies.

Therefore, programs aimed at improving patient adherence, even when promoted by pharmaceutical companies, should be well received by other players in the health system (namely physicians and regulators). Ongoing regulatory changes in Europe, for example, should facilitate direct targeting of adherence-related information to patients (European Commission 2008).

Unfortunately, there is only scarce empirical evidence on the link between patient empowerment and therapy adherence, which indicates that this is a topic that deserves urgently to be addressed (Joosten et al. 2008). As such, future research should strive to better understand non-adherence form a social network perspective and to clarify strategies that marketers can use to promote adherence.

Health improvements

Finally, shared decision-making may translate into better health outcomes, such as less patient discomfort, greater alleviation of symptoms and better general health condition (Brody et al. 1989). Di Blasi et al. (2001) reviewed the results of 25 randomized controlled studies and concluded that there is consistent evidence that physicians who adopt a warm, friendly and reassuring approach are associated with better patient outcomes - for example, less pain and improved speed of recovery - than physicians who adopt a more formal and less reassuring approach. Still, the authors acknowledge that more evidence is needed to confirm the robustness of these findings.

In another review, Guadagnoli and Ward (1998) concluded that although many studies find that shared decision-making yields positive consequences, other studies offer conflicting results. These conflicting results might be a reflection of patient heterogeneity. Not all patients seem to be willing to participate in their medical decisions. So, it is

important to understand what type of patient-physician relationship is most suitable for different types of patients. We will now use existing evidence to suggest new ways of understanding different segments of the patient population.

5. Considering Patient Types in Patient-Centered Marketing

We define *patient-centered marketing* as a strategic orientation whereby life sciences firms aim their marketing efforts at holistically targeting both patients and physicians in order to: (i) provide treatment solutions that match the specific needs of distinctive patient niches; (ii) offer objective, unbiased, transparent and up-to-date information about available treatments; and (iii) stimulate patient intrinsic motivation towards her health and towards therapy choice. These patient-centered marketing principles should lead to marketing strategies that contribute to improved interactions between patients and their physicians and, ultimately, to improvements in treatment effectiveness and desirable patient behaviors, such as adherence to medical treatment, even though some of these links still need empirical scrutiny. We argue that the current trend toward shared decision-making will accelerate the importance of patient-centered marketing for life sciences firms and influence the ongoing transformation of their business models. To more fully understand these trends, we now analyze market segmentation.

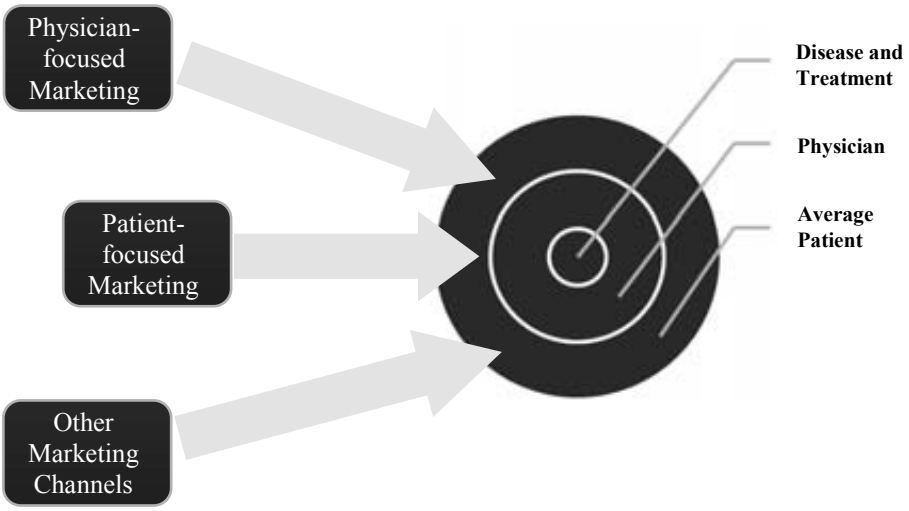
Market segmentation entails the development of specific marketing activities for homogenous sub-groups in the consumer population that exhibit significant differences in their consumption patterns (Kamakura and Russell 1989). Note that in the specific case of prescription drugs, the "consumer" is both the patient and the physician. Traditionally, the pharmaceutical industry has focused on segmentation strategies for the physician side of the market. This focus is coherent with the typical pattern of allocation of marketing resources in the pharmaceutical industry. Despite the significant rise in DTCA expenditures in recent decades, in 2005, DTCA still represented only 14.2% of total industry expenditures in the promotion of prescription drugs in the United States; direct-to-physician efforts like detailing, journal advertising and drug samples represented the bulk of pharmaceutical marketing expenditures (Donohue, Cevasco and Rosenthal 2007). In most other countries in which DTCA is typically not allowed, direct-to-physician efforts are even stronger.

Pharmaceutical marketers tend to focus on direct communication to physicians, with resource allocation being determined by physician characteristics, such as market potential, prescription volume, responsiveness to marketing, or capacity to influence other physicians. The models used for segmentation in the pharmaceutical industry also tend to be disease-focused, with the nature and severity of illnesses together with the nature of third-party payment agreements assuming key roles (Smith et al. 2002). In fact, for a certain *disease category*, the focus of most firms has been to *convince physicians* that they are capable of offering the best-in-class treatment, i.e., a treatment alternative that offers superior value for the *average patient* when compared with competing alternatives. We call this type of approach a *mass therapy marketing approach*; it is depicted in Figure 3.5.

This traditional mass-therapy approach is closely related with the prevailing 'blockbuster' model in the pharmaceutical industry; this business model focuses on finding innovative drugs, which are then converted into brands capable of generating annual revenues in excess of US$1,000,000,000. Despite its popularity during the last decades, the blockbuster model seems to be losing its appeal. Recent evidence suggests that life science firms need to shift away from blockbuster drugs to niche remedies and personalized medicine (The Economist 2007).

The current trend toward higher patient connectedness suggests that firms need to segment patients and address each patient niche with customized marketing strategies. There are two particular dimensions of patient heterogeneity worth discussing here: (i) heterogeneity in patient preferences for involvement; and (ii) heterogeneity in patient goals and expectations from medical treatment. We explore these in order to suggest how firms can understand underlying patient segments and improve the effectiveness of their marketing activities targeted at patients.

Figure 3.5 Mass-therapy Marketing Approach



Patient-level segmentation based on the desired level of involvement in healthcare decisions

Not all patients are moving toward shared decision-making at the same rate. Some patients seek higher involvement in their health decisions, while others prefer to maintain a traditional paternalistic relationship with their physicians. Different preferences for involvement translate into differences in patient trust in their physician's capability of making the right choice, patient health information needs, and patient adherence to recommended treatment plans. Thus, segmenting patients according to their desired level of involvement in healthcare decisions is of great value to marketers. Such an approach can help determine which patients are more responsive to information provided through DTCA or other direct-to-patient channels such as websites with health information.

Prior research has already shown that for some segments of patients, DTCA has positive effects, while for others it has negative effects (Bowman, Heilman and Seetharaman 2004). One important implication for the life sciences industry is that patients who wish to have an active role in medical decisions are the most valuable targets of DTCA. These patients want to play an active role in their own care and, therefore, are more likely to decide to visit their physician after seeing an advertisement. Ironically,

however, patients who are more in control of and involved in health decisions are also more likely to actively decide to not fill a prescription or adhere to a treatment regimen (Roselund et al. 2004). Therefore, firms need to understand the needs of different patient segments in order to leverage on their unique opportunities while addressing their specific threats.

In order to segment patients based on involvement, it is important to pinpoint what drives involvement preferences. Once such drivers are recognized, pharmaceutical firms can fine-tune their marketing activities in order to effectively and profitably influence these patient segments. Some demographic characteristics, for instance, have been found to affect the level of patient participation and interest in medical decisions. For example, someone who is white, female, relatively educated and enjoys a relatively high level of health is likely to have a higher preference for involvement in medical decisions (Flynn, Smith and Vanness 2006; Street 2005). Age also plays a role, with younger patients desiring more active participation in their medical decisions (Cassileth et al. 1980; Rotter and Hall 2006). This correlation between age and participation might be explained by physician stereotypes about older patients, their weaker health status, the presence of a visit companion during medical encounters (which is common among older patients), and an unwillingness to challenge the authority of physicians (Roter and Hall 2006).

Consistent with the importance of various patient characteristics, Stremersch, Landsman and Venkataraman (2008) found that physician responsiveness to patient requests is correlated with the demographic composition of the area in which the physician's practice is located[24]. This finding suggests that physicians do not treat all patient requests equally. Therefore, patient demographic characteristics (e.g., education, ethnicity, income) can moderate how physicians interpret and respond to patient requests.

Other, less explored patient characteristics that could lead to different preferences for involvement include differences in attitudes toward health and health providers as well as cultural or individual values. All of these characteristics may vary among people, regions

[24] We cannot directly infer participatory style from a physician's response to patient requests. Responsiveness to patient requests may occur even if participation is low (such as automatic accommodation of requests in the case of a consumerist relationship) and low responsiveness can also occur under participatory encounters (for example, a physician may persuade a patient against a certain medicine).

and countries. Contextual effects, such as the specific condition suffered by a patient, can also trigger higher or lower levels of desired involvement (Cassileth et al. 1980). Under some circumstances, patients might prefer to discuss treatment alternatives and illness-related information but still delegate final medical decisions to the physician.

Patient-level segmentation based on needs and expectations

Apart from a patient's desire for involvement, patient health needs and expectations about treatment can distinguish different niches of patients that subsequently can be addressed by distinct marketing strategies. We define patient *needs* as a feeling of dissatisfaction that motivates the patient to set specific goals to be achieved through medical treatment; patient *expectations* comprise the information the patient expects to receive about the treatment, the risks he or she is willing to incur and the effort he or she is willing to invest in reaching these predefined health goals.

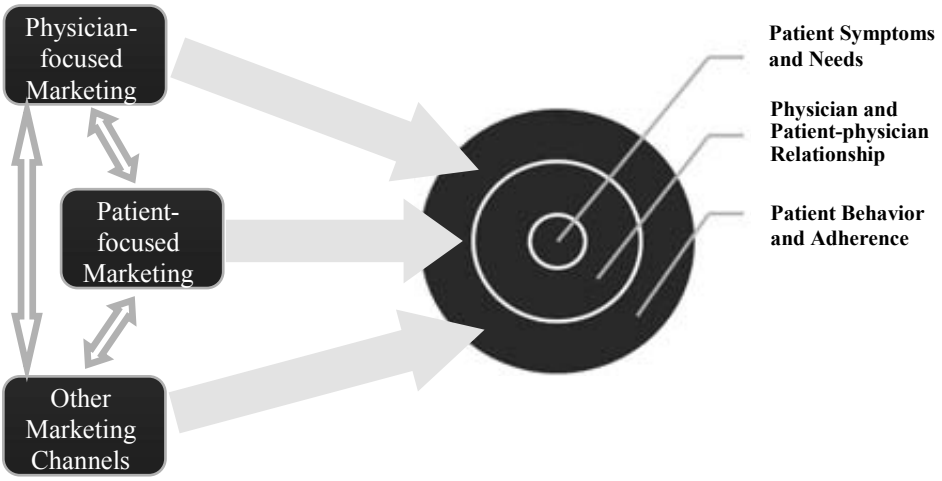
The different psychological reactions of patients to disease, including stress, emotional arousal and distress, have been related to different health behaviors and distinct ways of coping with disease (Baum and Posluszny 1999). Similarly, we argue that patients with different lifestyles, family and personal needs, pain tolerance and risk attitudes will require different types of information and treatment approaches. In terms of marketing strategy, a deeper acknowledgement and integration of this distinction should engender better ways of conveying information and even treatment solutions to different niches of patients.

Towards a patient-centered marketing approach

The critical and defining characteristic of the patient-centered philosophy is its focus on the patient, rather than on the patient's disease or the physician. Yet, by considering the pivotal role of the patient-physician relationship, and of mutual participation in treatment decisions, our call for more patient-centered marketing should not be confused with a call for more dissemination of health and therapy information online, or for more DTCA or, in any way, for a more consumerist view of healthcare. Rather, in order to adopt a patient-centered marketing philosophy, firms should focus their strategies, including those directed at physicians, on (i) offering the best treatment for each *patient niche*; (ii) promoting more productive *patient-physician relationships* (which may, or may not, entail more patient

empowerment); and (iii) achieving more *desirable patient behaviors*, for example, greater adherence to medical recommendations. We depict this approach in Figure 3.6, which summarizes the ideas developed in prior sections.

Figure 3.6 Patient-Centered Marketing Approach



The challenge for firms is to find creative ways to address both the opportunities as well as the threats (including regulation, potential for physician backlash and public backlash) that a patient-centered approach makes possible. It is important to understand which sources of health and therapy information are perceived by the patient as credible and leverage those channels to achieve the desirable goals of patient-centered marketing. In addition, firms and scholars need to gather empirical evidence on the benefits and risks of patient empowerment, in order to understand its limits and the opportunities it offers. The Internet, for example, might still provide many new opportunities for firms to interact with patients and their physicians (Lerer 2002). AstraZeneca's *MySymbicort.com* is a good example of how a pharmaceutical company can develop a channel to directly communicate with patients, share information about a specific brand and promote tips and ideas aimed at increasing patient quality of life and adherence to medical treatment. Life science firms are becoming more alert to these challenges. Consulting companies like *DKI Direct* and *The*

Patient Practice[25], for example, are offering services aimed at improving the effectiveness of direct-to-patient marketing efforts. As this trend develops, there are many opportunities for scholarly research to positively impact the transition from a mass-therapy to a patient-centered marketing approach. Firms would certainly benefit from new tools and answers to the many open questions.

Limitations of the patient-centered approach

There are three major barriers that may slow down the transition from a mass-therapy to a patient-centered marketing approach. First, there exists a "clash of mentalities." Sales and marketing managers have developed very high levels of expertise in steering marketing efforts toward physicians; they thus may be reluctant to adopt a patient-centered view. Second, regulators, physicians and the general population are not used to seeing pharmaceutical companies communicate directly with patients. This is especially true outside the U.S. and New Zealand. Third, a reinforced focus on the patient suggests that pharmaceutical firms may need to develop new skills and use new, potentially costly, consumer channels to promote their products.

The arguments we have presented suggest that the change toward patient-centered medicine is already in progress. Failure to adapt marketing strategies to this new paradigm for medical practice will be even costlier than investing in these new skills. Therefore, firms should look for opportunities, rather than ruminate on the threats, in these trends. Some opportunities may even help ameliorate the three major barriers just discussed.

First, it is important to integrate patient-directed efforts with existing marketing actions directed at physicians and other stakeholders. Investing in a patient-centered marketing approach should not be seen as a replacement for other marketing channels. On the contrary, the objectives defined above for patient-centered marketing can only be achieved by promoting a greater integration between marketing and sales as well as among

[25] DKI Direct (http://www.dkidirect.com/) works with pharmaceutical companies to elaborate profitable patient relationship marketing strategies. The Patient Practice (http://www.thepatientpractice.com/) is a consulting firm specialized in providing advice on how firms and organizations can interact with patients. It was founded by Di Stafford, former head of patient-focused marketing at Pfizer UK.

the different existing channels, which include patients, physicians, hospitals, pharmacies and wholesalers, regulators, and insurers.

Second, marketing researchers in life sciences firms will need to gather information about patient treatment goals and expectations as well as in-depth knowledge about the meanings that patients attach to the biomedical aspects of their diseases. The knowledge they obtain from these research efforts should be used to craft valuable information that is not only targeted at the patient but also coordinated with physicians and the views of other stakeholders. This will help guarantee that the life sciences industry is perceived as a "life saving" rather than "sickness selling" industry.

Third, in order to gather such information, firms may need to develop further patient-focused market research competencies and invest resources in new marketing and communication channels. However, some reallocation of resources from physician channels to patient channels seems appropriate and might appease potential cost concerns that arise with increased patient-level segmentation. The rationale for this substitution lies in the recognition that the law of diminishing returns might already be affecting direct-to-physician marketing. Evidence shows that nowadays, direct-to-physician marketing is not as effective as firms would expect and desire (Venkataraman and Stremersch 2007). Therefore, reallocating marketing resources from direct-to-physician channels to less saturated marketing channels, such as direct-to-patient channels, should bring new profit-improving opportunities for firms. We now conclude with a summary of the key strategic implications of patient connectedness.

6. Strategic Implications of Patient Connectedness

The discussion above highlights several important research topics that may be of interest to life sciences firms, patients, physicians and policy makers, as is synthesized in Figure 3.7.

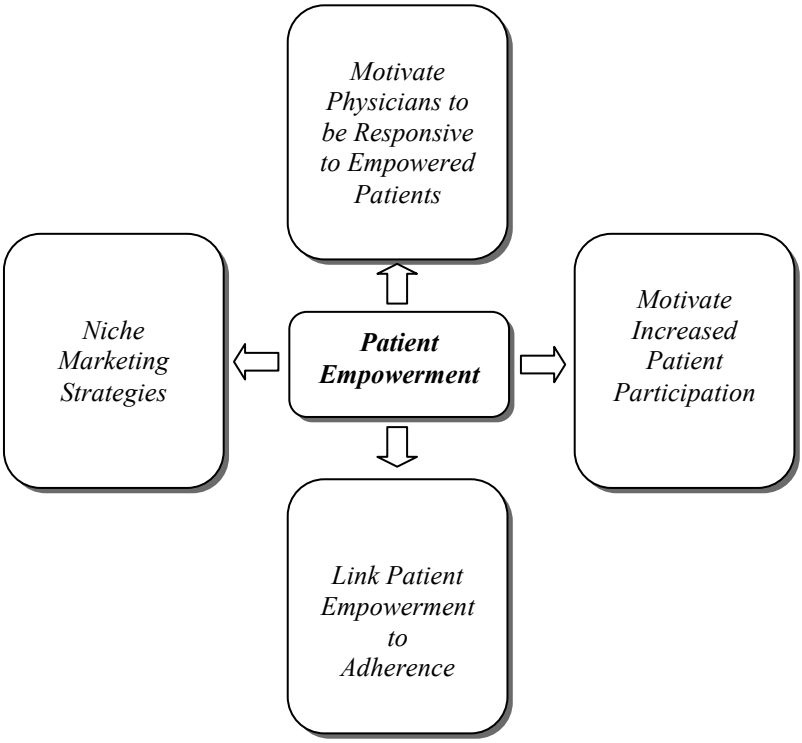
First, more effort needs to be devoted to motivate physicians to encourage patient participation in medical decisions. Most physicians do not engage in shared decision-making (Street et al. 2005; Young et al. 2008). One possible reason for this lack of enthusiasm is that physicians may still feel uncomfortable with patient empowerment. Another possible reason is that they fear that patients are unprepared and thus may react negatively to patient empowerment. In fact, there is evidence that many patients, when

asked to choose among therapies for instance (an empowerment act), feel that therapy choice is a competence of the physician and react negatively to such transfer of responsibility (McNutt 2004). Other patients may become overconfident when empowered by physicians, leading them to make health and therapy decisions on their own, which can be undesirable (see Chapter 4). However, if a patient is intrinsically motivated to participate in therapy choice, physicians should be able to leverage on that motivation and use it to maximize treatment effectiveness, for instance via increased patient adherence to therapy advice. If firms, patients and policy makers want to promote shared decision-making, some work still needs to be done to persuade physicians of the importance of shared decision-making. Other stakeholders such as payers (insurance companies, or governments), financial intermediaries, and pharmaceutical firms[26] may also indirectly benefit from increased patient participation in medical decisions.

Second, firms should strive to understand patient needs and preferences regarding participation in medical decisions. Whenever deemed possible and desirable, firms can provide more information to patients in order to trigger self-motivated participation in medical decisions. This can be accomplished through DTCA, by supporting patient organizations, or promoting websites directed to patients. However, if firms are too forthright in motivating patients to participate in treatment decisions without also persuading physicians regarding the usefulness of such an approach, they may be accused of interfering in undesirable ways with the patient-physician relationship (Hollon 1999; Moynihan, Heath, and Henry 2002; Wilkes, Bell, and Kravitz 2000). Therefore, it is important to consider all the direct and indirect effects of marketing actions on the health system. Especially during the first trials of new patient-centered marketing strategies, pre-testing the proposed marketing actions in limited geographic areas or therapeutic markets may be wise.

[26] See the value chain in the pharmaceutical industry in Stremersch and Van Dyck (2009).

Figure 3.7 Policy Recommendations to Leverage the Trend toward Patient Empowerment



Third, firms can use these reinforced patient-physician relationships to promote adherence to treatment and medical advice. Please note that for patients to adhere more to therapy, the effects of patient empowerment in patient comprehension, persuasion, recall, treatment confidence and persistence need to be carefully considered. We have taken a first step towards a better understanding of patient empowerment and therapy adherence (see Chapter 4), but this is an area that needs further research. In short, patient empowerment needs to be intrinsically motivated to increase therapy adherence, so firms, physicians and policy-makers need to use a pull, rather than push, approach to motivate patients to participate in therapy choice. Increasing therapy adherence is a desirable goal from the perspective of all involved stakeholders (Wosinska 2005; World Health Organization 2003). Thus, it is a particularly useful objective to pursue, since more collaboration among all agents involved in the health value chain can be expected as a result (according to

Stremersch and Van Dyck (2009), stimulating patient adherence is one of the most impactful research topics in life sciences marketing).

Fourth, given the above analysis, firms may choose to focus more on smaller patient niches. Life science firms should complement their business model, which still is very dependent on the blockbuster model discussed above, with niche-marketing strategies. This can be achieved through careful patient segmentation in which segments are defined using traditional demographic and health status variables as well as through more psychological constructs like patient beliefs, expectations, needs and their level of involvement in their health in general. Another important strategy in this realm relates to the launch of new therapies. As discussed in Chapter 2, a controlled roll-out of a new therapy – targeting first those patient niches to whom the firm knows, based on clinical trial data, the new therapy will have the highest efficacy and lowest side effects – contributes faster physician learning and adoption of the new drug.

Future research in marketing should address the challenges and opportunities that increases in patient connectedness create to life science firms. We hope this chapter has at least achieved the following two goals: (i) to stimulate interest among marketing scholars to examine patient-physician relationships; and (ii) to emphasize the role of the patient as increasingly central in medical decision-making research.

CHAPTER 4: TOWARDS A MODEL OF INTRINSICALLY-MOTIVATED PATIENT EMPOWERMENT FOR THERAPY ADHERENCE[27]

Marketing scholars have taken a keen interest in consumer or customer compliance with, or adherence to, marketers' recommendations in domains ranging from suppliers' requests to channel partners (Payan and McFarland 2005), advice on product-usage (Hoffer, Pruit and Reilly 1994; Taylor and Bower 2004), advice on product and service choices (Gershoff, Mukherjee and Mukhopadhyay 2003). Customer adherence to recommendations and advice is particularly important in credence services like medical care, financial or legal services and management consulting. In such services, customers often need expert advice to choose between alternative services, products or actions (Pesendorfer and Wolinsky 2003). Due to its economic and social consequences, the topic of medical therapy adherence has already received some attention in the marketing literature (Bowman, Heilman and Seetharaman 2004; Dellande, Gilly and Graham 2004; Kahn and Luce 2003; Luce and Kahn 1999; Wosinska 2005).

Therapy adherence is the extent to which a consumer follows a treatment plan, such as taking medication, in accordance with the recommendations from her medical care provider (World Health Organization 2003). Non-adherence to medical therapy may result in low efficacy of the treatment for the patient, additional costs to society, and lost business for the firm. Non-adherence contributes to disease progression and unnecessary morbidity and mortality, resulting in direct and indirect healthcare costs in excess of $177 billion in the U.S. (National Council on Patient Information and Education 2007).Between a third and half of all patients - irrespectively of their health status, social status, income and education - are typically considered non-adherent, which makes therapy non-adherence "a worldwide problem of striking magnitude" (World Health Organization 2003, p.7).

The costs of non-adherence for pharmaceutical firms are also enormous. For instance, analysts at the Datamonitor Group estimated that lost sales due to non-adherence cost

[27] This Chapter is based on a working paper co-authored with Stefan Stremersch and Martijn De Jong. It is currently being revised for first submission to *Journal of Marketing Research,* please do not reproduce or cite without authors' permission.

pharmaceutical companies over $30 billion a year, i.e. an increase of 5% in adherence can generate $30-$40 million in additional sales for a $1 billion blockbuster drug (Greener 2007). For these reasons, medical adherence is seen as a high-impact research area in life-sciences marketing (Stremersch and Van Dyck 2009; Wosinska 2005), and a primary concern for pharmaceutical firms (Lee, Fader and Hardie 2007). Managerial interest in the topic of therapy non-adherence is also clear from industry conferences dedicated to the topic (for instance EyeForPharma's annual patient adherence and engagement summit) and research publications on non-adherence emanating from industry (e.g. McHorney 2009).

Given the magnitude of the therapy non-adherence problem, researchers have proposed non-adherence reduction strategies. Some scholars suggest that an effective way to decrease therapy non-adherence is to increase patients' power in the medical encounter (e.g. Loh et al. 2007; McGinnis et al. 2007; Roth 1994; Wilson et al. 2010). More generally, the marketing literature has documented the positive impact of multiple forms of consumer participation in the marketplace, namely word-of-mouth activity (Trusov, Bucklin and Pauwels 2009; Villanueva, Yoo and Hanssens 2008) and consumer reviews for products or services (Chevalier and Mayzlin 2006). Given this accumulated evidence, it is not surprising that both managers and scholars have converged to a belief that the customer should be seen as an active participant in the value-creation process (Prahalad and Ramaswamy 2000; Vargo and Lusch 2004). Thus, even in high-stakes decisions requiring specialized training and knowledge – like the choice of medical treatments – consumer empowerment is nowadays seen as the normative standard (e.g. Epstein, Alper and Quill 2004; Krahn and Naglie 2008).

Even though prior research on therapy non-adherence and on consumer empowerment has provided valuable insights, three main shortcomings remain. First, the literature has not adopted a unified definition of patient empowerment, often looking at different dimensions of physician-patient interaction in isolation (e.g. Horne 2006; Lerman et al. 1990). Second, empirical evidence to inform managers, physicians and policy-makers about the effect of patient empowerment on non-adherence to medical therapy is very scarce (e.g. Joosten et al. 2008). Third, prior research is not culturally sensitive and is often situated in the U.S. or a selected set of Western nations, endangering the generalizability of its findings (Botti, Orfali and Iyengar 2009; Charles et al. 2006).

Against this backdrop, the present study seeks to address these three shortcomings. We conceptually discern informational and decisional empowerment and organize different medical decision-making models according to these dimensions of empowerment. We then examine which of these different empowerment dimensions leads to lower non-adherence. To achieve this goal, we study the role of patient empowerment on therapy non-adherence using self-reported data from 11,735 patients in 17 countries in 4 continents. To the best of our knowledge, this is, by far, the largest and geographically most diverse test of the relationship between patient empowerment and therapy adherence to date.

We empirically demonstrate that there are important differences in the effects of different dimensions of consumer empowerment on therapy non-adherence. We show that decisional empowerment leads to higher therapy non-adherence and informational empowerment is only helpful when initiated by the patient, rather than the physician. These results show that the optimal treatment decision-making model, in terms of therapy adherence, is not to maximize patient empowerment as currently assumed by physicians, policy makers and pharmaceutical marketers. In fact, external pressure to boost patients' participation in treatment choice should be avoided as it increases non-adherence to medical treatment. The rest of the paper is structured as follows. We first review the existing literature and discuss why self-determination theory (Ryan and Deci 2000) has contributed to a commonly held belief that patient empowerment improves therapy adherence. Next, we organize the literature on patient empowerment to discern two dimensions, informational and decisional empowerment, and organize medical decision-making styles according to these two dimensions. In section 3, we discuss competing predictions from well-established psychological theories and develop the hypotheses to be tested. We then introduce the method, discuss the results and conclude with managerial and public policy implications of our findings.

2. Theoretical Background

Therapy Non-Adherence

Therapy non-adherence has received particular attention in the marketing literature (Bowman, Heilman and Seetharaman 2003; Dellande, Gilly and Graham 2004; Luce and

Kahn 1999; Kahn and Luce 2003; Wosinska 2005). Bowman, Heilman and Seetharaman (2003) infer non-adherence from the actual versus expected time-to-refill a medication. They find that therapy non-adherence tends to increase between doctor visits, as patients may become complacent (Bowman, Heilman and Seetharaman 2004). Wosinska (2005) uses a 4-year panel of prescription claims and shows that direct-to-consumer advertising (DTCA) decreases patient non-adherence, even though the economic impact is small.

Most studies of therapy non-adherence in marketing rely on self-reported data. Dellande, Gilly and Graham (2004), for instance, ask weight-clinic patients whether they adhered to their nurses' recommendations. They estimate a structural equation model and show that provider characteristics (patient-nurse similarity, or homophily, and nurse expertise) and patient characteristics (role clarity, perceived ability to handle medical treatment and motivation) are important antecedents of non-adherence. Specifically, homophily increases role clarity and motivation. Role clarity, perceived ability and motivation, in turn, translate into higher patient adherence. Kahn and Luce (2003) asked women in mammography waiting rooms to imagine different results of their test and indicate their planned adherence to future mammography tests. They found that false-positive results reduce planned adherence.

The antecedents and consequences of therapy non-adherence have also been studied by scholars in medicine and medical decision-making, mostly using self-reports, which is a simple and effective method to measure non-adherence (Gehi et al. 2007; Osterberg and Blaschke 2005), that correlates highly with objective measures like pill counts (Haynes et al. 1980), electronic monitoring systems or biological measures like plasma viraemia (Walsh, Mandalia and Gazzard 2002). We provide an overview of the major medical publications studying therapy non-adherence in Appendix IV.A. An important insight from the medical literature is that patients are heterogeneous in their propensity for therapy non-adherence but that the exact drivers of such heterogeneity are poorly understood. In addition, most empirical applications, both in medicine and marketing, have not distinguished between unintentional and reasoned non-adherence. Yet, these two forms of therapy non-adherence may have very distinct behavioral and attitudinal antecedents (Wroe 2002). Unintentional non-adherence is a patient's unintentional failure to follow the treatment advice of her physician, triggered by, for example, forgetfulness or incapacity to

meet the treatment plan requirements. Reasoned non-adherence is a patient's deliberate decision to not follow the treatment advice of her physician (e.g. due to a lack of belief in the treatment, fear of side effects, financial reasons). A better understanding of these distinct constructs is crucial to help inform marketing and public health interventions aimed at reducing therapy non-adherence.

Patient Empowerment

Empowerment is defined as mechanisms that equip people with sufficient knowledge and skills to allow them to exercise greater control over a certain event (Ozer and Bandura 1990). In the case of treatment decision-making, patient empowerment encompasses two dimensions that characterize the interaction between a patient and her physician during clinical encounters: (i) decisional empowerment and (ii) informational empowerment. Decisional empowerment refers to patients' perceived control over the actual choice of a treatment, which may range from decision delegation (the choice is made by the physician) to autonomy (the choice is made by the patient). Informational empowerment depends on the level of information exchanged between the patient and the physician. Proponents of patient empowerment defend that both diagnostic information (information the physician needs to identify the illness suffered by the patient) and non-diagnostic information - knowledge about the interaction between the illness, the treatment, and the patient's preferences and values - need to be taken into account in treatment choices (Epstein, Alper and Quill 2004). Hence, informational empowerment increases as patients and physicians exchange non-diagnostic information (e.g. patient's opinions about different treatments, details about a treatment's risks and benefits) during a clinical encounter.

Furthermore, the initiative to share, during a clinical encounter, non-diagnostic information can rest with the patient (patient-initiated information exchange) or with the physician (doctor-initiated information exchange). Patient-initiated information exchange refers to patients' intrinsically motivated initiative to exchange non-diagnostic information with their physicians (e.g. asking the physician to explain treatments in detail, voicing her opinion about alternative treatments). Doctor-initiated information exchange refers to physicians' initiatives to promote the exchange of non-diagnostic information with the

patient during a clinical encounter (e.g. asking the patient's opinion about the medical treatment or the disease).

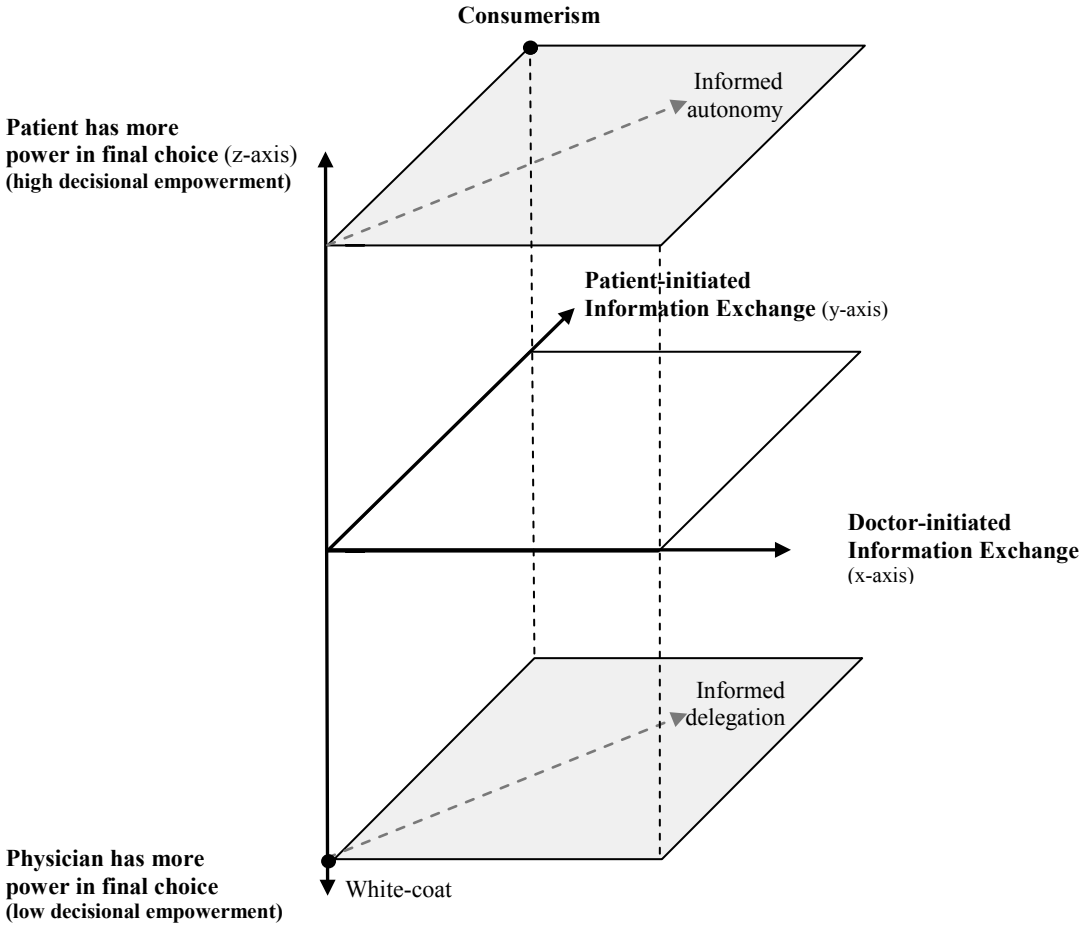
Patient Empowerment and Alternative Treatment Decision-Making Models

Figure 4.1 organizes different treatment decision-making models proposed in the literature along decisional and informational empowerment (either doctor-initiated of patient-initiated). The vertical axis (z-axis) depicts decisional empowerment. The hyperplane at the bottom of the graph describes choice delegation, the traditional view of medical decision-making whereby the final choice of a medical treatment is made by the physician. Choice delegation is normally defended on the grounds that patients are not experts in biomedical issues and, therefore, "physicians, by training and obligation, will not and should not let patients have more power over them" (Ding and Eliashberg 2008, p. 831).

The top hyperplane describes the opposite situation, i.e. treatment decision-making models characterized by patients who are in charge of therapy choice. Typical examples include physician accommodation of patient requests for a specific brand of medication (pure consumerism), or situations where the physician informs the patients about alternative treatment options but asks the patient to make the final choice (informed autonomy). The regions in between the upper and lower hyperplanes in Figure 4.1 describe decision-making models where the final choice is negotiated between the patient and the physician.

In the horizontal axes we depict different levels of informational empowerment, either doctor-initiated (x-axis) or patient-initiated (y-axis). Moving Eastwards in the x-axis means increasing levels of doctor-initiated exchange of non-diagnostic information, while moving Northeastwards in the y-axis means increasing levels of patient-initiated exchange of non-diagnostic information. This figure thus facilitates our goal of organizing different medical decision-making models proposed in the literature according to their levels of patient empowerment.

Figure 4.1 Patient (decisional and informational) empowerment and alternative treatment decision-making models



In the bottom left of the graph, we depict the traditional white-coat model which is characterized by choice delegation and by low informational empowerment (both patient-initiated and doctor-initiated). In a white-coat model, the physician is in charge of the clinical encounter and only needs to exchange diagnostic information with the patient in order learn about the illness suffered by the patient, and choose the best therapy conditional on such diagnosis (this model has also been referred to as the paternalistic model, see Charles, Gafni and Wheelan 1999). The patient is a largely passive actor who is

expected to be cooperative and facilitate the application, by the physician, of specialized medical knowledge to reach the choice of the best treatment plan for the patient (Arrow 1963). Despite the increasing number of proponents of patient empowerment, the white-coat model still describes how treatment choices are made by many physicians (Epstein, Alper and Quill 2004; Young et al. 2008). Please note that in the white-coat model, non-diagnostic information is not needed as the physician maximizes the patient's health status conditional on her medical knowledge and beliefs alone. In order words, in the white-coat model a physician is "paternalistically valuing patient functioning instead of patient utility" (De Jaegher and Jegers 2000, p. 250).

Closely positioned to the white-coat model are informed delegation models. Informed delegation is a concept akin to perfect agency, as it requires patients and physicians to exchange information regarding the preferences and values of the patient (i.e. exchange of non-diagnostic information), to allow the physician to choose the best treatment on behalf of the patient (Phelps 1992). In other words, conditional on the non-diagnostic information she collects during the clinical encounter, the physicians applies her biomedical knowledge to choose the treatment that maximizes the patient's utility (Phelps 1992, p. 214). Thus, in informed delegation models patients have access to non-diagnostic information but that the final choice still rests with the physician.

The top hyperplane of Figure 4.1 depicts informed autonomy models, which deviate from informed delegation as patients not only discuss non-diagnostic information with their physician but they also determine the final treatment choice. The consumerist model, for example, maintains that physicians and patients often have conflicting interests and, therefore, it is up to the patient to communicate her preferences for information or for a specific treatment to the physician and retain sovereignty over the final choice (Charles, Gafni and Whelan 1999). If the physician feels obliged to elucidate and interpret patient values and preferences (i.e. to facilitate patient exchange of non-diagnostic information) but still leaves the final therapy choice to the patient, then we move away from the consumerist model in the direction of an informed autonomy model, sometimes simply called informative model (Emanuel and Emanuel 1992), or enhanced autonomy model (Quill and Brody 1996).

Finally, the regions between the bottom and top hyperplanes of Figure 4.1 depict situations where a treatment decision is made both by the patient and the physician, which is one of the pillars of shared decision-making models (Charles, Gafni and Whelan 1999; McNutt 2004). In sum, in the patient-physician relationship, patients decide whether or not to delegate a specific decision (the choice of a therapy) to an expert (the physician). The extent of delegation is conditional on the control preferences of both the patient and the physician (Li and Suen 2004). Hence, different levels of decisional empowerment, patient-initiated information exchange and doctor-initiated information exchange lead to different treatment decision-making models. We now develop hypotheses relating these different dimensions of patient empowerment to therapy non-adherence.

3. The Effect of Patient Empowerment on Therapy Non-Adherence

The current belief that patient empowerment leads to lower therapy non-adherence finds its roots in self-determination theory, which shows that behavior which is based on intrinsic motivations - a true sense of volition and autonomous choice –leads to more confidence and higher persistence than behavior that is motivated by external pressure or control (Ryan and Deci 2000; Williams et al. 1996). Yet, self-determination theory posits that for higher motivation and persistence in behavioral change requires such behavioral change to be deeply internalized, which is only achieveable if it is perceived as autonomously motivated rather than externally imposed (Williams et al. 1996). Thus, the mainstream interpretation that patient empowerment during clinical encounters leads to lower non-adherence implicitly assumes that all forms of patient empowerment contribute positively to the perception, by the patient, that theapy choice has been intrinsically motivated. In addition, self-determination theory neglects other key drivers of unintentional and reasoned non-adherence such as patient comprehension, persuasion and capacity to recall the physician advice (Wroe 2002).

In effect, mainstream interpretation of self-determination theory also assumes that patients are both receptive and capable of processing non-diagnostic information and engaging in choice autonomy. Yet, if the patient doesn't comprehend the non-diagnostic information shared by the physician, she will be unable to recall the physician's advice later on, preventing her from correctly following the treatment plan even if that was her

intention, resulting in higher unintentional non-adherence. Moreover, some patients may actually expect the physician to be in charge of the medical encounter and, thus, be less persuaded by a physician who deviates from her expected role (McNutt 2004). In such cases, the patient may be less convinced of the benefits of the recommended therapy and, consequently, less motivated to follow and persist in such treatment plan. In such cases the patient may deliberately deviate from the physician's advice, resulting in higher reasoned non-adherence.

In order to accommodate these effects, we build on theories from cognitive psychology to theorize on the effects of different dimensions of patient empowerment on therapy non-adherence. First, *episodic trace models of memory*, which belong to the class of spreading activation models, are some of the most validated theories in cognitive psychology (Raaijmakers and Shiffrin 1992) and are frequently used in marketing to model information comprehension (Mick 1992) as well as encoding and recall (Puntoni, De Langhe and Van Osselaer 2009; Wedel and Pieters 2000). These models establish that when exposed to a message (e.g. a treatment advice) people encode it by storing several traces in memory, each of which referring to a distinct piece of information (Anderson 1983). For example, in a therapy advice, one memory trace could store dosing, another could store the exact times of intake, and yet another the treatment duration. During the encoding process, the level of comprehension depends on the extent to which the receiver of a message initiates self-motivated meaning-making process (Mick 1992). Later ease-of-recall of each memory trace is determined by its salience when compared with competing traces (Anderson 1983; Raaijmakers and Shiffrin 1992).

Second, even if a patient is able to comprehend and recall therapeutic advice, the patient will only follow the treatment plan if she has a positive attitude towards the therapy and is confident of her capacity to implement and persist with the treatment plan (Rosenstock 1974; Taylor 1990). *Argument structure theory* suggests that more complete arguments are better able to persuade consumers (Areni 2002).

Finally, self-determination theory argues that a key benefit of patient empowerment is the positive impact on patient confidence on her capacity to execute and persist in the treatment plan, which is perceived as intrisincally-motivated. Yet, self-determination theory ignores the fact that increasing patient autonomy in decision-making may also lead

to patient overconfidence. *Overconfidence* - the tendency of people to overestimate their ability or the reliability of their knowledge (DeBondt and Thaler 1995) - is one of the most common regularities of human judgment, especially in situations where decision feedback is delayed (Daniel, Hirshleifer and Subrahmanyam 1998).

Figure 4.2 Conceptual framework: Patient empowerment and therapy non-adherence

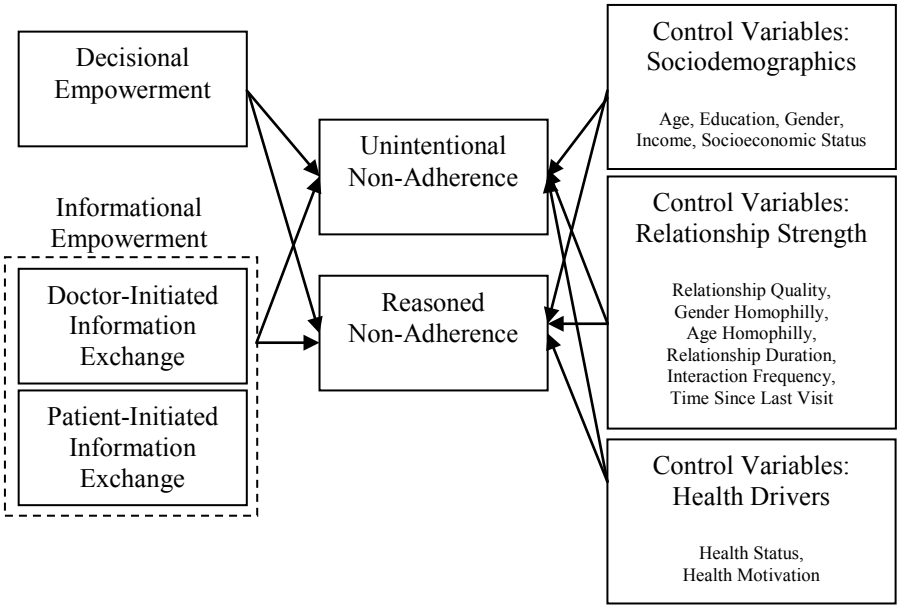


Figure 4.2 summarizes our framework to study the effect of patient empowerment on therapy non-adherence. We now build on the theories just discussed to develop our hypotheses – many of which in direct contradiction to self-determination theory - for the effects of different dimensions of patient empowerment on therapy non-adherence.

Decisional Empowerment and Therapy Non-Adherence

In contradiction to self-determination theory, we expect decisional empowerment to increase both unintentional and reasoned non-adherence. First, choice autonomy presupposes that, instead of focusing on diagnosing a patient's illness and choosing the best option to treat such illness, the physician will spend part of the medical encounter discussing non-diagnostic information, and alternative treatment options, with the patient.

The problem is that physicians are severely time-constrained (McNutt 2004). Therefore, allocating scarce time to the discussion of the benefits and costs of multiple treatment alternatives means that less time is spent in the discussion of the treatment that is ultimately chosen. According to spreading activation theories of memory recall, this means that the focal memory traces that the patient needs to recall to be able to follow therapy advice will be less salient and harder to recall (Anderson 1983; Raaijmakers and Shiffrin 1992). To make matters worse, when trying to process the information needed for therapy choice - a process which can often be perceived as stressful (Quill and Brody 1996) - patients tend to suffer from attentional narrowing, a phenomenon that limits the patient's attention and makes it harder for her to remember and follow the physician's advice later on (Kessels 2003). Hence, we hypothesize:

H_{1a}: Decisional empowerment increases unintentional non-adherence.

In addition, social-cognitive theories suggest that increasing a person's autonomy leads to higher self-confidence (Ozer and Bandura 1990). Hence, decisional empowerment should contribute to increase patients' belief in their capacity to make treatment decisions, which is often mentioned as a main advantage of empowerment. However, psychologists have established that people tend to generalize self-efficacy perceptions (like treatment self-confidence) from the focal domain of empowerment to domains outside the original scope of empowerment (Weitlauf et al. 2001). According to this line of reasoning, decisional empowerment may lead patients to become more self-confident in their capacity to make their treatment choices but, also, in their capacity to discern when or whether to alter or discontinue treatment, reducing reasoned non-adherence. In fact, Bowman, Heilman and Seetharaman (2004), to justify their finding that patients who request a specific brand of medication from their physician are more likely to non-adhere to the recommended treatment plan, conjecture that *"the associated perception of empowerment and control [triggered by decisional empowerment] should persist such that the patient also believes that he or she is capable of changing dosage or stopping usage altogether without physician consultation"* (p. 325). Therefore, we expect decisional empowerment to increase reasoned non-adherence:

H_{1b}: Decisional empowerment increases reasoned non-adherence.

Doctor-initiated Information Exchange and Therapy Non-Adherence.

The benefits accredited to doctor-initiated informational empowerment assume physicians are able to clearly communicate non-diagnostic information to their patients. Nevertheless, for many conditions and treatments, medical science's information base is limited, noisy, complex or unknown (McNutt 2004). This means that discussing non-diagnostic information with patients entails discussing complex information that could otherwise be omitted (e.g. information regarding medical symptoms, interaction between patient lifestyle and her health, etc). A consequence of discussing these additional topics is that the focal memory traces that the patient will need to recall for therapy adherence (dosing, schedule of intake and duration of treatment, for instance) will now have to compete with a myriad of other memory traces. Spreading activation theories of memory recall suggest that such additional memory trace competition makes the therapy less salient in the patient's memory and the physician's advice harder to recall (Anderson 1983; Raaijmakers and Shiffrin 1992). Hence, we hypothesize:

H_{2a}: Doctor-initiated information exchange increases unintentional non-adherence to medical treatment.

In terms of reasoned non-adherence, higher physician-initiated information exchange results in an increased usage of consultation time by the physician to share non-diagnostic information with the patient, necessarily at the expense of time reserved for reinforcing the exchange of diagnostic information or answering patient questions. Health communication scholars consider that a higher ratio of physician to patient talk is an indication of physician control of communication or *"verbal dominance"* (Roter and McNeilis 2003, p. 127), which can hinder, rather than help, patients' perceived autonomy (Roter et al. 1997). In this account, doctor-initiated informational empowerment may not act as a valid source of empowerment, as it violates one of the tenets of self-determination theory by increasing patients perceptions that the treatment plan is extrinsically motivated, reducing their intrinsic motivation to persist in the treatment (Ryan and Deci 2000). Moreover, prior

research in marketing demonstrates that when experts provide unsolicited information, and that information contradicts consumers' initial impressions, consumers become reactant and intentionally deviate from their advice (Fitzsimons and Lehmann 2004). Such tensions and disagreement could also lead the patient to disagree with the doctor's recommendation. We therefore hypothesize:

H_{2b}: Doctor-initiated information exchange increases reasoned non-adherence to medical treatment.

Patient-initiated Information Exchange and Therapy Non-Adherence.

According to subjective comprehension theory (Mick 1992), a self-initiated meaning-making process contributes to deeper levels of comprehension. Patient-initiated information exchange should then be more likely to result in discussion of information that the patient finds personally relevant and needed for her meaning-making process. In other words, patient-initiated information exchange should facilitate the activation and storage of the necessary and relevant pieces of information (or cognitive units) which the patient deems necessary to understand and be able to recall the recommended therapy during treatment duration. Hence, the patient-guided meaning making should reduce the number of competing memory traces that need to be stored during the medical encounter, and as a consequence ensure that the relevant memory traces for therapy adherence become salient in the patient's memory. Salience of the focal memory traces should result in higher ease-of-recall of the treatment advice (Anderson 1983; Raaijmakers and Shiffrin 1992):

H_{3a}: Patient-initiated information exchange decreases unintentional non-adherence to medical treatment.

Patient-initiated information exchange should also facilitate patient persuasion for the recommended therapy. First, deeper levels of comprehension facilitate the activation of positive attitudes toward a message's content (Mick 1992). Thus, patients who take initiative to ask their physicians for non-diagnostic information, should be more easily

persuaded by the physician advice. Second, if patients take the initiative to discuss non-diagnostic information with their physician, they should also perceive the physician argumentation in favor of the recommended therapy as more complete. According to argument structure theory, argument completeness should also facilitate patient persuasion (Areni 2002). Third, when patients actively ask questions to their physician, they signal their belief in their capacity to *learn* more about the treatment from such dialogue, not necessarily to make treatment decisions on their own. Such capacity, known as *dialogical capability*, is in fact a key predictor of consumers' willingness to *collaborate* in the production of value together with a service provider (Ballantyne and Varey 2006). Thus, patient-initiated information exchange should facilitate patient persuasion, persistence and confidence in her capacity to understand and learn about the therapy, which leads us to hypothesize:

> **H_{3b}**: Patient-initiated information exchange decreases reasoned non-adherence to medical treatment.

Control Variables

When examining the role of patient empowerment in therapy non-adherence, we need to control for other drivers of unintentional and reasoned non-adherence. First, in addition to its direct effect on therapy non-adherence, physicians' initiative to discuss non-diagnostic information with patients may influence patients' initiative to participate in the medical encounter. In fact, one of the most common claims by patient empowerment enthusiasts is that physicians need to create an atmosphere, during clinical encounters, that facilitates patient participation in treatment deliberation (Charles, Gafni and Wheelan 1999; Epstein, Alper and Quill 2004). We control for this effect by including, in our model, the path between doctor-initiated information exchange to patient-initiated information exchange.

In addition, we control for observed patient heterogeneity in the baseline level of adherence using the sociodemographic predictors of non-adherence typically used in the medical literature (age, education, gender, socioeconomic status, income and patient health status, see DiMatteo 2004). We also build on the marketing literature and control for time since the patient's last clinical encounter (Bowman, Heilman and Seetharaman 2004),

patient's health motivation (Moorman and Matulich 1993) and patient-physician relationship quality and strength. We follow existing literature in relationship marketing and define relationship quality as a higher-order construct that captures how much the patient values the relational interaction she maintains with her physician, a construct determined by different but interrelated relational dimensions (De Wulf, Odekerken-Schröder and Iacobucci 2001; Kumar, Scheer and Steenkamp 1995). There is no agreement about which exact dimensions should be included in relationship quality measures, but the two more consensual ones are trust and commitment, either taken together (Morgan and Hunt 1994), or even trust (Doney and Canon 1997) or commitment (Anderson and Weitz 1992) in isolation. Furthermore, patient-physician relationship strength can also be influenced by the perceived similarity between the patient and the physician, or homophily (Dellande, Gilly and Graham 2004) and by the age of the relationship and frequency of interaction between the patient and the physician (Doney and Cannon 1997).

4. Method

Data Collection

We investigate the effect of patient empowerment on therapy non-adherence using a unique dataset in terms of its size and geographical scope. We surveyed 11,735 patients in Belgium, Brazil, Canada, Denmark, Estonia, France, Germany, India, Italy, Japan, Netherlands, Poland, Portugal, Singapore, Switzerland, United Kingdom and United States of America. To the best of our knowledge, this is the largest study of the relationship between patient empowerment and therapy non-adherence to date. We contracted SSI (Survey Sampling International) to execute our survey on their online panels. Recruiting and rewarding procedures for SSI panels are constantly evaluated in terms of sample representativeness and respondent's attention and motivation (see Table 4.1 for sample descriptives).

We constructed the original survey in English and organized its translation to the 10 native languages (Danish, Dutch, English, Estonian, French, German, Italian, Japanese, Polish and Portuguese) that are spoken in the 17 countries included in our sample, by native speakers. The native speakers we used as translators were all doctoral students in

social sciences attending programs at our respective universities, which are located in Europe and the U.S., both having a large international student population. The vast majority of these graduate students are familiar with survey research methods, often through their coursework, which allowed us to discuss survey items, and their meanings, in great detail.

We organized the translation process in accordance to best-practices in international survey research. First, for each language, the English version was translated by a native speaker (the translator) who was proficient in English. Second, another native speaker (the back-translator) translated the survey from his native tongue back to English. Third, we discussed the translated surveys with both translators and back-translators, iteratively, until we were sure that the final survey retained exactly the same meaning in all languages.

Our selection of countries was guided by three major criteria. First, we wanted to obtain sufficient cross-cultural variation, in order to test whether our hypothesized relationships are culturally sensitive. Second, we only selected countries in which patients are free to choose their physician and typically develop repeated interactions with the same physician. Third, we screened out countries that were too expensive to survey in (> USD 10,000 per country). Table 4.1 presents some key descriptives of our dataset. In addition, our sample is subject to two exclusion criteria: (i) it's only composed of adults (≥ 25 years of age) and (ii) each respondent needed to have had at least 3 visits with their current general practitioner, in order to guarantee respondent ability to assess the relationship with her physician.

Measurement

We operationalize all measures in accordance to existing literature. We provide our measures (including the item operationalization), their respective sources and, when applicable, the mean Cronbach's alpha across the 17 countries in Table 4.2. In order to fine-tune our instruments we discussed all items with researchers in medical decision-making and health psychology (including two doctoral students in medicine and several colleagues working in health marketing).

We found our scales to be highly reliable. The only scale with reliability below .6 was the two-item measure for patient health motivation (Spearman's ρ=.58). In our final scales,

we used multiple items to measure unintentional non-adherence (4 items), reasoned non-adherence (5 items), doctor-initiated information exchange (4 items), patient-initiated information exchange (3 items), relationship quality (6 items) and health motivation (2 items). In the case of decisional empowerment, the measurement object (treatment decision) and its associated attribute (who is in charge of treatment choice) can both be easily envisioned by respondents and, consequently, a single-item measure should be used (Bergkvist and Rossiter 2007). Therefore, we use a direct item to ask respondents who, in their clinical encounters with their physician, has more influence determining the treatment chosen. We also used single items for health status (in line with Safran et al. 1998), age, education, gender, income, socioeconomic status, relationship duration, interaction frequency and time since last visit.

5. Model

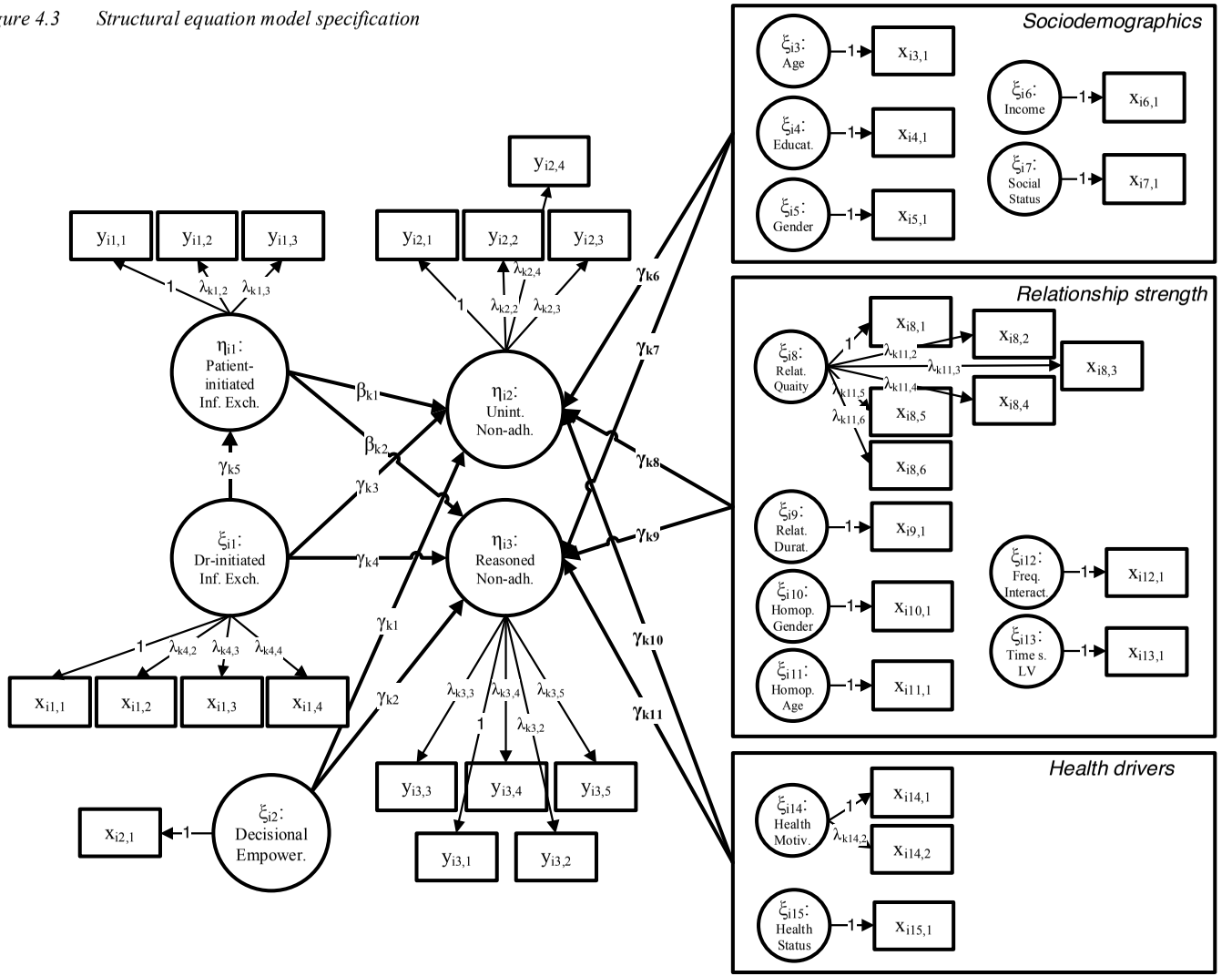
Figure 4.3 summarizes our model specification[28]. In order to avoid bias in our parameter estimates due to patient heterogeneity in their response to patient empowerment, we specify a finite-mixture structural equation model (FM-SEM), which is the most appropriate approach when existing evidence characterizing such heterogeneity is scarce (Jedidi, Jagpal and DeSarbo 1997). Estimation of FM-SEM's is not straightforward but Bayesian MCMC techniques have recently been shown to offer a robust and practical approach to these problems (e.g. Zhu and Lee 2001; Van Der Lans et al. 2009). We now formalize our model specification.

[28] Note: For simplicity of exposition, instead of linking all exogenous control variables to the endogenous latent variables of interest, we opted to depict these relationships per block (sociodemographics, relationship strength and health drivers). The bolded parameters γk6-γk11 denote vectors of unknown parameters to be estimated for the responses, in terms of unintentional and reasoned therapy non-adherence, to the control variables.

Table 4.1 *Descriptive statistics*

Country	*Sample Size*	*Patient*				*Physician*				*Patient-Physician Dyad*			
		Age		*Gender*		*Age*		*Gender*		*Relat. Length*		*Gender Conc.*	
		Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Belgium	669	50.69	12.16	0.49	0.50	48.25	8.35	0.79	0.41	14.82	10.17	0.55	0.50
Brazil	785	42.66	10.53	0.47	0.50	48.97	8.62	0.75	0.43	8.95	7.58	0.58	0.49
Canada	540	47.18	13.57	0.49	0.50	47.77	8.56	0.70	0.46	10.56	8.98	0.58	0.49
Denmark	570	49.87	13.18	0.42	0.49	50.92	7.31	0.65	0.48	11.66	9.33	0.57	0.50
Estonia	523	44.66	12.06	0.38	0.49	46.92	8.02	0.10	0.30	9.59	6.40	0.62	0.49
France	776	47.44	12.98	0.41	0.49	48.33	7.13	0.77	0.42	11.81	9.06	0.50	0.50
Germany	783	47.51	12.87	0.51	0.50	49.45	7.69	0.71	0.46	10.70	8.58	0.52	0.50
India	521	35.96	9.00	0.65	0.48	49.48	8.62	0.86	0.35	10.42	7.86	0.73	0.44
Italy	818	46.67	13.74	0.47	0.50	51.00	6.14	0.76	0.43	12.80	8.66	0.54	0.50
Japan	758	50.83	12.06	0.50	0.50	51.99	9.49	0.91	0.29	9.02	8.49	0.52	0.50
The Netherlands	795	48.32	12.65	0.46	0.50	47.87	7.36	0.76	0.43	12.99	9.56	0.51	0.50
Poland	760	40.34	11.16	0.44	0.50	46.15	7.29	0.41	0.49	8.38	6.29	0.56	0.50
Portugal	524	41.15	11.25	0.49	0.50	49.72	7.11	0.52	0.50	12.98	8.78	0.50	0.50
Singapore	815	39.62	9.99	0.45	0.50	45.17	7.22	0.78	0.42	9.04	7.01	0.51	0.50
Switzerland	547	47.92	12.25	0.48	0.50	50.24	7.02	0.86	0.34	12.08	9.01	0.50	0.50
U.K.	781	52.90	12.53	0.50	0.50	46.27	8.10	0.72	0.45	11.58	9.35	0.56	0.50
U.S.A.	770	46.30	13.40	0.54	0.50	47.45	8.62	0.74	0.44	7.56	7.33	0.63	0.48

Figure 4.3 Structural equation model specification



Model Specification

Whenever we use mathematical symbols, i indexes respondents (i=1,…,N with N= 11,735), k indexes clusters of respondents (k=1,…,K), c indexes countries (c=1,…,C with C=17), p indexes the response items we used to measure our constructs (p=1,…,P with P=36), q indexes the endogenous constructs (q=1,…,Q with Q=3) and r indexes the exogenous constructs (r=1,…,R with R=15). We now collect all response items in a common (P×1) vector, which for simplicity of notation we denote $\mathbf{y_i}$. We also define a [(Q+R)×1] vector $\boldsymbol{\omega}_{\mathbf{ik}}$, which we partition as $\boldsymbol{\omega}_{\mathbf{ik}}=(\boldsymbol{\eta}_{\mathbf{ik}}^T, \boldsymbol{\xi}_{\mathbf{ik}}^T)^T$. Now, we explicitly consider response heterogeneity by specifying cluster-specific measurement equations as follows:

$$\mathbf{y_i} \mid k = \boldsymbol{\tau}_{\mathbf{k}} + \boldsymbol{\Lambda}_{\mathbf{k}} \boldsymbol{\omega}_{\mathbf{ik}} + \boldsymbol{\varepsilon}_{\mathbf{ik}} \tag{4.1}$$

where $\boldsymbol{\tau}_{\mathbf{k}}$ is a (P×1) vector of measurement intercepts, $\boldsymbol{\Lambda}_{\mathbf{k}}$ is a [P×(Q+R)] matrix of factor loadings, and $\boldsymbol{\varepsilon}_{\mathbf{ik}}$ is a (P×1) random vector of residuals which is assumed to be normally distributed as N($\mathbf{0}$,$\boldsymbol{\Psi}_k$), where $\boldsymbol{\Psi}_k$ is a (P×P) diagonal covariance matrix conditional on cluster k. We also assume $\boldsymbol{\varepsilon}_{\mathbf{ik}}$ and $\boldsymbol{\omega}_{\mathbf{ik}}$ are independent.

We now define our structural model as:

$$\boldsymbol{\eta}_{\mathbf{ik}} = \boldsymbol{\Pi}_{\mathbf{k}} \boldsymbol{\eta}_{\mathbf{ik}} + \boldsymbol{\Gamma}_{\mathbf{k}} \boldsymbol{\xi}_{\mathbf{ik}} + \boldsymbol{\delta}_{\mathbf{ik}} \tag{4.2}$$

where $\boldsymbol{\Pi}_{\mathbf{k}}$ is a (Q×Q) and $\boldsymbol{\Gamma}_{\mathbf{k}}$ a (Q×R) matrix containing the unknown parameters we want to estimate, such that ($\mathbf{I}$-$\boldsymbol{\Pi}_{\mathbf{k}}$) is nonsingular, $\boldsymbol{\delta}_{\mathbf{ik}}$ is a (Q×1) vector of residuals (assumed independent of $\boldsymbol{\xi}_{\mathbf{ik}}$) and distributed as N($\mathbf{0}$,$\boldsymbol{\Psi}_{\boldsymbol{\delta}\mathbf{k}}$), where $\boldsymbol{\Psi}_{\boldsymbol{\delta}\mathbf{k}}$ is a (Q×Q) diagonal covariance matrix and $\boldsymbol{\xi}_{\mathbf{ik}}$ is distributed according to N($\mathbf{0}$,$\boldsymbol{\Phi}_{\mathbf{k}}$), where $\boldsymbol{\Phi}_{\mathbf{k}}$ is a (R×R) diagonal matrix.

Let us now collect all unknown coefficients to be estimated in a cluster-specific parameter vector $\boldsymbol{\theta}_{\mathbf{k}}$ which will thus contain $\boldsymbol{\Lambda}_k$,$\boldsymbol{\Phi}_k$, $\boldsymbol{\Pi}_k$, $\boldsymbol{\Gamma}_k$, $\boldsymbol{\Psi}_k$, $\boldsymbol{\Psi}_{\delta k}$. The implied covariance structure of the model specified in Equations (1)-(2) is:

$$\boldsymbol{\Sigma}_{\boldsymbol{\omega}\mathbf{k}} = \begin{pmatrix} (\mathbf{I}-\boldsymbol{\Pi}_{\mathbf{k}})^{-1}(\boldsymbol{\Gamma}_{\mathbf{k}}\boldsymbol{\Phi}_{\mathbf{k}}\boldsymbol{\Gamma}_{\mathbf{k}}^T + \boldsymbol{\Psi}_{\boldsymbol{\delta}\mathbf{k}})[(\mathbf{I}-\boldsymbol{\Pi}_{\mathbf{k}})^{-1}]^T & (\mathbf{I}-\boldsymbol{\Pi}_{\mathbf{k}})^{-1}\boldsymbol{\Gamma}_{\mathbf{k}}\boldsymbol{\Phi}_{\mathbf{k}} \\ \boldsymbol{\Phi}_{\mathbf{k}}\boldsymbol{\Gamma}_{\mathbf{k}}^T[(\mathbf{I}-\boldsymbol{\Pi}_{\mathbf{k}})^{-1}]^T & \boldsymbol{\Phi}_{\mathbf{k}} \end{pmatrix} \tag{4.3}$$

Equations (1)-(3) clarify that we explicitly model heterogeneity in both the measurement and the structural models, in the spirit of DeSarbo et al. (2006). We now introduce a latent allocation variable z_i, which allows us to classify respondents in the different clusters (in line with Zhu and Lee 2001):

$$p(z_i = k) = \pi_k \text{ , for } k = 1,...,K \tag{4.4}$$

where π_k are latent mixing proportions that need to satisfy $\pi_k>0$ and $\pi_1+\pi_2+\ldots+\pi_K=1$. Let $\boldsymbol{\tau} = \{\boldsymbol{\tau}_1,\ldots,\boldsymbol{\tau}_K\}$, $\boldsymbol{\pi} = \{\pi_1,\ldots,\pi_K\}$ and let $\boldsymbol{\theta} =\{\boldsymbol{\theta}_1,\ldots,\boldsymbol{\theta}_K\}$ denote the parameter vector across clusters.

Model Estimation and Identification

Let us now collect all the observations in the matrix $\mathbf{Y}=(\mathbf{y}_1,\ldots,\mathbf{y}_N)$, all latent variables in the matrix $\boldsymbol{\Omega}=(\boldsymbol{\omega}_1,\ldots,\boldsymbol{\omega}_N)$, with $\boldsymbol{\omega}_i = (\boldsymbol{\omega}_{i1},\ldots, \boldsymbol{\omega}_{iK})$, and define a matrix for the allocation variables $\mathbf{Z}=(\mathbf{z}_1,\ldots,\mathbf{z}_N)$, we can write the complete-data model likelihood (i.e. the joint likelihood of the data and the latent variables) as follows:

$$\begin{aligned} L(\boldsymbol{\theta},\boldsymbol{\tau},\boldsymbol{\pi}) &= p(\mathbf{Y},\mathbf{Z},\boldsymbol{\Omega} \mid \boldsymbol{\theta},\boldsymbol{\tau},\boldsymbol{\pi}) \\ &= \prod_{i=1}^{N}\sum_{k=1}^{K}\pi_k f_k\left(\mathbf{y}_\mathbf{i},\boldsymbol{\omega}_\mathbf{ik} \mid \boldsymbol{\tau}_\mathbf{k},\boldsymbol{\theta}_\mathbf{k}\right) \end{aligned} \tag{4.5}$$

where K is the number of clusters and $f_k\left(\mathbf{y}_\mathbf{i},\boldsymbol{\omega}_\mathbf{ik} \mid \boldsymbol{\tau}_\mathbf{k},\boldsymbol{\theta}_\mathbf{k}\right)$ is the (multivariate normal) probability density function of the observed data and unobserved latent variables, for respondent *i* allocated to cluster *k*. Please note that the marginal likelihood $f_k\left(\mathbf{y}_\mathbf{i} \mid \boldsymbol{\tau}_\mathbf{k},\boldsymbol{\theta}_\mathbf{k}\right)=\int f_k\left(\mathbf{y}_\mathbf{i},\boldsymbol{\omega}_\mathbf{ik} \mid \boldsymbol{\tau}_\mathbf{k},\boldsymbol{\theta}_\mathbf{k}\right)\cdot f_k\left(\boldsymbol{\omega}_\mathbf{ik} \mid \boldsymbol{\tau}_\mathbf{k},\boldsymbol{\theta}_\mathbf{k}\right)\cdot d\omega$ is thus distributed according to $N(\boldsymbol{\tau}_\mathbf{k},\boldsymbol{\Sigma}_\mathbf{k}(\boldsymbol{\theta}_\mathbf{k}))$ with $\boldsymbol{\Sigma}_\mathbf{k}(\boldsymbol{\theta}_\mathbf{k}) = \boldsymbol{\Lambda}_\mathbf{k}\boldsymbol{\Sigma}_{\omega\mathbf{k}}\boldsymbol{\Lambda}_\mathbf{k}^\mathbf{T}+\boldsymbol{\Psi}_\mathbf{k}$. As standard in covariance structure models, we need to guarantee that our model is identified by imposing additional identification restrictions to avoid over-parameterization. We follow the normal practice of setting the factor loading of one item per construct to unity. Moreover, a common concern in finite-mixture structural equation models is the fact that the distribution of observed responses is invariant to the classification of each respondent in different clusters, which can generate the well-known problem of label switching (see e.g. Rossi, Allenby and McCulloch 2005). We solve this problem by implementing an ordering in the latent mixing proportions, such that $\pi_1<\pi_2 <\ldots<\pi_K$, in line with Lenk and DeSarbo (2000). A convenient way to implement this ordering involves specifying an ordered Dirichlet prior for these mixing probabilities (De Jong and Steenkamp 2010).

Conditional upon the identification restrictions just discussed we sample the model parameters from their posterior distributions using the Gibbs sampler (see Casella and

George 1992 for a review) together with data augmentation, which allows us to sample the latent constructs and allocation variables alongside the model parameters (Tanner and Wong 1987). Our Gibbs sampler starts with m=0. We first sample the latent indicators for each patient's cluster membership ($\mathbf{Z}$) conditional on the model parameters ($\boldsymbol{\theta}$) and latent constructs ($\boldsymbol{\Omega}$). Next, defining the number of clusters as K, and given the assignment of respondents to each of these clusters, data augmentation is used to update the latent variables from K independent multivariate normal distributions. Finally, conditional on these latent variables and on the cluster membership assignment, model parameters (factor loadings, structural parameters, error variances) are again sampled from K independent multivariate normal distributions. In sum, at each iteration, m, our sampling scheme cycles over the following conditional distributions:

Step 1: Sample $\mathbf{Z}^{(m+1)}$ from $p(\mathbf{Z}|\mathbf{Y},\boldsymbol{\theta}^{(m)})$

Step 2: Sample $\boldsymbol{\Omega}^{(m+1)}$ from $p(\boldsymbol{\Omega}|\mathbf{Y},\boldsymbol{\theta}^{(m)}, \mathbf{Z}^{(m+1)})$

Step 3: Sample $\boldsymbol{\theta}^{(m+1)}$, from $p(\boldsymbol{\theta}|\mathbf{Y}, \boldsymbol{\Omega}^{(m+1)}, \mathbf{Z}^{(m+1)})$

For brevity, we relay the details on the computation of the prior distributions and conditional posteriors used for the remaining parameters in $\boldsymbol{\theta}$ to Appendix IV.B.

6. Results

Model Selection

We follow the approach of Lenk and DeSarbo (2000) and estimate several models, each of which with a different number of clusters, and select the model with largest posterior probability. We used the two measures suggested by Jedidi, Jagpal and DeSarbo (1997) for the selection of the number of clusters in finite-mixture SEM's: (i) the consistent Akaike Information Criterion (or CAIC; Bozdogan 1987) and (ii) the Bayesian Information Criterion (or BIC; Schwarz 1978). We also provide the log-marginal densities (LMDs), computed according to Newton-Raftery's (1994) procedure. All three measures indicate that a three-cluster solution fits the data much better than alternative models (e.g. LMD(K=3) = -514,400 while LMD(K=2) = -538,300 and LMD(K=4) = -552,400). We compared the median factor loadings for each cluster across the three-cluster solution and found that all clusters had a very similar factor structure, which is evidence of

measurement and configural invariance in line with the tests proposed by Steenkamp and Baumgartner (1998).

We let all chains converge and used subsequent 5,000 draws for posterior inference. The estimates we present below are the posterior medians obtained from the MCMC chains from our Gibbs-sampler and, within brackets, their 95% Credible Intervals (which we abbreviate to '95% CI' and where the lower value is the 2.5th percentile and the higher value the 97.5th percentile of the distribution of MCMC draws).

Estimation Results

Table 4.2 present the estimates for the focal structural paths in our model using a pooled structural equation model (i.e. the model with K=1, colored in grey) and from our three-cluster FM-SEM of patients' response – in terms of unintentional and reasoned non-adherence – to patient empowerment. The first important finding from the FM-SEM is that there is substantial patient heterogeneity, with the models allowing for cluster-specific response parameters fitting the data much better than the pooled model (LMD_{pool} = -1,311,500). Second, about 25% of all patients were classified in cluster 1, 36% in cluster 2 and 39% in cluster 3. Third, and importantly, even though the magnitude (and significance) of the relationships is quite different between clusters (see Table 4.2), there are no sign reversals and the findings from the pooled model are not threatened by considering patient heterogeneity. For parsimony, we thus test our hypotheses using the pooled model estimates.

Decisional empowerment leads to both higher unintentional non-adherence (γ_1 = .03; 95% CI = [.014; .039]) and reasoned non-adherence (γ_2 = .05; 95% CI = [.040; .065]), in support of hypotheses H_{1a} and H_{1b}. We also find that doctor-initiated information exchange increases both unintentional non-adherence (γ_3 = .27; 95% CI = [.229; .319]) and reasoned non-adherence (γ_4 = .23; 95% CI = [.181; .269]), in support of $H_{2a}$and H_{2b}. In contrast with decisional empowerment and doctor-initiated information exchange, however, patient-initiated information exchange leads to lower unintentional (β_1 = -.14; 95% CI = [-.176; -.100]) and reasoned therapy non-adherence (β_2 = -.04; 95% CI = [-.080; -.005]), in support of H_{3a} and H_{3b}.

Table 4.2 *Estimation Results: Patient Empowerment and Therapy Non-adherence*

Response	Cluster	Decisional empower.	Doctor-initiated info. exch.	Patient-initiated info. exch.
Unintentional non-adherence	*Pooled*	**.03**	**.27**	**-.14**
		[.01; .04]	[.23; .32]	[-.18; -.10]
	1	**.04**	.06	-.05
		[.02;.07]	[-.01;.13]	[-.13;.02]
	2	.01	**.41**	**-.20**
		[-.01;.03]	[.29;.83]	[-.26;-.14]
	3	.01	**.44**	**-.28**
		[-.02;.03]	[.34;.56]	[-.37;-.20]
Reasoned non-adherence	*Pooled*	**.05**	**.23**	**-.04**
		[.04; .07]	[.18; .27]	[-.08; -.01]
	1	**.05**	.01	.03
		[.03;.07]	[-.05;.08]	[-.04;.10]
	2	**.05**	**.24**	**-.05**
		[.02;.07]	[.14;.66]	[-.11;-.00]
	3	.02	**.48**	**-.22**
		[-.01;.04]	[.38;.60]	[-.31;-.14]

Control Variables.

We also controlled for several antecedents of unintentional and reasoned non-adherence. Table 4.3 presents the estimation results for these control variables. In addition, we control for a possible feedback effect between doctor-initiated information exchange and patient-initiated information exchange. For simplicity we report here the pooled model estimates (the results of the three-cluster solution are very similar and available upon request). Most results are in line with existing literature.

First, doctor-initiated information exchange seems to motivate higher patient-initiated information exchange (in the pooled model, the path from doctor-initiated information exchange to patient-initiated information exchange is γ_5 = .57; 95% CI = [.548; .589]). This finding is in line with medical literature showing that when physicians share non-diagnostic information with their patients, patients perceive the atmosphere in the clinical

encounter as more open for their participation in therapy deliberation and choice (Charles, Gafni and Wheelan 1999; Epstein, Alper and Quill 2004; Lerman 1990). Yet, the net effect of doctor-initiated information exchange on both unintentional and reasoned non-adherence is still positive.

Second, in terms of patient sociodemographics, older patients show lower therapy non-adherence ($\gamma_{6,1}$ = -.11; 95% CI = [-.121; -.093] and $\gamma_{7,1}$ = -.09; 95% CI = [-.105; -.078]), which is consistent with recent research in marketing (Neslin, Rhoads and Wolfson 2009). More educated patients show higher levels of therapy non-adherence, but the effect is only marginally significant ($\gamma_{6,2}$ = .02; 95% CI = [.008; .031] and $\gamma_{7,2}$ = .01; 95% CI = [.000; .024]). Prior research in medicine typically finds a negative effect of education on non-adherence, but the effect is also rather modest and limited to patients suffering from chronic conditions (DiMatteo 2004).

Patient gender is not correlated neither with unintentional ($\gamma_{6,3}$ = .01; 95% CI = [-.019; .037]) nor with reasoned non-adherence ($\gamma_{7,3}$ = .00; 95% CI = [-.032; .023]), in line with research in medicine (DiMatteo 2004). Higher patient income and socioeconomic status lead to lower levels of non-adherence ($\gamma_{6,4}$ = -.01; 95% CI = [-.014; .003] and $\gamma_{7,4}$ = -.02; 95% CI = [-.022; -.011]; $\gamma_{6,5}$ = -.01; 95% CI = [-.024; .003] and $\gamma_{7,5}$ = -.03; 95% CI = [-.043; -.017]), which is also in line with existing literature (Benner et al. 2002; DiMatteo 2004).

Third, in terms of relationship strength, higher quality of the patient-physician relationship results in lower unintentional non-adherence ($\gamma_{8,1}$ = -.58; 95% CI = [-.629; -.522]) and in lower reasoned non-adherence ($\gamma_{9,1}$ = -.72; 95% CI = [-.776; -.670]). This finding is consistent with the relationship marketing literature, which shows that relationship quality facilitates the achievement of mutual goals (Palmatier et al. 2006) and with the medical literature which sees trust as the cornerstone of patient-physician relationships (Kao et al. 1998).

Table 4.3 Pooled Model Results : Control Variables

Control Variable	Unintentional Non-Adherence	Reasoned Non-Adherence
Age	**-.11**	**-.09**
	[-.121; -.093]	[-.105; -.078]
Education	**.02**	**.01**
	[.008; .031]	[.000; .024]
Gender	.01	.00
	[-.019; .037]	[-.032; .023]
Income	**-.01**	**-.02**
	[-.014; -.003]	[-.022; -.011]
Socioeconomic status	-.01	**-.03**
	[-.024; .003]	[-.043; -.017]
Relationship quality	**-.58**	**-.72**
	[-.629; -.522]	[-.776; -.670]
Age homophily	.00	.00
	[-.016; .009]	[-.011; .014]
Gender homophily	-.02	.01
	[-.043; .012]	[-.016; .038]
Relationship duration	**-.03**	-.01
	[-.039; -.013]	[-.022; .003]
Interaction frequency	**.02**	-.01
	[.005; .029]	[-.018; .005]
Time since last visit	.00	**.01**
	[-.012; .014]	[.000; .026]
Health status	**-.04**	.00
	[-.053; -.022]	[-.017; .013]
Health motivation	**-.08**	**.03**
	[-.103; -.061]	[.007; .048]

Age and gender concordance, or homophily, are not related to therapy non-adherence ($\gamma_{8,2}$ = .00; 95% CI = [-.016; .009] and $\gamma_{9,2}$ = .00; 95% CI = [-.011; .014]; $\gamma_{8,3}$ = -.02; 95% CI = [-.043; .012] and $\gamma_{9,3}$ = .01; 95% CI = [-.016; .038]), which is in line with prior research in marketing (Dellande, Gilly and Graham 2004). Relationship duration leads to lower unintentional non-adherence ($\gamma_{8,4}$ = -.03; 95% CI = [-.039; -.013]) but not reasoned

non-adherence ($\gamma_{9,4}$ = -.01; 95% CI = [-.022; .0033]), while frequency of interaction leads (marginally) to higher unintentional non-adherence ($\gamma_{8,5}$ = .02; 95% CI = [.005; .029]). Reasoned non-adherence also tends to (marginally) increase between visits ($\gamma_{9,6}$ = .01; 95% CI = [.000; .026]), a finding with high face validity (Cramer, Scheyer and Mattson 1990). This result may be driven by the fact that, as time since last visit to the physician elapses, complacency may creep in increasing the likelihood that the patient decides to stop following the treatment based on a (potentially erroneous) belief that the therapy is no longer needed (Bowman, Heilman and Seetharaman 2004).

Finally, in terms of health drivers of therapy non-adherence, we find that better health status leads to lower unintentional ($\gamma_{10,1}$ = -.04; 95% CI = [-.053; -.022]) but not reasoned non-adherence ($\gamma_{11,1}$ = .00; 95% CI = [-.017; .013]) and higher patient health motivation leads to lower unintentional ($\gamma_{10,2}$ = -.08; 95% CI = [-.103; -.061]) but higher reasoned non-adherence ($\gamma_{11,2}$ = .03; 95% CI = [.007; .048]). The first finding is consistent with prior literature, which has documented that non-adherence increases when patients' health status requires them to more frequently take drugs (Bowman, Heilman and Seetharaman 2004) or as treatments become more complex (WHO 2003). The effect of patient health motivation on unintentional non-adherence is consistent with existing literature (Dellande, Gilly and Graham 2004), while the positive effect on reasoned non-adherence seems to reinforce the finding that patient motivation interacts with health behaviors in complex manners, with its impact depending on the specific health behavior under analysis (Moorman and Matulich 1993).

7. Conclusion

In this paper we have studied the link between patient empowerment and therapy non-adherence. According to self-determination theory, patient empowerment increases patients' perceived autonomy and leads to increased persistence in desirable behaviors, resulting in lower therapy non-adherence (Williams et al. 1996). Based on these arguments, medical scholars and public health officials increasingly voice patient empowerment as a desirable new paradigm for patient-physician relationships, with many advocates claiming it should be defended both due to moral considerations and due to expected positive effects of empowerment in patient adherence. However, physicians often

complain that despite the grandiose ideal of shared decision-making and its moral appeal, when offered unrequested non-diagnostic information or asked to choose among alternative treatments, most patients react negatively often retorting *"you're the physician, you tell me what to do"* (McNutt 2004, p.2518). The scant existing empirical evidence is insufficient to inform practitioners and pharmaceutical firms about the desirability of patient empowerment as a strategy to improve patient adherence.

We have collected a very large and geographically dispersed dataset with self-reported data on adherence and patient empowerment perceptions from 11,735 patients in 17 countries. We find that, even though patients are heterogeneous in their responses to patient empowerment, several robust and systematic patterns emerge. Patient empowerment is only beneficial when intrinsically motivated. That is, if patients request more information from their physicians such additional interaction will result in better comprehension, persuasion, easier recall and better treatment self-confidence and persistence, contributing to lower therapy non-adherence. In contrast, if patients directly participate in treatment choice (decisional empowerment) or if physicians push unrequested information during the medical encounter, non-adherence tends to increase. Decision empowerment may be cognitively and emotionally taxing for patients and also lead patients to become overconfident about their capacity to make treatment decisions (including the decision to stop or alter treatment). Doctor-initiated informational empowerment, in turn, may be perceived by patients as "verbal dominance" (Roter and McNeilis 2003), leading to lower rather than higher perceived autonomy.

These are troubling findings, if we take into account that both the medical profession and pharmaceutical industry are currently convinced that asking patients to participate in the medical encounter is actually a good strategy to reduce non-adherence. If direct-to-consumer advertising (DTCA), for example, increases brand requests but also therapy non-adherence, that may explain why many researchers conclude that the effect of DTCA in drug prescriptions is null or very modest (Donohue and Berndt 2004; Manchanda, Xie and Youn 2008).

These findings are thus important both for marketers and policy makers willing to reduce therapy non-adherence (which results in higher sales, better patient health and lower costs for the healthcare system). Specifically, our study suggests that patient-

initiated information exchange should be promoted via disease-awareness or empowerment-awareness campaigns rather than via physician facilitation during medical encounters.

Like all studies, our research suffers from certain limitations which can open new avenues for future research. First, it would be interesting to test some of our hypotheses using revealed preference data, rather than self-reports. The inferences one can make with such data are necessarily less rich in terms of characterization of patients' beliefs and attitudes (e.g. distinguishing unintentional versus reasoned non-adherence would be nearly impossible). Yet, researchers with enough resources to collect revealed behavioral data with sufficient geographical and cultural scope could help generalizing our findings. Second, future research could also try to get data from the physician population and jointly model patient and physician beliefs in order to better understand dyadic processes that may be driving therapy non-adherence. We think this is a fruitful area for future research in therapy non-adherence. Third, we follow the tradition of health psychology of looking at therapy non-adherence as a behavioral trait of patients (DiMatteo et al. 1993). Also in marketing, scholars have recognized that patients do have a baseline propensity for adherence (Bowman, Heilman and Seetharaman 2004). Still, it would be interesting to explore differences in the effect of patient empowerment on therapy non-adherence across disease categories[29]. Finally, we believe the effects we document here are generalizable to many other types of credence services. However, this claim needs further scrutiny.

In sum, before pushing the patient empowerment agenda even further, public policy officials, physicians and managers in the pharmaceutical industry need to first guarantee that enough effort is put on educating the patient population about their new role in patient-physician relationships and on understanding the benefits and limitations of different dimensions of patient empowerment.

[29] We actually have also collected disease-specific data in our survey. We have checked the robustness of our results using this data. Our focal results are generally applicable to disease-specific measures of therapy non-adherence, but a more detailed study would still be worthwhile.

Appendix IV.A - Overview of medical literature on patient-physician relationship and therapy non-adherence

Authors	Journal	Type of Approach	Empirical Base	Main Findings
Cooper (2009)	*JAMA*	Systematic literature review and in-depth interpretation of a clinical case	129 published medical studies are discussed in this review paper and the knowledge derived from these papers is applied to the case of a specific patient	- adherence antecedents are (1) socioeconomic factors, (2) condition or therapy-related factors, (3) health system and doctor-specific factors, (4) patient-specific factors and (5) patient-physician relationship. - patient empowerment should help reduce therapy non-adherence via patient access to information and patient's confidence in her ability to make treatment decisions.
Roter and Hall (2009)	*Medical Care*	Editorial	Not empirical	- more information transmitted by the physician, more empathy and positive affect and less negative talk increases patients' trust in their physician, satisfaction and adherence - worse health status is associated with lower adherence
DiMatteo, Haskard and Williams (2007)	*Medical Care*	Meta-analysis	116 medical studies published between 1948 and 2005	- patients adhere more in diseases with higher perceived severity - patients with worse health status (more severely ill in more severe diseases) are the ones with higher risk of becoming non-adherent
Gehi et al. (2007)	*Archives of Internal Medicine*	Self-reports / cross-sectional analysis (prospective cohort study)	1,015 patients with coronary heart disease	- a single item questioning patients about their overall medication adherence was able to predict patients' risk of cardiovascular complications - the authors conclude that self-reported adherence is a simple and effective method to measure therapy non-adherence - non-adherent patients were younger, more likely to be female, less likely to be white and less educated
Lowenstein, Brennan and Volpp (2007)	*JAMA*	Conceptual	Not empirical	- many unhealthy behaviors, including non-adherence, have its roots in behavioral biases widely documented by behavioral economists
Horne (2006)	*Chest*	Conceptual	Not empirical	- the term compliance needs to be superseded by the term adherence - patients need to be involved in medical decisions (work in partnership with their physicians)
Roter and Hall (2006)	*Book*	Systematic literature review	Dozens of medical studies	- patient-physician relationship quality and communication are major determinants of adherence - little is known about what types of patients are likely to react more positively or negatively to patient empowerment

Appendix IV.A (Cont.): Overview of medical literature on patient-physician relationship and therapy non-adherence

Authors	Journal	Type of Approach	Empirical Base	Main Findings
Simpson et al. (2006)	*British Medical Journal*	Meta-analysis	21 published studies in medicine. *Note: from 6,231 references on adherence, 79 qualified as studies on the relationship between adherence and health outcomes; after elimination of 58 additional articles due to measurement issues the final set of 21 articles was reached.*	- good adherence was associated with lower mortality - the "healthy adherer" trait: good adherence to placebo was also associated with lower mortality, which was interpreted by the authors as evidence that there is a certain psychological or behavioral trait that leads some patients to have higher propensity to behave in a healthier way (which includes adherence to medication but also other lifestyle changes)
Coleman et al. (2005)	*Archives of Internal Medicine*	Self-reports	375 patients aged 65 years or older	- non-adherence among older patients is caused both by patient and health-system related factors - the larger the number of medications taken by a patient, the higher the likelihood of non-adherence
Osterberg and Blaschke (2005)	*New England Journal of Medicine*	Systematic literature review	127 published medical studies reviewed	- increasing the patient-physician collaboration should improve adherence - all measurement methods have disadvantages and, therefore, there is no gold standard in adherence measurement - most common reasons for non-adherence are forgetfulness, other priorities and patient decision to omit doses
DiMatteo (2004)	*Medical Care*	Meta-analysis	569 medical studies published between 1948 and 1998 reporting adherence to medical treatment by non-psychiatric physician	- average non-adherence rate is 24.8% - socio-demographics are poor predictors of non-adherence - non-adherence is a problem across a wide range of diseases, even though non-adherence rates show some heterogeneity across diseases
Schneider et al. (2004)	*Journal of General Internal Medicine*	Self-reports	554 patients following HIV treatment	- self-reports are a valid method to measure non-adherence - the authors measure participatory decision-making as a composite of physician conferral of decision autonomy to the patient and information exchange - controlling for the other variables, participatory decision-making had a negative but non-significant effect in therapy non-adherence ($p = .12$)

Appendix IV.A (Cont.): Overview of medical literature on patient-physician relationship and therapy non-adherence

Authors	Journal	Type of Approach	Empirical Base	Main Findings
Benner et al. (2002)	*JAMA*	Cross-sectional analysis (retrospective cohort study)	34,501 patients aged 65 or older who initiated statin treatment between 1990 and 1998 and were followed until December, 31, 1999	- persistence with statin therapy decreases significantly over time for older patients - lower income, older age, worse health status and nonwhite race were associated with lower persistence
Heisler et al. (2002)	*Journal of General Internal Medicine*	Self-reports	1,314 patients evaluating their patient-physician relationship and adherence in 25 Veterans' Affairs facilities in the U.S.	- self-efficacy and communication had a positive effect on patient adherence intentions; physicians' participatory decision-making style did not significantly affect adherence
Walsh, Mandalia and Gazzard (2002)	*AIDS*	Self-reports / cross-sectional analysis (prospective cohort study)	78 patients taking antiretroviral therapy (HIV)	- self-reports provide a valid measure of adherence, when compared against more objective measures (pill counts, an medication bottles with an electronic event monitoring system installed in its cap and plasma HIV viraemia)
Wroe (2002)	*Journal of Behavioral Medicine*	Self-reports	160 patients surveyed	- intentional non-adherence (missing or altering doses to suit the patient's needs) should be distinguished from unintentional non-adherence (e.g. forgetting to take medication) - consultation style was not found to be a significant predictor of intentional or unintentional non-adherence - still, correlation analyses show that more information exchange is associated with lower intentional non-adherence
DiMatteo, Lepper and Croghan (2000)	*Archives of Internal Medicine*	Systematic literature review	25 medical studies published between 1968 and 1998	- the overall effects of anxiety on non-adherence, despite some variation, are usually small and non-significant
Avorn et al. (1998)	*JAMA*	Cross-sectional analysis (cohort study)	7,287 patients (5,611 from the U.S. and 1,676 from Canada) aged 65 or older on January 1, 1989 and who started lipid-lowering treatment in 1990 (long-term follow-up until June 30 1996)	- patients failed to fill their prescriptions for about 40% of the study year - socieconomic status was a significant predictor of treatment persistence - after 5 years about half of the patients had stopped taking their medications

Appendix IV.A (Cont.): Overview of medical literature on patient-physician relationship and therapy non-adherence

Authors	Journal	Type of Approach	Empirical Base	Main Findings
Lerner, Gulick and Dubler (1998)	*Annals of Internal Medicine*	Conceptual / Systematic literature review	94 studies reviewed	- physicians should involve the patient in her treatment decisions and give patients more autonomy - still, in certain situations, the authors acknowledge that the physician may still need to retain "veto power"
Kjellgren, Ahlner and Säljö (1995)	*International Journal of Cardiology*	Systematic literature review	About 65 published medical studies reviewed	- there is an almost complete lack of knowledge about treatment decision-making and adherence in the case of antyhipertensive medications (e.g. conflicting results among primary factors like age, gender, education) - most research conducted in the U.S. and generalizability of the results to other countries and cultures is questionable
The Taskforce for Compliance (1994)	*Report*	Systematic literature review	Dozens of medical studies	- to improve adherence, it is important to improve the patient-physician relationship - it is also crucial to increase the quantity and quality of patient-physician communication - promoting patient choice of treatment and patient responsibility for the outcomes should help improving adherence
DiMatteo et al. (1993)	*Health Psychology*	Self-reports (2-year longitudinal study of physicians and their patients)	186 non-psychiatric physicians and their diabetes, hypertension and heart disease patients (n=2,546) followed for two years in 1986-1988	- there is a strong positive and significant relationship between patients' baseline adherence and adherence at a 2-year follow-up, suggesting that there is a trait-like patient propensity for adherence
Haynes et al. (1980)	*Hypertension*	Self-reports / cross-sectional analysis (prospective cohort study)	134 patients newly treated for hypertension	- patients' self-reported adherence correlated highly with pill count measurement (r=0.74) - the authors conclude that self-reported adherence is a simple and useful approach to measure the problem in hypertensive patients

Appendix IV.B

In order to discuss the details of our model, please let us expand the expression in Equation 5 in the main text. For this we use the allocation of respondents to clusters as well as the distributional assumptions discussed in the main text. We can thus rewrite the complete model likelihood as follows:

$$L(\boldsymbol{\theta},\boldsymbol{\tau},\boldsymbol{\pi}) = \prod_{i=1}^{N}\sum_{k=1}^{K}\pi_k \cdot \left\{ \begin{array}{l} (2\pi)^{-P/2}\left|\boldsymbol{\Psi}_{\mathbf{k}}\right|^{-1/2}\cdot\exp\left[-\frac{1}{2}(\mathbf{y_i}-\boldsymbol{\tau}_{\mathbf{k}}-\boldsymbol{\Lambda}_{\mathbf{k}}\boldsymbol{\omega}_{\mathbf{ik}})^T\boldsymbol{\Psi}_{\mathbf{k}}^{-1}(\mathbf{y_i}-\boldsymbol{\tau}_{\mathbf{k}}-\boldsymbol{\Lambda}_{\mathbf{k}}\boldsymbol{\omega}_{\mathbf{ik}})\right] \\ \cdot(2\pi)^{-Q/2}\left|\mathbf{I}_{\mathbf{Q}}-\boldsymbol{\Pi}_{\mathbf{k}}\right|\left|\boldsymbol{\Psi}_{\boldsymbol{\delta}\mathbf{k}}\right|^{-1/2}\cdot\exp\left[-\frac{1}{2}(\boldsymbol{\eta}_{\mathbf{ik}}-(\boldsymbol{\Pi}_{\mathbf{k}}\quad\boldsymbol{\Gamma}_{\mathbf{k}})\cdot\boldsymbol{\omega}_{\mathbf{ik}})^T\boldsymbol{\Psi}_{\boldsymbol{\delta}\mathbf{k}}^{-1}(\boldsymbol{\eta}_{\mathbf{ik}}-(\boldsymbol{\Pi}_{\mathbf{k}}\quad\boldsymbol{\Gamma}_{\mathbf{k}})\cdot\boldsymbol{\omega}_{\mathbf{ik}})\right] \\ \cdot(2\pi)^{-R/2}\left|\boldsymbol{\Phi}_{\mathbf{k}}\right|^{-1/2}\cdot\exp\left[-\frac{1}{2}\boldsymbol{\xi}_{\mathbf{ik}}^T\boldsymbol{\Phi}_{\mathbf{k}}^{-1}\boldsymbol{\xi}_{\mathbf{ik}}\right]\cdot \end{array} \right\} \tag{A.4.1}$$

Conditional on the identification restrictions discussed in the *model estimation and identification* section of the main paper, we sample the parameters from our FM-SEM model from their respective posterior distributions using a Gibbs sampler (see Casella and George 1992, for a review) together with data augmentation for the latent variables (Diebolt and Robert 1994; Tanner and Wong 1987). As explained in the paper, we first sample the latent indicators for each patient's cluster membership (**Z**) conditional on the model parameters (**θ**) and latent constructs (**Ω**). Next, defining the number of clusters as *K*, and given the assignment of respondents to each of these clusters, data augmentation is used to update the latent variables from K independent multivariate normal distributions. Finally, conditional on these latent variables and on the cluster membership assignment, model parameters (factor loadings, structural parameters, error variances) are again sampled from *K* independent multivariate normal distributions. In sum, at each iteration, *m*, our sampling scheme cycles over the following conditional distributions:

<u>Step 1: Sample $\mathbf{Z}^{(m+1)}$ from $p(\mathbf{Z}|\mathbf{Y}, \boldsymbol{\theta}^{(m)})$ using:</u>

$$p(z_i = k \mid \mathbf{y_i}, \boldsymbol{\theta}) = \frac{\pi_k f_k(\mathbf{y_i} \mid \boldsymbol{\tau}_{\mathbf{k}}, \boldsymbol{\theta}_{\boldsymbol{\kappa}})}{p(\mathbf{y_i} \mid \boldsymbol{\theta})} = \frac{\pi_k f_k(\mathbf{y_i} \mid \boldsymbol{\tau}_{\mathbf{k}}, \boldsymbol{\theta}_{\boldsymbol{\kappa}})}{\sum_{k=1}^{K}\pi_k f_k(\mathbf{y_i} \mid \boldsymbol{\tau}_{\mathbf{k}}, \boldsymbol{\theta}_{\boldsymbol{\kappa}})} \tag{A.4.2}$$

<u>Step 2: Sample $\boldsymbol{\Omega}^{(m+1)}$ from $p(\boldsymbol{\Omega}|\mathbf{Y}, \boldsymbol{\theta}^{(m)}, \mathbf{Z}^{(m+1)})$</u>. To simplify notation let us first define $\mathbf{C_k} = \boldsymbol{\Sigma}_{\boldsymbol{\omega}\mathbf{k}}^{-1} + \boldsymbol{\Lambda}_{\mathbf{k}}^T\boldsymbol{\Psi}_{\mathbf{k}}^{-1}\boldsymbol{\Lambda}_{\mathbf{k}}$ we can then use, for a respondent *i* assigned to cluster *κ*:

$$p(\boldsymbol{\omega}_{ik} \mid \mathbf{y}_i, \boldsymbol{\theta}_k) \sim N\left(\mathbf{C}_k^{-1}\boldsymbol{\Lambda}_k^T\boldsymbol{\Psi}_k^{-1}(\mathbf{y}_i - \boldsymbol{\tau}_k), \mathbf{C}_k^{-1}\right) \tag{A.4.3}$$

Step 3: Generate $\boldsymbol{\theta}^{(m+1)}$, from $p(\boldsymbol{\theta}|\mathbf{Y}, \boldsymbol{\Omega}^{(m+1)}, \mathbf{Z}^{(m+1)})$. This is the most complex conditional distribution in our Gibbs sampler. Yet, sampling from it can be made easier by assuming that the prior distribution of $\boldsymbol{\pi}$ is independent of the prior distributions for $\boldsymbol{\tau}$ and $\boldsymbol{\theta}$, which are also assumed independent between themselves, and that - conditional on $\boldsymbol{\Omega}^{(m)}$ - the priors for $\{\boldsymbol{\Pi}_k, \boldsymbol{\Gamma}_k, \boldsymbol{\Psi}_k, \boldsymbol{\Phi}_k\}$ are also assumed independent of $\{\boldsymbol{\Lambda}_k, \boldsymbol{\Psi}_{\delta k}\}$ such that (see Lee 2007, section 11.3):

$$p(\boldsymbol{\theta}, \boldsymbol{\tau}, \boldsymbol{\pi}) = p(\boldsymbol{\pi})\, p(\boldsymbol{\tau})\, p(\boldsymbol{\Pi}_k, \boldsymbol{\Gamma}_k, \boldsymbol{\Psi}_k, \boldsymbol{\Phi}_k) p(\boldsymbol{\Lambda}_k, \boldsymbol{\Psi}_{\delta k}) \tag{A.4.4}$$

Which, together with the model definition, allows us to write the joint conditional posterior of $\boldsymbol{\theta}$ in a computationally more convenient form:

$$p(\boldsymbol{\theta} \mid \mathbf{Y}, \boldsymbol{\Omega}, \mathbf{Z}) = \left\{ \begin{array}{l} \left[p(\boldsymbol{\pi}) p(\mathbf{Z} \mid \boldsymbol{\pi})\right] \cdot \left[p(\boldsymbol{\tau}) p(\boldsymbol{\Lambda}_k, \boldsymbol{\Psi}_{\delta k}) p(\mathbf{Y} \mid \boldsymbol{\Omega}, \mathbf{Z}, \boldsymbol{\tau}, \boldsymbol{\Lambda}_k, \boldsymbol{\Psi}_{\delta k})\right] \\ \cdot \left[p(\boldsymbol{\Pi}_k, \boldsymbol{\Gamma}_k, \boldsymbol{\Psi}_k, \boldsymbol{\Phi}_k) p(\boldsymbol{\Omega} \mid \boldsymbol{\Pi}_k, \boldsymbol{\Gamma}_k, \boldsymbol{\Psi}_k, \boldsymbol{\Phi}_k)\right] \end{array} \right\} \tag{A.4.5}$$

which allows to sample the marginal densities $p(\boldsymbol{\pi}|\bullet)$, $p(\boldsymbol{\tau}, \boldsymbol{\Lambda}_k, \boldsymbol{\Psi}_{\delta k}|\bullet)$ and $p(\boldsymbol{\Pi}_k, \boldsymbol{\Gamma}_k, \boldsymbol{\Psi}_k, \boldsymbol{\Phi}_k|\bullet)$ one at a time.

First, with the ordered Dirichlet prior discussed above for $\boldsymbol{\pi}$, i.e., with hyperparameters $\boldsymbol{\iota}$ (that is $p(\boldsymbol{\pi}) \sim$Ord-D($\boldsymbol{\iota}$)), we sample $\boldsymbol{\pi}$ form the following posterior which is also ordered Dirichlet:

$$p(\boldsymbol{\pi} \mid \bullet) \sim \text{Ord-}D(\hat{\boldsymbol{\iota}}) \tag{A.4.6}$$

where$\bullet$ refers to the remaining parameters on which we condition this draw. A slice sampler is used to draw from this ordered Dirichlet distribution.

We specify the following priors for the model parameters in $\boldsymbol{\theta}$. Let $\mathbf{Y}_k$ and $\boldsymbol{\Omega}_k$ be the submatrices of $\mathbf{Y}$ and $\boldsymbol{\Omega}$ where only the data and latent variables from respondents assigned to cluster k are collected (i.e. all the ith observations where $\kappa \neq k$ are deleted). Also, let us define a joint matrix for the endogenous and exogenous latent variables $\boldsymbol{\Lambda}_{\omega k} = (\Pi_k \boldsymbol{\Gamma}_k)$. We use the following conjugate priors, which have been shown to work well in Bayesian analysis of mixture models[30] (Roeder and Wasserman 1997):

[30] In fact, as pointed out by Roeder and Wasserman (1997), standard reference priors of the fully uninformative type, do not work well with mixture models as they often lead to improper posteriors, thus the current priors are a practical and well-accepted solution for the complexities associated with estimation of FM-SEM's.

$$\boldsymbol{\tau}_{\mathbf{k}} \sim N(\underline{\boldsymbol{\tau}_{\mathbf{k}}}, \underline{\boldsymbol{\Sigma}_{\mathbf{0}}}),$$
with $\underline{\boldsymbol{\tau}_{\mathbf{k}}} = 3$ and $\underline{\boldsymbol{\Sigma}_{\mathbf{0}}} = 5 \cdot \mathbf{I}_{\mathbf{P}}$ (A.4.7)

$$\boldsymbol{\Lambda}_{\mathbf{pk}} \mid \psi_{pk} \sim N(\underline{\boldsymbol{\Lambda}_{\mathbf{pk}}}, \psi_{pk} \cdot \underline{\mathbf{H}_{\mathbf{ypk}}}),$$ (A.4.8)

with $\boldsymbol{\Lambda}_{\mathbf{pk}}$ being the pth row of $\boldsymbol{\Lambda}_{\mathbf{k}}$, $\underline{\boldsymbol{\Lambda}_{\mathbf{pk}}} = \boldsymbol{\iota}_{\mathbf{(Q+R)}}$, $\boldsymbol{\iota}_{\mathbf{(Q+R)}}$ a (Q+R) vector of ones, ψ_{pk} being the pth diagonal element of $\boldsymbol{\Psi}_{\mathbf{k}}$ and $\underline{\mathbf{H}_{\mathbf{ypk}}} = 5 \cdot \mathbf{I}_{\mathbf{(Q+R)}}$.

$$\boldsymbol{\Lambda}_{\boldsymbol{\omega}\mathbf{qk}} \mid \psi_{q\delta k} \sim N(\underline{\boldsymbol{\Lambda}_{\boldsymbol{\omega}\mathbf{qk}}}, \psi_{q\delta k} \cdot \underline{\mathbf{H}_{\boldsymbol{\omega}\mathbf{qk}}}),$$
with $\underline{\boldsymbol{\Lambda}_{\boldsymbol{\omega}\mathbf{qk}}}$ a (Q+R)-dimensional vector of zeros, $\psi_{q\delta k}$ being the qth diagonal element of $\boldsymbol{\Psi}_{\boldsymbol{\delta}\mathbf{k}}$ and $\underline{\mathbf{H}_{\boldsymbol{\omega}\mathbf{qk}}} = 5 \cdot \mathbf{I}_{\mathbf{(Q+R)}}$. (A.4.9)

$$\psi_{pk} \sim Inverse - Gamma\left(r_{0pk}, \underline{s_{pk}}\right),$$ with $r_{0pk} = 2$ and $\underline{s_{pk}} = 2$. (A.4.10)

$$\psi_{q\delta k} \sim Inverse - Gamma\left(r_{0q\delta k}, \underline{s_{q\delta k}}\right),$$ with $r_{0q\delta k} = 2$ and $\underline{s_{q\delta k}} = 2$. (A.4.11)

$$\boldsymbol{\Phi}_{\mathbf{k}}^{-1} \sim Wish(\mathbf{R}_{\mathbf{0}}, \rho_0),$$
with $\mathbf{R}_{\mathbf{0}} = .1 \cdot \mathbf{I}_{\mathbf{R}}$ and $\rho_0 = \text{R}+1$. (A.4.12)

Let $\boldsymbol{\Omega}_{1k}$ and $\boldsymbol{\Omega}_{2k}$ be subsets of the matrix $\boldsymbol{\Omega}_{\mathrm{k}}$ containing the Q rows of $\boldsymbol{\eta}_k$ and the remaining R rows of $\boldsymbol{\xi}_k$. Given these definitions and the priors above, we can specify the conditional posteriors we use to sample $p(\boldsymbol{\theta}|\mathbf{Y}, \boldsymbol{\Omega}^{(m+1)}, \mathbf{Z}^{(m+1)})$ by applying standard results from Bayesian analysis, i.e.:

$$\boldsymbol{\tau}_{\mathbf{k}} \mid \mathbf{Y}_{\mathbf{k}}, \boldsymbol{\Omega}_{\mathbf{k}}, \boldsymbol{\Lambda}_{\mathbf{k}}, \boldsymbol{\Phi}_{\mathbf{k}} \sim N\left((\underline{\boldsymbol{\Sigma}_{\mathbf{0}}^{-1}} + n_k \boldsymbol{\Psi}_{\mathbf{k}}^{-1})^{-1} (\underline{\boldsymbol{\Sigma}_{\mathbf{0}}^{-1}} \underline{\boldsymbol{\tau}_{\mathbf{k}}} + n_k \boldsymbol{\Psi}_{\mathbf{k}}^{-1} \overline{\mathbf{Y}_{\mathbf{k}}}), (\underline{\boldsymbol{\Sigma}_{\mathbf{0}}^{-1}} + n_k \boldsymbol{\Psi}_{\mathbf{k}}^{-1})^{-1}\right)$$ (A.4.13)

$$\boldsymbol{\Lambda}_{\mathbf{pk}} \mid \mathbf{Y}_{\mathbf{k}}, \boldsymbol{\Omega}_{\mathbf{k}}, \tau_{pk}, \psi_{pk}^{-1} \sim N\left(\mathbf{a}_{\mathbf{ypk}}, \psi_{pk} \mathbf{A}_{\mathbf{ypk}}\right)$$ (A.4.14)

$$\psi_{pk}^{-1} \mid \mathbf{Y}_{\mathbf{k}}, \boldsymbol{\Omega}_{\mathbf{k}}, \tau_{pk} \sim Gamma\left(n_k/2 + r_{0pk}, \overline{s_{pk}}\right)$$ (A.4.15)

$$\boldsymbol{\Lambda}_{\boldsymbol{\omega}\mathbf{qk}} \mid \mathbf{Y}_{\mathbf{k}}, \boldsymbol{\Omega}_{\mathbf{k}}, \psi_{q\delta k}^{-1} \sim N(\mathbf{a}_{\boldsymbol{\delta}\mathbf{qk}}, \psi_{q\delta k} \cdot \mathbf{A}_{\boldsymbol{\omega}\mathbf{kq}})$$ (A.4.16)

$$\psi_{\delta qk}^{-1} \mid \mathbf{Y}_{\mathbf{k}}, \boldsymbol{\Omega}_{\mathbf{k}} \sim Gamma(n_k/2 + r_{0q\delta k}, \overline{s_{q\delta k}})$$ (A.4.17)

$$\mathbf{\Phi_k} \mid \mathbf{\Omega_{2k}} \sim IW\left(\mathbf{\Omega_{2k}}\mathbf{\Omega_{2k}^T} + \mathbf{R_0^{-1}}, n_k + \rho_0\right) \tag{A.4.18}$$

with:

$$\overline{\mathbf{Y_k}} = \sum_{i:\kappa=k} (\mathbf{y_i} - \mathbf{\Lambda_k}\boldsymbol{\omega}_\mathbf{ik})/n_k \tag{A.4.19}$$

$$\mathbf{a_{ypk}} = \mathbf{A_{ypk}}\left(\underline{\mathbf{H_{ypk}^{-1}}}\,\underline{\mathbf{\Lambda_{pk}^T}} + \mathbf{\Omega_k}\widetilde{\mathbf{Y}}_\mathbf{pk}^T\right), \text{ with } \mathbf{A_{ypk}} = \left(\underline{\mathbf{H_{ypk}^{-1}}} + \mathbf{\Omega_k}\mathbf{\Omega_k^T}\right)^{-1} \tag{A.4.20}$$

$$\overline{s_{pk}} = \underline{s_{pk}} + 0.5 \cdot \left(\widetilde{\mathbf{Y}}_\mathbf{pk}\widetilde{\mathbf{Y}}_\mathbf{pk}^T - \mathbf{a_{ypk}^T}\mathbf{A_{ypk}^{-1}}\mathbf{a_{ypk}} + \underline{\mathbf{\Lambda_{pk}^T}}\,\underline{\mathbf{H_{ypk}^{-1}}}\,\underline{\mathbf{\Lambda_{pk}}}\right) \tag{A.4.21}$$

$$\mathbf{a_{\delta qk}} = \mathbf{A_{\omega qk}}\left(\underline{\mathbf{H_{\omega qk}^{-1}}}\,\underline{\mathbf{\Lambda_{\omega qk}}} + \mathbf{\Omega_k}\mathbf{\Omega_{1qk}^T}\right), \text{ with } \mathbf{A_{\omega qk}} = \left(\underline{\mathbf{H_{\omega qk}^{-1}}} + \mathbf{\Omega_k^T}\mathbf{\Omega_k}\right)^{-1} \tag{A.4.22}$$

$$\overline{s_{q\delta k}} = \underline{s_{q\delta k}} + 0.5 \cdot \left(\mathbf{\Omega_{1qk}}\mathbf{\Omega_{1qk}^T} - \mathbf{a_{\delta qk}^T}\mathbf{A_{\omega qk}^{-1}}\mathbf{a_{\delta qk}^T} + \underline{\mathbf{\Lambda_{\omega qk}^T}}\,\underline{\mathbf{H_{\omega qk}^{-1}}}\,\underline{\mathbf{\Lambda_{\omega qk}}}\right) \tag{A.4.23}$$

In these expressions, $\widetilde{\mathbf{Y}}_\mathbf{pk}$ is the pth row of $\widetilde{\mathbf{Y}}_\mathbf{k}$, which is a matrix whose columns are equal to the columns of $\mathbf{Y_k}$ minus $\boldsymbol{\tau}_\mathbf{k}$, and $\mathbf{\Omega_{1qk}}$ is the qth row of $\mathbf{\Omega_{1k}}$.

Model Convergence. We assess model convergence using Geweke's (1992) convergence diagnostic test and by visually inspecting plots of the log-likelihood and of parameters' posterior draws, which confirmed that the chains had converged. Specifically, all focal parameters had unimodal and relatively narrow posterior densities and autocorrelation was not a problem.

Appendix IV.C–Measures and data sources (unless otherwise noted, responses were on a 5-point Likert scale)

Variable/Operationalization	***Reliability***	***Source***
Therapy Non-Adherence		
Unintentional Non-Adherence "Please tell us how often you can imagine yourself …" …forgetting to take your medicines? / …having a hard time doing what your doctor suggested you to do? / …being unable to do what was necessary to follow your doctor's treatment plans? / …missing taking your medications because you were away from home or busy with other things?	$\alpha = 0.83$	DiMatteo et al. (1993) Chesney et al. (2000)
Reasoned non-adherence "Please tell us how often you can imagine yourself missing taking your medications because…" … you seemed to need less medicine? / … you didn't believe in the treatment your doctor was recommending you? / … you wanted to avoid side effects or felt like the drug was toxic or harmful? / … you wanted to try alternative therapies (e.g. herbalist, homeopathic or acupuncture treatments…)? / …missing taking your medications because the medication was too expensive. *1 = "never," 2 = "rarely," 3 = "sometimes," 4 = "often," 5 = "very often."*	$\alpha = 0.86$	DiMatteo et al. (1993) Chesney et al. (2000)
Patient Empowerment		
Doctor-initiated information exchange My doctor asks me about how my family or living situation might affect my health. My doctor shares with me the risks and benefits associated with alternative treatment options. My doctor asks me what I believe is causing my medical symptoms. My doctor encourages me to give my opinion about medical treatments.	$\alpha = 0.83$	Kao et al. (1998) Lerman et al. (1990)
Patient-initiated information exchange I ask my doctor to explain to me the treatments or procedures in detail. I ask my doctor a lot of questions about my medical symptoms. I give my opinion (agreement or disagreement) about the types of test or treatment that my doctor orders.	$\alpha = 0.78$	Lerman et al. (1990)
Decisional empowerment Who possesses more power in treatment decisions, that is, who has more influence in determining the treatment(s) you follow? *1 = "my doctor has more power," 2 = "my doctor has slightly more power," 3 = "me and my doctor have about the same power," 4 = "I have slightly more power," 5 = "I have more power."*		Own development

Appendix IV.C–Control variables: Measures and data sources (unless otherwise noted, responses were on a 5-point Likert scale)

Variable/Operationalization	***Reliability***	***Source***
Age (we use the standardized score)		SSI
Education (*1 = "no formal education," 2 = "education up to age 12," 3 = "education up to age 14," 4 = "education up to age 18," 5 = "higher education," 6 = "university"*)		Steenkamp, Van Heerde and Geyskens (2010)
Gender *(Dummy: 1 = men, and 0 = women)*		SSI
Income(*1 = "up to [$2,000] per year," 2 = "between [$2,000] and [$4,999] per year," 3 = "between [$5,000] and [$9,999] per year," 4 = "between [$10,000] and [$19,999] per year," 5 = "between [$20,000] and [$39,999] per year," 6 = "between [$40,000] and [$74,999])*		Own development
Health status ("In general, would you say your health is…"; 1 = *"poor," 2 = "fair," 3 = "good," 4 = "very good," 5 = "excellent."*)		PCAS (Safran et al. 1998)
Health motivation I try to prevent health problems before I feel any symptoms. I try to protect myself against health hazards I hear about.	$\rho = 0.58$	Moorman and Matulich (1993)
Relationship Quality I trust that my doctor keeps personally sensitive medical information private. I trust my doctor's judgment about my medical care. I trust that my doctor performs necessary medical tests and procedures regardless of cost. I trust that my doctor performs only medically necessary tests and procedures. The relationship I have with my doctor is something I am very committed to. The relationship I have with my doctor is something I intend to maintain indefinitely.	$\alpha = 0.83$	Kao et al. (1998) Morgan and Hunt (1994)
Homophily		
Age homophily (-1**[Standardized score of the difference, in absolute value, between the patient and the physician's age]*)		Own development
Gender homophily (*Dummy: 1 = patient and physician of the same gender, and 0 = otherwise*)		Own development
Relationship duration (standardized score of the relationship duration in years)		Own development
Interaction frequency ("How regularly do you visit your doctor?"; *1 = "usually less than once every two years ,"2 = "at least once every two years ,"3 = "at least once a year,"4 = "usually once every six months,"5 = "once every three months,"6 = "once every month,"7 = "every other week,"8 = "once a week or more.")*		Own development
Time since last visit ("When was your last visit to your doctor?"; *1 = "less than one month ago,"2 = "one to three months ago,"3 = "four to six months ago,"4 = "seven months to one year ago,"5 = "more than one year ago.")*		Own development

CHAPTER 5: PATIENTS' PROPENSITY AND PHYSICIANS' RESPONSE TO BRAND REQUESTS: A SOCIAL EXCHANGE PERSPECTIVE[31].

Many consumer choices are made in a dyad or group setting (Aribarg, Arora and Bodur 2002), and such group choices typically deviate from the choices individuals would make in isolation (Ariely and Levav 2000; Kurt, Inman and Argo 2011; Yang and Allenby 2003). Dyadic choices necessarily involve some degree of negotiation and mutual influence to achieve a desirable choice outcome (Su, Fern and Ye 2003). Such dyadic bargaining is, more often than not, unequal in nature. Potentially asymmetric dyads include familial decisions such as in parent-teen dyads (Aribarg, Arora and Kang 2010), certain choices among husband and wives (Baumeister and Vohs 2004) and decision delegation to experts (Fitzsimons and Lehmann 2004; Li and Suen 2004). There are many examples of joint decision-making between consumers and experts, including consumer choice among alternative legal options, financial investments, available technologies or health-related products and services.

In this article, we develop and test a theoretical model to the study of consumer-expert dyadic decision-making in the context of prescription drug choices. Due to its economic and welfare relevance, prescription choice in the patient-physician dyad is a prime example of dyadic decision-making (Ding and Eliashberg 2008). We focus on two key behavioral interactions occurring during patient-physician negotiation and therapy choice: (i) patient requests of drugs by brand name and (ii) physician accommodation of such requests. In addition, we also examine whether physician accommodation of patient requests influences patients' intention to voice more requests in the future. Existing evidence shows that patients make a request for a specific medication in about 10% of all office visits and outright rejection of such requests by physicians is rare (Paterniti et al. 2010). When asked whether they ever requested a drug by brand name from their physicians, about a third of all patients in France, Germany, U.K. and U.S. admit having made such a request at a certain point (Calabro 2003).

[31]This Chapter is based on a working paper co-authored with Stefan Stremersch and Martijn De Jong. Please do not reproduce or cite without authors' permission.

Physician accommodation of patient requests, in turn, leads to more positive patient evaluation of care (Kravitz et al. 2002), while refusals have been associated with patient dissatisfaction (Bell, Wilkes, and Kravitz 1999). Hence, patient requests have been shown to influence physician prescription behavior. For example, using a panel with physician prescription behavior in three major therapeutic categories (statins, gastroinstestinal and coagulation drugs, and erectile dysfunction), Venkataraman and Stremersch (2007) show that patient requests increase physicians' prescriptions of the requested brand. In fact, physician accommodation of patient requests has even been found in settings where the condition suffered by the patient could perhaps influence her judgment, like in psychiatric consultations (Kravitz et al. 2005; Paterniti 2010).

Physician accommodation of patient requests sparks enormous controversy among physicians, medical scholars and public health officials, who often blame direct-to-consumer advertising (DTCA) or direct-to-consumer information broadcasted via mass media channels for the rise in patient requests (Bell, Kravitz and Wilkes 1999; Government Accountability Office 2006; Hollon 1999; McKillen 2002). The controversy is so strong that the assumed relationship between direct-to-consumer information and patient requests is arguably the most contentious topic for the pharmaceutical industry, with some authors claiming that it *"has the potential to fundamentally alter the roles of doctor and patient"* (Wilkes, Bell, and Kravitz 2000, p.122). Take the case of Pfizer's ad campaign "Viva Viagra," launched in July 2007. Shortly after its launch, Michael Weinstein - at the time the President of the AIDS Healthcare Foundation – criticized (and later sued) Pfizer claiming that its campaign was promoting patient requests and, ultimately, the usage of the erectile dysfunction blockbuster, thereby increasing consumer exposure to sexually transmitted diseases (CBS News 2007). These controversies surrounding direct-to-consumer information have also led medical scholars and lawmakers to express concern for FDA's weak enforcement of existing laws (Donohue, Cevasco and Rosenthal 2007) and the need for more regulation (Government Accountability Office 2006).

The exact drivers of patient requests and physician accommodation of such requests are not yet known, and the existing controversy is based on non-empirical arguments. For instance, there are at least two major macro-level trends which could also explain the rise

in patient requests to their physicians. First, post-industrialization and economic development has triggered important cultural changes, notably an inclination for more participatory values and for higher self-expression (Inglehart and Baker 2000). Second, today we live in an information-rich environment, which challenges traditional knowledge asymmetries that helped sustain unequal relations and traditional reinforcement schemes between partners. For example, in the context of the patient-physician relationship, the advent of health information on the Internet has been dubbed *"most important techno-cultural medical revolution of the past century"* (Ferguson and Frydman 2004, p.1149). In fact, patients can now easily interact with other patients using health social-networks online like PatientsLikeMe.com or even with healthcare professionals, using websites like WebMD.com, which often host blogs of healthcare professionals[32]. Thus, more than ever before, a complete understanding of dyadic decision-making processes requires us to consider how consumers' knowledge and access to different sources of information (like peer-to-peer communications and exposure to marketing) affect their decisions and behavior.

In the present article, we build on *social exchange theory* (Blau 1964; Homans 1958; Thibaut and Kelley 1959) to help us illuminate the importance of different drivers of patient requests and physician accommodation of such requests. With its roots in economics, psychology and sociology, social exchange theory postulates that human relationships can be understood as an *exchange* between partners which is maintained through repeated cost-benefit analyses (Emerson 1976). Despite its more than 50 years of existence, applications of social exchange theory continue to be very popular both in psychology (e.g. Baumeister and Vohs 2004; Kamdar and Van Dyne 2007) and in economics (Dur and Roelfsema 2010). We see prescription choices as a culturally-shaped transaction between the physician and the patient, where the degree of interaction between the patient and the physician, in therapy choice, depends on the value of the resources each party brings to the negotiation.

The current literature on dyadic decision-making in general, and patient-physician relationships in particular, suffers from two main limitations. First, prior literature has

[32] See e.g. http://blogs.webmd.com/cosmetic-surgery/, the professional blog of Robert Kotler, MD, a cosmetic surgeon in Beverly Hills.

neglected a crucial determinant of patient willingness to participate in therapy choice: personal values, which will be an important consideration of the current paper. In our setting, personal values refer to patients' goals that serve as life guiding principles and which tend to be trans-situational and relatively homogenous within a certain society or social group (Schwartz et al. 2001). The literature so far has neglected patient values as a possible driver of request behavior. However, asking for a specific drug brand can be seen as a form of empowerment and education (Holmer 1999) or as a distortion in the traditional patient-physician relationship (Hollon 1999; Wilkes, Bell and Kravitz 2000). The extent to which requests are seen, by the consumer, as a disruption or as a legitimate form of self-expression will probably be dictated by her values, a topic that has not been explored neither in the marketing nor in the medical literature (Charles et al. 2006). In addition, the scarce literature on patient requests and accommodation so far has been focused on data from the U.S. or Canada, limiting the generalizability of its findings, given the variance on personal values across countries all around the world.

Second, there is basically no empirical evidence quantifying the strength of different drivers of patient requests and physician accommodation of such requests. In particular, there is no empirical evidence comparing the strength of different sources of therapeutic and health information on patient request behavior. Yet, very different public policy implications emerge if patient requests are mainly driven by direct-to-consumer information, by word-of-mouth (with healthcare providers or with other consumers), by pharmaceutical marketing activities (like free samples and branded materials displayed in physicians' offices) or by patients' personal values and beliefs.

In this paper we try to contribute on both fronts. We collect patient-level data on requests and physician propensity for request accommodation, which allows us to explore in greater depth the drivers of this dyadic decision. We have conducted a survey among 11,735 patients in 17 countries located in four continents, the largest study we are aware of, on the drivers of patients' requests and physician accommodation of such requests. Our selection of countries was chosen with the objectives of maximizing variation in patients' personal values, which are known to vary across countries. We use this data to study if different sources of therapy and health information, as well as patient values are capable of driving patient requests, controlling for other patient, physician and dyad characteristics.

We compare the impact of different non-partisan sources of information (word-of-mouth from peers or from healthcare professionals), therapy information distributed through mass media channels (which can be firm-generated or generated by other parties) and direct-to-physician marketing efforts (samples and promotion materials in physicians' offices) on patients' propensity to request drugs by brand name and physician accommodation of such requests.

Several interesting findings emerge from our study. First, there is strong cross-national heterogeneity in patient requests and physician accommodation of such requests. For example, the percentage of patients answering that they have requested a drug by brand name to their physician in the past ranged from 16% in Japan to 81% in Brazil. The percentage of patients saying that, when they request a drug by brand name, their doctor *often* or *very often* accommodates their requests (versus never, rarely or sometimes accommodates) also ranged from 46% in Singapore to 83% in Denmark. Second, we find that patient requests are more driven by direct-to-physician marketing, especially free samples, and by word-of-mouth than by information patients gather from mass media. We also find that direct-to-physician marketing (sampling and promotion materials) do not seem to influence physician accommodation of drug requests, which are mainly driven by characteristics of the physician and of the patient-physician dyad. Third, patients' cultural values matter. Patients with strong self-transcendence values, i.e. those who are very concerned with the welfare of other people and preservation of human relations, make fewer requests to their physicians when compared with patients who value power and achievement. Yet, if physicians accommodate the requests of these self-transcendent patients, they become significantly more likely to repeat such requests in the future.

We organize the paper as follows. We first discuss the two theories that will guide our hypotheses development. Next, we discuss our hypotheses for patient requests and physician accommodation of such requests and present our method. We conclude the study by presenting the results of our analyses, interpreting these results from a managerial and public-policy standpoint and proposing avenues for future research.

2. Theoretical Background

The Patient-Physician Relationship as a Social Exchange

At least since Homans (1958) and Thibaut and Kelley (1959), that scholars in social psychology recognize long-term relationships between two parties - rather than individual decisions - as the fundamental unit of analysis. *Social Exchange Theory* postulates that the attitudes and behaviors of different parties in a relational exchange depend on the costs and benefits each party extracts from the interaction (Blau 1964). Despite its long tradition, social exchange theory still garners significant interest among social scientists. For example, social exchange theory has recently been used to study interaction between workers and their supervisors (Kamdar and Van Dyne 2007; Dur and Roelfsema 2010), interaction between clients and public sector organizations (Alford 2002), alliances between firms (Das and Teng 2002), and even negotiation of sexual activity between partners in a relationship (Baumeister and Vohs 2004).

With its focus on the relational unit, social exchange theory provides an ideal theoretical backbone for a model of patient-physician relationships capable of explaining patient requests and physician accommodation of such requests. Let us use the prototypical exchange described by Emerson (1976, p.357) to illustrate the traditional patient-physician interaction in the context of social exchange theory. In the traditional model of the patient-physician relationship, the physician applies her biomedical knowledge to paternalistically choose the therapy on behalf of the patient[33] (Emanuel and Emanuel 1992). In terms of social exchange theory, such a "white-coat" model would be seen as a *simple exchange* where (i) the physician possesses biomedical knowledge as a resource, (ii) the patient possesses money as a resource and (iii) both parties value a common output – patient's health restoration - the patient because she seeks physical and mental welfare and the physician because she seeks reassurance of her professional competence, reputation and recurring financial rewards for her services. Hence, in a white-coat model, the patient simply exchanges money for the physician knowledge and then uses the physician advice

[33]An assumption implicitly made by perfect agent models as well, which are very popular in economics (e.g. Phelps 1992) and marketing (e.g. Narayanan, Manchanda and Chintagunta 2004).

as input in order to restore her own health, an effort that is observable by the physician. There is no role for patients' opinion and requests.

However, boosted by the availability of health information and by current trends toward consumer self-expression, patients are assuming an increasingly participatory role in therapy choice (Charles, Gafni, and Whelan 1999). A more participatory patient-physician relationship goes beyond the simple exchange of biomedical knowledge for money discussed above. In modern patient-physician interactions, the physician and the patient *jointly* contribute with their respective knowledge to the "production" of health restoration, with the patient still having to pay the physician for the additional expertise she brings to the decision-making process, but assuming an increasingly active role in therapy choice. In the terminology of social exchange theory, patients' access to health information and knowledge transforms the patient-physician dyad from one focused on a simple exchange to one focused on a *productive exchange* (Emerson 1976). Furthermore, according to social exchange theory, patient power in treatment choice - translated into more requests for specific medication brands or higher physician accommodation of their requests - depends on patients' ability to bring more value (i.e. information or knowledge) to the interaction.

Patients may acquire therapy-related information from several sources. Moorman and Matulich (1993) define *health information acquisition* as the degree to which consumers acquire health information from different sources including word-of-mouth from non-experts (e.g. friends, family and healthcare professionals like nurses or pharmacists), from experts (e.g. specialist physicians, nurses or pharmacists) and the mass media (which includes direct-to-consumer ads but also therapy-related information made available over the Internet, books, newspapers or pamphlets). Yet, not all sources of information are perceived by the patient, by physicians and public health officials, as having the same information value. For example, healthcare professionals, like nurses, from whom patients may request a second opinion are seen as trustworthy sources of information both by patients and by physicians (see e.g. Guadagnoli and Ward 1998). Mass-media sources of health information, in contrast, are often seen with great suspicion. In particular, people, namely physicians, are often worried with the independence, quality and reliability of

health information disseminated via mass media (Berland et al. 2001; Moynihan et al. 2000).

Due to its negative image, therapy and health information disseminated via mass-media channels is often accused of being the culprit of consumer (both patient and physician) overexcitement with therapy leading patients to voice more requests for specific brands of medication and physicians to accommodate more of such requests (Almasi et al. 2006; Moynihan et al. 2000). This belief persists despite evidence that the effect of other sources of information may be more relevant. For instance, word-of-mouth is a known driver of consumer preferences and choices (Chevalier and Mayzlin 2006; Godes and Mayzlin 2004, 2009; Manchanda et al. 2008). Patients can obtain therapy information from other consumers (non-expert word-of-mouth) or from healthcare professionals (expert word-of-mouth, i.e. second opinions from another physician, a nurse or a pharmacist). In addition, direct-to-physician marketing efforts may not only influence the physician's accommodation decision but, indirectly, also the patient's inclination to request drugs by brand name.

The Role of Patient Personal Values

Prior research applying social exchange theory to study dyadic decision-making neglected a crucial driver of relational interactions: personal values. In part, this gap may stem exactly from social exchange theory's focus on the relationship as the unit of analysis, which is also its major strength. For instance, Emmerson (1976) explicitly states that, by choosing to focus on the relationship between two agents, social exchange theory researchers typically neglect people's values when explaining an individual's behavior. Yet, we expect patient behavior in the patient-physician dyad, specifically patient propensity to voice requests for specific medications, to be strongly driven by personal values.

A major goal of our study is, hence, to enhance the framework suggested by social exchange theory by allowing patient values to drive patient request behavior. In our study, we rely on the framework proposed by Schwartz (1992), which measures people's goals that serve as life guiding principles. According to *Schwartz's Values Theory,* people's values tend to be trans-situational and relatively homogenous within a certain society or

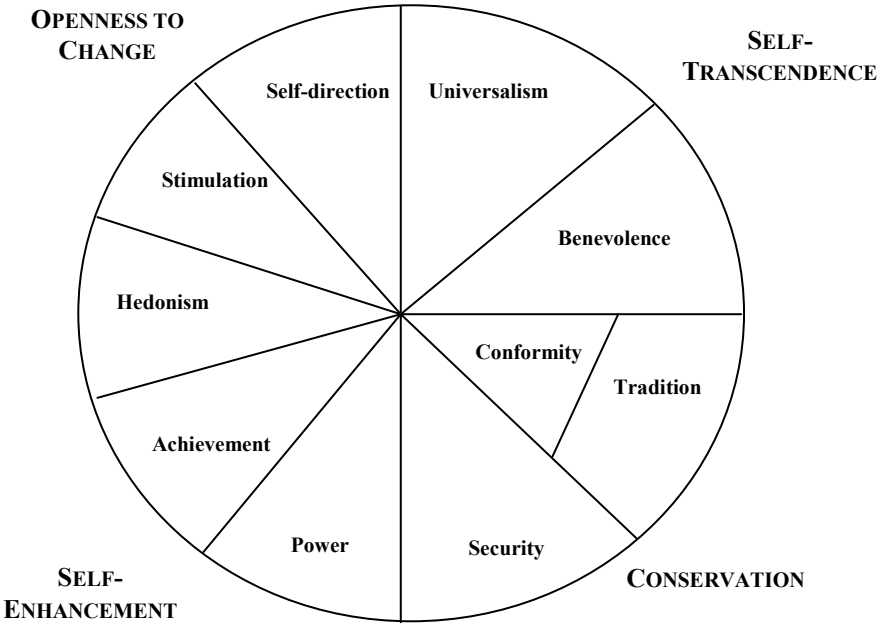
social group (e.g. Schwartz et al. 2001). The theory organizes people's values around their perceptions about the importance of 10 life-guiding principles (see Figure 5.1): (1) power - social status and prestige, control over people and resources, (2) achievement – personal success through demonstrating competence according to social standards, (3) hedonism – pleasure and sensuous gratification for oneself, (4) stimulation – excitement, novelty, and challenge in life, (5) self-direction – independent thought and action-choosing, creating, exploring (6) universalism – understanding, appreciation, tolerance and protection for the welfare of all people and for nature, (7) benevolence – preservation and enhancement of the welfare of people with whom one is in frequent personal contact, (8) tradition – respect, commitment and acceptance of the customs and ideas that traditional culture or religion provide the self, (9) conformity – restraint of actions, inclinations, and impulses likely to upset or harm others and violate social expectations or norms and (10) security – safety, harmony and stability of society, of relationships, and of self.

Figure 5.1 depicts the prototypical motivational continuum underlying Schwartz's Values Theory, where the closer two values are of each other in multidimensional space, the more they share underlying motivations (Schwartz et al. 2001). This structure has been found in 95% of samples studying human values in 63 nations: 8 of the 10 values are distinctively mapped in multidimensional space and 2 (conformity and tradition) are often intermixed both in theory and in empirical studies (Schwartz and Sagiv 1995). The distinctiveness of the 10 values in Schwartz's Values Theory is also one of the more robust findings in cultural research, supported by studies in more than 200 samples from 60 countries from every continent, involving over 100,000 persons (Schwartz et al. 2001).

As it becomes clear from Figure 5.1, the 10 values in Schwartz's Values Theory can be conveniently summarized by four higher-order values which define two orthogonal dimensions: (i) *self-enhancement* - driven by power and achievement values - is opposed to *self-transcendence* – driven by benevolence and universalism values and (ii) *openness to change* – driven by values of self-direction and stimulation - is opposed to *conservatism* – driven by values of security, conformity and tradition (Schwartz et al. 2001). Hedonism is a more ambivalent value that tends to load highly both on self-enhancement and openness (Schwartz et al. 2001). In general, we expect values which lie on the left half of Figure 5.1 (which tend to praise more participatory behaviors) to lead to more patient requests and

values which lie on the right part of Figure 5.1 (which tend to praise more harmonious or conforming behaviors) to lead to less patient requests.

Figure 5.1 Structural relation among the 10 values in Schwartz's Values Theory and two higher-order orthogonal dimensions



Source: Schwartz et al. 2001

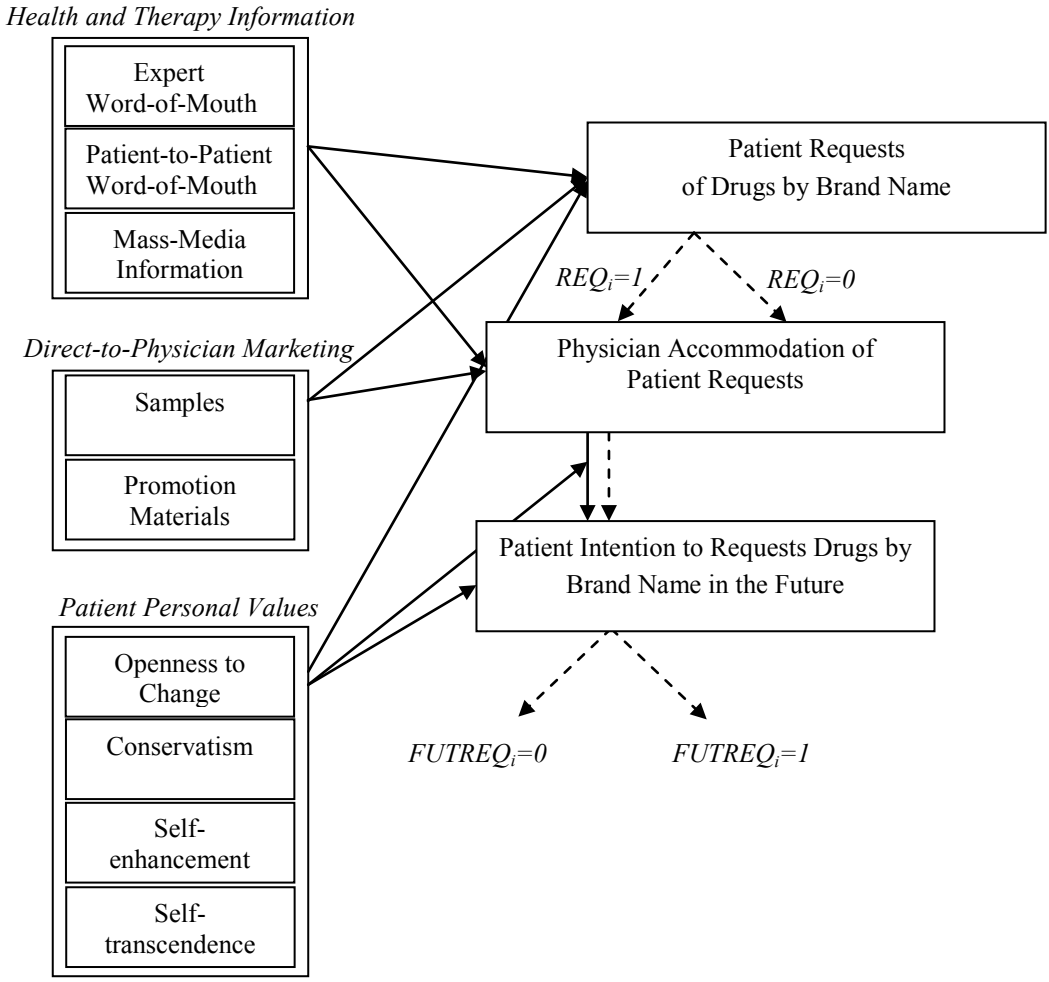
3. Hypotheses: Drivers of Patient Requests and Physician Accommodation

Our proposed model focuses on two related patient and physician behaviors: *patient requests* of medications by brand name and *physician accommodation* of such requests. In addition, we also examine whether physician accommodation influences patients' *future request intentions* (i.e. patient intentions to request medications by brand name in the future). Figure 5.2 depicts our model. The solid arrows depict the conceptual relationships we are interested in while the dashed arrows depict the response process for the three dependent variables just discussed (where REQ_i denotes a respondent's answer to the

question on past requests of medications by brand name and $FUTREQ_i$ her future request intentions), using a tree diagram (Bradlow and Zaslavsky 1999).

We examine three sets of antecedents of these variables: (i) health and therapy information acquired by the patient (which include information obtained from mass-media, expert word-of-mouth and non-expert word-of-mouth, see Moorman and Matulich 1993), (ii) direct-to-physician marketing (namely samples and promotion materials distributed to physicians) and (iii) patient values (Schwartz et al. 2001). We now develop hypotheses on the effects of these antecedents on patient requests and physician accommodation of patient requests.

Figure 5.2 Conceptual Model



Therapy and Health Information Acquisition Behaviors

According to social exchange theory, different actors in a social relation possess different resources, or abilities, which give them the capacity to reward or punish their partners (Emerson 1976). In the context of the patient-physician relationship, biomedical knowledge – i.e. knowledge regarding illnesses and possible therapies to treat such illnesses – is the key resource determining power in therapy choice.

Patients nowadays have access to a plethora of sources for therapy and health information, which they may bring to the medical encounter in order to jointly produce health restoration with their physician. However, acquiring such information is costly and not all patients will be equally motivated to incur in such cost (Moorman and Matulich 1993). According to social exchange theory, we thus hypothesize that patients who acquire more information will become more participatory, i.e.:

H_{1a}: Patients who more actively acquire therapy and health information are more likely to request drugs by brand name.

A key question we need to ask, however, is which sources of health information are more capable of driving patients' requests for branded medications. As discussed above, physicians and policy-makers see mass-media sources of therapeutic and health information with suspicion. Hence, the belief that information with lower credibility is significantly driving patient requests implicitly assumes that patients do not share the same discomfort with such information sources. Yet, patients willing to learn about existing therapies also seem to share the same concerns. A recent survey conducted by the marketing research agency iCrossing (2008) shows that, when acquiring health and therapy information, patients trust their own physician in the first place and, afterwards, specialist physicians, nurses and pharmacists. Mass media, pharmaceutical companies and TV were among the least trusted sources and relatives and friends fell somewhere in between (iCrossing 2008). This finding may explain why recent studies suggest that, across many diseases and brands, patient requests triggered by mass-media information or direct-to-consumer-advertising occur in less than 3% of visits (Verilogue 2009).

According to social exchange theory, the influence of different sources of therapy and health information on patients' propensity to make request drugs by brand name depends

on the value of such information as perceived by the patient. When compared with less trusted sources (like mass media), more trusted sources (like expert word-of-mouth) will make the patient feel more capable of bringing value to a productive exchange (instead of a simple exchange) with her physician. Hence, in contrast with current belief that therapeutic and health information in mass-media is the main driver of patient requests, we expect word-of-mouth to have a stronger influence, in particular word-of-mouth from expert consumers, a phenomenon akin to the responsiveness of physicians to key opinion leaders (Nair, Manchanda and Bhatia 2010), i.e.:

H_{1b}: Patients who learnt about a medication by acquiring therapy and health information via word-of-mouth are more likely to request drugs by brand name than patients who acquire such information via mass-media.

H_{1c}: Patients who learnt about a medication by acquiring therapy and health information via word-of-mouth with expert consumers (e.g. healthcare professionals) are more likely to request drugs by brand name than patients who acquire such information via word-of-mouth with other consumers.

By the same token, we believe physicians will not regard sources of information which they believe have low credibility (e.g. mass-media) as a sufficiently strong resource to allow the exchange with the patient to move from a simple to a productive exchange. We thus expect physicians to accommodate more readily requests from patients who acquired health information from expert sources like expert word-of-mouth (e.g. a second opinion from a specialist physician, a pharmacist or a nurse) rather than patients who acquired health information from peers or mass media, thus:

H_{2a}: Physicians are more likely to accommodate drug requests by brand name from patients who learnt about a medication via word-of-mouth, than from patients who learnt about a medication via mass-media.

H_{2b}: Physicians are more likely to accommodate drug requests by brand name from patients who learnt about a medication via word-of-mouth with expert consumers (e.g. healthcare professionals), than from patients who learnt about a medication via word-of-mouth with other consumers.

Direct-to-Physician Marketing

Although direct-to-patient information is an increasingly important marketing tool for pharmaceutical firms, the bulk of pharmaceutical firms' marketing resources is still invested in direct-to-physician marketing (DTP). The two major types of DTP are samples and detailing visits, which entails having sales reps visiting physicians to discuss therapy information (Shankar 2008). In 2005, the total retail value of distributed free samples in the U.S. amounted to USD 18.4 billion, total spending in detailing to USD 6.8 billion while DTCA represented USD 4.2 billion (Donohue, Cevasco and Rosenthal 2007). Although the main target of DTP is the physician, there are reasons to expect DTP to also influence patient requests.

From each dollar invested in DTP, about 62 cents are invested in free samples (using retail value of such samples, see Donohue, Cevasco and Rosenthal 2007). Physicians then dispense these free samples to their patients in order to pass financial savings to their patients, to educate patients about the appropriate usage of a medication or to facilitate immediate start of therapy (Chew et al. 2000; Morgan et al. 2006). Sample-dispensing by physicians has been shown to correlate positively with patient requests (Venkataraman and Stremersch 2007) and to affect future physician prescription choices (Morelli and Koenigsberg 1992). When physicians dispense free samples to patients, they also tend to transfer important information regarding the dispensed therapy to the patient. Such knowledge, transmitted by a highly trusted source (their physician), should make patients feel more knowledgeable about their illness and existing therapies and better prepared to participate, in future visits, in therapy choice by voicing their requests for specific medications, thus:

H_{3a}: Patients who have received free samples in the past are more likely to request drugs by brand name.

The second major marketing expenditure by pharmaceutical firms is detailing, i.e. sending sales reps to the physician office to discuss therapy information. Besides discussing drugs, sales reps often leave gifts or "freebies" like textbooks or branded stethoscopes, pens and pads (Shankar 2008). Physicians and policy-makers are often concerned with the effects of these "freebies" on physician prescription behavior. Their

concern stems from evidence from social sciences suggesting that self-serving biases lead physicians to unintentionally reciprocate these gifts by changing their prescription behavior (Dana and Loewenstein 2003). Yet, branded gifts, which are typically visible in physicians' offices, may also have a secondary effect on patient behavior, namely on patients' propensity to voice requests for specific brands of medication.

If the patient is exposed to branded gifts in the physician's office, the physician's main resource in the productive exchange – her independent biomedical knowledge – may be devalued by the perception that such gifts may be driving her advice, increasing the patient's perceived right to request drugs by brand name. Research in medicine indeed shows that patients see gifts as inappropriate influencers of physician advice (Gibbons et al. 1998). Such perceptions alter the value of the physician's advice, altering the prevailing exchange rate in a productive exchange (i.e. voicing a request becomes relatively "cheaper" for the patient).

This process of marketing-induced devaluation of physician advice is also supported by prevailing theories in modern sociology. According to Giddens (1991), the social roles of agents participating in a dyadic relation, are constantly being revised given new knowledge or information, a process known as *reflexivity*. Reflexivity implies that patient trust in the physician's expertise and independence is constantly being re-evaluated in a process of reflexive doubt (Giddens 1991). A well-known source of consumer skepticism towards expert advice are compromising relations between the expert and non-partisan corporations (Beck 1999). Hence, any cues alerting the patient that her physician may have been exposed to non-partisan sources of information will increase patient doubt in the independence of the advice, reducing its value. We thus hypothesize:

H_{3b}: Patients exposed to branded promotion materials in a physician's office are more likely to request drugs by brand name.

When a firm engages in DTP it seeks to influence physician prescription behavior through provision of information. In a detailing visit, which typically lasts two to five minutes, a sales representative discusses information (dosing, side effects, efficacy, new formulations…) regarding one to three of her company's drugs (Zigler et al. 1995). Through the detailing visit, physicians will have the opportunity to learn more about the

promoted medication. For example, in a recent physician survey of 251 physicians, 73% replied that they rely on information provided by sales reps when prescribing a new drug (29% reported they rely on such information "often" or "almost always", and 44% of the physicians reported they "sometimes" rely on such information). Higher physician exposure to therapy information increases the value of the physician participation in the productive exchange with the patient. Such increase should make the exchange rate tilt in favor of the physician, making her less likely to accommodate a patient's requests for a specific brand of medication:

H_{4a}: Physicians who receive free samples are less likely to accommodate drug requests by brand name from their patients.

H_{4b}: Physicians who have visible branded promotion materials in their office are less likely to accommodate drug requests by brand name from their patients.

Physician Accommodation and Future Patient Requests

A basic tenet of social exchange theory is the psychological principle of reinforcement, clearly defined by Homans' (1974) *success proposition*, which simply states that people tend to repeat actions that have been rewarded in the past. In the case of the patient-physician encounter, patients who have voiced a request for a specific brand of medication (operant behavior) to their physician are more likely to repeat such requests if physicians accommodate their requests (i.e. accommodation acts as the reward leading to reinforcement). Hence:

H_5: Physician accommodation of patient requests for drugs by brand name significantly increases patients' intention to voice more requests in the future.

Patient Personal Values

We expect patient values to have both a direct effect on patient requests and to moderate patients' reaction to physician accommodation of requests (i.e. the reinforcement hypothesis H_5). First, voicing a brand request in a medical encounter can be perceived by the patient both as a personal achievement ("I'm so well informed that I'm able to influence my physician's prescription choices") and as an expression of power ("I'm the one in charge of my own health, so I should choose my treatment"). For these patients,

accepting a simple exchange interaction is particularly costly. Therefore, we expect patients with high self-enhancement values to be more likely to request drugs by brand name.

In contrast, according to Schwartz's Values Theory, the two life-guiding values characterizing self-transcendence both express a personal concern with the welfare of others, be it of other people who are close to oneself (benevolence) or the welfare of mankind and natural environment –(universalism; see Schwartz 2007). We expect patients who praise such benevolence and universalism values to be particularly concerned with conflict-avoidance and maintaining a good relationship with their physician. In terms of social exchange theory this means that, for patients with high self-transcendence values, refraining from requesting drugs by brand name is perceived as having an important relational benefit, one for which they are willing to pay the cost of not voicing their opinion. Therefore, we hypothesize:

H_{6a}: Patients high in power and achievement values (i.e. who have high self-enhancement) are more likely to request drugs by brand name.

H_{6b}: Patients high in benevolence and universalism values (i.e. who have high self-transcendence) are less likely to request drugs by brand name.

Second, according to Schwartz's Values Theory, patients who are more *open to change* are those who prioritize independent thought and action-choosing in their system of values (self-direction), as well as novelty and change (stimulation). In contrast, more *conservative* patients tend to prioritize values of conformity, tradition and security instead. Consequently, self-directed patients should feel comfortable with a more participatory role and perceive voicing a request as a relatively low cost activity. In contrast, more conservative patients value preservation of the traditional patient role more than they value their right for self-expression, and thus hold back their self-determination in order to avoid violation of socially imposed roles and norms (Schwartz and Bilsky 1990). Thus:

H_{7a}: Patients high in self-direction and stimulation values (i.e. who have high openness to change) are more likely to request drugs by brand name.

H_{7b}: Patients high in security, conformity and tradition values (i.e. who have high conservatism) are less likely to request drugs by brand name.

Third, we expect those personal values which motivate patients to refrain from requesting drugs by brand name (i.e. conservatism and self-transcendence) to moderate the patient reaction toward physician accommodation of prior requests. In fact, patients who have high conservatism and self-transcendence values refrain from requesting drugs by brand name in order to be consistent with their life-guiding principles. Conservative patients suppress drug requests because they believe in the acceptance of the customs and ideas that tradition or religion provides them and are willing to restraint from actions likely to upset the status quo or endanger their safety and the safety of their relations. Self-transcendent patients believe strongly that the value preserving of the welfare of others, in this case the value of preserving physician welfare and relational harmony, is larger than the cost of suppressing their opinion and preference for a certain brand of medication. However, if for some reason a conservative or self-transcendent patient voices a request for a specific medication brand and the physician accommodates such request, such agreement signals to the patient that – contrary to her own initial belief – requesting drugs by brand name is a permissible form of self-expression in the relationship with her physician. In terms of Giddens' reflexivity (1991), conservative and self-transcendent patients thus use physician accommodation to reflexively alter their beliefs about the appropriateness of patient requests and change their perception of their role in therapy choice:

H_{8a}: For patients high in security, conformity and tradition values (i.e. who have high conservatism), physician accommodation of their requests for drugs by brand name leads to higher intention to voice more requests in the future.

H_{8b}: For patients high in benevolence and universalism values (i.e. who have high self-transcendence), physician accommodation of their requests for drugs by brand name leads to higher intention to voice more requests in the future.

Control Variables

Although they are not the focus of our study, we control for a series of physician, patient and dyad characteristics which may influence patient requests and physician accommodation of such requests. The variables included are: (i) physician age and gender,

(ii) patient age, education, gender, health consciousness, health motivation and confidence, health status, income and propensity to self-disclose and (iii) doctor-initiated information exchange, gender concordance, patient power in therapy choice, patient-initiated information exchange, frequency of visits, relationship duration and relationship quality.

4. Method

Data Collection

We calibrate our model on unique dataset in terms of its size and geographical/cultural scope. We surveyed 11,735 patients in Belgium, Brazil, Canada, Denmark, Estonia, France, Germany, India, Italy, Japan, Netherlands, Poland, Portugal, Singapore, Switzerland, United Kingdom and United States of America. To the best of our knowledge, this is the largest study of the relationship between patient empowerment and therapy non-adherence to date. We contracted SSI (Survey Sampling International) to execute our survey on their online panels. Recruiting and rewarding procedures for SSI panels are constantly evaluated in terms of sample representativeness and respondent's attention and motivation (see Table 5.1 and Table 5.2 for sample descriptives).

We constructed the original survey in English and organized its translation to the 10 native languages (Danish, Dutch, English, Estonian, French, German, Italian, Japanese, Polish and Portuguese) that are spoken in the 17 countries included in our sample, by native speakers. The native speakers we used as translators were all doctoral students in social sciences attending programs at our respective universities, which are located in Europe and the U.S., both having a large international student population. The vast majority of these graduate students are familiar with survey research methods, often through their coursework, which allowed us to discuss survey items, and their meanings, in great detail.

We organized the translation process in accordance to best-practices in international survey research. First, for each language, the English version was translated by a native speaker (the translator) who was proficient in English. Second, another native speaker (the back-translator) translated the survey from his native tongue back to English. Third, we discussed the translated surveys with both translators and back-translators, iteratively, until we were sure that the final survey retained exactly the same meaning in all languages.

Our selection of countries was guided by three major criteria. First, we wanted to obtain sufficient cross-cultural variation, in order to test whether our hypothesized relationships are culturally sensitive. Second, we only selected countries in which patients are free to choose their physician and typically develop repeated interactions with the same physician. Third, we screened out countries that were too expensive to survey in (> USD 10,000 per country). Table 5.1 presents some key descriptives of our dataset. In addition, our sample is subject to two exclusion criteria: (i) it's only composed of adults (≥ 25 years of age) and (ii) each respondent needed to have had at least 3 visits with their current general practitioner, in order to guarantee respondent ability to assess the relationship with her physician.

Tbale 5.1 *Descriptives: Patient Requests and Physician Accommodation*

Country	*Patient Requests*			*Frequency of Accommodation*					
	N	*% Yes (past req.)*	*% Yes (fut. req.)*	*N (REQ=1)*	*None of the time*	*Rare-ly*	*Some-times*	*Most of the time*	*All of the time*
Belgium	669	47.83	32.44	320	0.63	6.25	26.56	51.56	15.00
Brazil	785	81.40	49.94	639	0.63	4.23	23.47	46.01	25.67
Canada	540	40.00	20.19	216	1.39	3.70	26.39	48.15	20.37
Denmark	570	39.12	17.54	223	0.45	2.69	13.45	56.95	26.46
Estonia	523	21.80	11.28	114	0.88	4.39	21.93	61.40	11.40
France	776	39.56	24.36	307	1.63	12.38	36.16	38.76	11.07
Germany	783	18.26	15.84	143	2.10	2.80	20.98	44.06	30.07
India	521	62.38	44.34	325	2.46	8.92	41.54	39.08	8.00
Italy	818	76.77	50.49	628	0.32	3.03	25.32	55.25	16.08
Japan	758	16.23	18.47	123	0.00	4.07	35.77	43.90	16.26
The Netherlands	795	28.18	12.45	224	1.79	1.79	24.55	30.36	41.52
Poland	760	72.76	49.61	553	0.90	5.61	24.05	53.71	15.73
Portugal	524	42.94	29.20	225	0.44	5.33	28.44	33.78	32.00
Singapore	815	34.72	24.29	283	0.00	3.18	50.88	40.64	5.30
Switzerland	547	31.63	19.20	173	1.16	4.05	20.81	52.60	21.39
U.K.	781	32.52	15.11	254	1.18	3.54	33.46	48.82	12.99
U.S.A.	770	41.69	24.16	321	0.62	2.18	23.36	52.65	21.18
Total	11,735	43.21	27.35	5,071	0.39	2.05	12.08	20.54	8.16

Measures

Dependent variables. In order to measure patient requests (REQ), we first asked respondents whether they have ever requested a drug by its brand name. If the respondent answered 'yes' to this question, we then measured doctor's frequency of accommodation (Dr.Acc.) by asking the same respondent how often did her doctor accommodate her requests, a question they had to answer using a 5-point frequency scale ranging from 'None of the time' to 'All of the time' (see Table 5.1). Irrespectively of the respondent's answer to the patient requests question (REQ) we then asked the respondent to indicate whether it was likely that, in her next 3 encounters with her doctor, she would request a drug by its brand name (F-REQ). Table 5.1, above, provides descriptives for our dependent variables.

Table 5.2 Therapy and Health Information Acquisition and Direct-to-Physician Marketing

Construct	***Operationalization (items)***	***Response Scale***
Therapy and Health Information Acquisition Behaviors (Based on Moorman and Matulich 1993)		
Mass-media information	…the mass media (for example Internet, Television and radio programming, ads, books, newspapers, magazines or pamphlets about health)	1 = "strongly disagree," 2 = "disagree," 3 = "neither agree nor disagree," 4 = "agree," and 5 = "strongly agree."
Expert word-of-mouth information	…other healthcare professionals (specialists, nurses, physical therapists, pharmacists)	
Non-expert word-of-mouth information	…other people (friends, spouse, parents, relatives, work associates or patient support organizations)	
Direct-to-Physician Marketing (Own Development)		
Samples	Did your doctor ever give you a medicine for which you did not have to pay for (e.g. a sample from his or her cabinet)?	Dummy: 1 = "yes," and 0 = "no."
Promotion materials	Does your doctor have visible promotional materials from branded drugs in his or her office?	Dummy: 1 = "yes," and 0 = "no."

Independent variables. In Table 5.2 we present our measures for the therapy and health information and direct-to-physician marketing, including item operationalization. Recall that we developed hypotheses on the likelihood of patients requesting a drug by brand name, and physician accommodation of such requests, after patients learnt about the medication via (i) mass-media or word-of-mouth with (ii) expert consumers or (iii) non-

expert consumers. Thus, we introduced the questions regarding therapy and health information acquisition behaviors with the following statement: *"I can imagine myself asking my doctor for a specific drug if I learned about it through…."* We then measure the level of each information source using the items indicated on Table 5.2 (based on Moorman and Matulich 1993).

We measure cultural values using the Portrait Values Questionnaire (PVQ), a more concrete and less cognitively taxing alternative to the often used Schwartz Values Survey (see Schwartz et al. 2001). The idea of the PVQ is to ask respondents to rate how close to his or her own values are the goals, aspirations and wishes of different people presented to them using "verbal portraits" (see Schwartz et al. 2001 for the specific portraits used). In our online survey, gender was asked at the start and then the gender used in the portrait examples was made congruent with the respondent's gender to facilitate the comparison task and improve response reliability.

We describe our remaining measures, all based in existing literature, for physician (i.e. age and gender) and dyad characteristics (patient- and doctor-initiated information exchange, relationship quality, decisional empowerment, age homophily, gender homophily, duration of the patient-physician relationship and frequency of interaction) in Appendix V.A. Our measure of relationship quality contains items measuring trust, satisfaction and commitment (in line with the current tradition in relationship marketing, see Palmatier et al. 2006), plus four items measuring the quality of patient-physician communication, which is seen as an important driver of patient-physician relationship quality (Kao et al. 1998).

Finally, we found our scales to be highly reliable (see Table A.5.1 in Appendix V.A). No scale had a reliability below .6 and the scale with lowest reliability was health motivation and confidence which contained 4 items, two measuring patient motivation toward healthy behaviors and two measuring patient confidence in her capacity to prevent and cure illness (see Moorman and Matulich 1993). All sociodemographic and dyadic characteristics items were operationalized in line with existing literature. We compute each construct by averaging, across the items measuring each construct, a respondent's score on these items.

Table 5.3 Sample Descriptives

	Mean	*Std. Dev.*
Physician		
Doctor age (raw score)	48.52	8.05
Doctor gender (0 = "female," 1 = "male")	0.70	0.46
Patient-physician Dyad		
Doctor-initiated information exchange	3.58	0.81
Gender concordance (1 = "same gender", 0 = "otherwise")	0.55	0.50
Patient-initiated information exchange	3.70	0.70
Relationship duration (in years, raw score)	10.82	8.65
Relationship quality	4.00	0.61
Patient		
Age (raw score)	46.03	12.92
Gender (0 = "female," 1 = "male")	0.48	0.50
Health consciousness	3.36	0.76
Health motivation	3.56	0.60
Health status	2.76	0.91
Knowledge about medical treatment	3.33	0.91
Self-disclosure	3.23	1.12
Conservatism	3.05	0.85
Openness	2.61	0.91
Self-enhancement	3.09	0.79
Self-transcendence	3.68	0.78

Note: unless otherwise noted, all variables are measured in a 5-point scale. Scales are assumed to have interval properties.

Sample Descriptives

We surveyed adult patients (≥ 25 years of age) registered in SSI panels. Recruiting and rewarding procedures, as well as sample composition, are constantly supervised by SSI in order to guarantee both sample representativeness and respondent's motivation. All patients in our sample had visited their general practitioner at least 3 times, to guarantee that they could reliably evaluate the relationship they maintain with their doctor. Finally, the selection of countries was (i) made with the goal of obtain sufficient cross-cultural variation, in order to obtain generalizable findings, (ii) restricted to countries where patients can freely choose their physician and typically develop long-term relationships

with the same physician and (iii) restricted to countries where sampling costs were considered reasonable (we did not include countries where the survey would cost USD 10,000 or more). For sample descriptives, see Table 5.3.

Model Estimation

We have three dependent variables: past requests (REQ_i), physician accommodation (ACC_i) and likelihood (i.e. intention) of future requests ($FUTREQ_i$). Our first and third dependent variables are dummy variables (1 = "yes," 0 = "no") while ACC_i was measured using a 5-point frequency scale (see Table 5.2). Moreover, please recall that we only observe ACC_i for a part of the sample as only patients who answered that they had made a request in the past (i.e. those with REQ_i=1) were asked the accommodation question, which means that we face a sample selection issue. Please note that as ACC_i is used as independent variable in the future requests equation, we also face a selection issue in the regression of $FUTREQ_i$ due to missing values, thus we need to account for this in our estimation.

We estimated a binary Probit model for the requests (REQ_i) and future requests ($FUTREQ_i$) equations and a linear regression model for the accommodation equation (ACC_i). However, due to the sample selection issues already discussed, it is well known that OLS regression of ACC_i and $FUTREQ_i$ on the independent variables of interest leads to inconsistent parameter estimates (unless one could safely assume that the errors of the requests equation and the accommodation and future requests equations were uncorrelated). Hence, for the accommodation equation we apply a Heckit estimator, which augments the OLS regression with an estimate of the omitted drivers of self-selection (i.e. the drivers of past patient requests) to solve the sample selection issue (Greene 2003). For the future requests equation, we estimate a bivariate Probit model to account for possible correlation between the requests equation and the future requests equation.

Thus we first estimate the equation for patient requests. In the nomenclature of Heckman's (1979) Heckit estimator this is the "participation" or "selection" equation:

$$REQ_i = \begin{cases} 1 & if\ REQ_i^* > 0 \\ 0 & if\ REQ_i^* \leq 0 \end{cases} \tag{5.1}$$

with $REQ_i^* = \sum_{c=1}^{C} I(c_i = c) \cdot \gamma_{1c} + \mathbf{x_{1i}}'\boldsymbol{\beta}_{\mathbf{REQ}} + \varepsilon_{i1}$, with the error term $\varepsilon_{i1} \sim N(0,1)$, i.e. for identification purposes we set the variance of the error term in Equation 5.1 to one, which means that $\Pr[REQ_i^* > 0] = \Phi\left(\sum_{c=1}^{C} I(c_i = c) \cdot \gamma_{1c} + \mathbf{x_{1i}}'\boldsymbol{\beta}_{\mathbf{REQ}}\right)$. In the first term in REQ_i^*, $I(c_i = c)$ is an indicator function assuming the value 1 if patient *i* resides in country *c* (with *c* = 1,…,17) and γ_{1c} is a country-specific fixed-effect controlling for unobserved country-specific drivers of patient propensity to request medications by brand name.

Let us assume that the error terms of the requests equation is correlated with the error term of the accommodation equation as follows:

$$\begin{pmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \sigma_{12} \\ \sigma_{12} & \sigma_{ACC}^2 \end{pmatrix}\right] \tag{5.2}$$

where for. Also please note that σ_{12} can then be rewritten as $\rho_1 \cdot \sigma_{ACC}^2$, where ρ_1 is the correlation between ε_{i1} and ε_{i2}.

Given this assumption, we can now estimate the accommodation, or "outcome", equation as follows:

$$ACC_i = \sum_{c=1}^{C} I(c_i = c) \cdot \gamma_{2c} + \mathbf{x_{2i}}'\boldsymbol{\beta}_{\mathbf{ACC}} + \sigma_{12} \cdot \lambda\left(\sum_{c=1}^{C} I(c_i = c) \cdot \gamma_{1c} + \mathbf{x_{1i}}'\hat{\boldsymbol{\beta}}_{\mathbf{REQ}}\right) + \nu_{i2} \tag{5.3}$$

where ν_{2i} is the error term (still not corrected for possible correlation between physician accommodation and patient requests), $\hat{\boldsymbol{\beta}}_{\mathbf{REQ}}$ is the vector of estimated coefficients obtained from Equation 5.1 and $\lambda\left(\sum_{c=1}^{C} I(c_i = c) \cdot \gamma_{1c} + \mathbf{x_{1i}}'\hat{\boldsymbol{\beta}}_{\mathbf{REQ}}\right)$ is our estimated inverse Mills ratio, i.e. $\lambda\left(\sum_{c=1}^{C} I(c_i = c) \cdot \gamma_{1c} + \mathbf{x_{1i}}'\hat{\boldsymbol{\beta}}_{\mathbf{REQ}}\right) = \phi\left(\sum_{c=1}^{C} I(c_i = c) \cdot \gamma_{1c} + \mathbf{x_{1i}}'\hat{\boldsymbol{\beta}}_{\mathbf{REQ}}\right) \Big/ \Phi\left(\sum_{c=1}^{C} I(c_i = c) \cdot \gamma_{1c} + \mathbf{x_{1i}}'\hat{\boldsymbol{\beta}}_{\mathbf{REQ}}\right)$, which captures $E(\varepsilon_{i2} | REQ_i^* > 0)$ and γ_{2c} is a fixed effect controlling for unobserved country-specific drivers of physician accommodation of patient requests.

Please note that the error variance we are interested in for our inferences (σ_{ACC}^2) is not directly obtained from OLS estimation of Equation 5.2, unless $\sigma_{12} = 0$ (in which case

there is no evidence for a selection effect and OLS estimation of the "outcome" equation would yield unbiased and consistent estimates). In order to obtain σ^2_{ACC}, we first save the OLS residuals from the estimation of Equation 5.2 ($\hat{v}_{2i}$), then compute the estimated inverse Mills ratio as $\hat{\lambda}_i = \lambda\left(\sum_{c=1}^{C} I(c_i = c)\cdot \gamma_{1c} + \mathbf{x_{1i}}'\hat{\boldsymbol{\beta}}_{\mathbf{REQ}}\right)$, and finally estimate $\hat{\sigma}^2_{ACC}$ using the following truncated variance (Cameron and Trivedi 2005):

$$\hat{\sigma}^2_{ACC} = N^{-1}\sum_{i=1}^{N}\left[(\hat{v}_{i2})^2 + (\hat{\sigma}_{12})^2 \cdot (\sum_{c=1}^{C} I(c_i = c)\cdot \gamma_{1c} + \mathbf{x_{1i}}'\hat{\boldsymbol{\beta}}_{\mathbf{REQ}} + \hat{\lambda}_{1i})\cdot \hat{\lambda}_i\right] \qquad (5.4)$$

the correlation between ε_{i1} and ε_{i2} can then be obtained simply by $\hat{\rho}_1 = \hat{\sigma}_{12}/\hat{\sigma}_{ACC}$.

In terms of model identification, besides setting the variance of the error term of the first Probit equation to 5.1 (i.e. $\sigma^2_{REQ} = 1$), exclusion restrictions in the "outcome" equation are advisable to ensure model identifiability (Cameron and Trivedi 2005). Fortunately, in our case, those restrictions emerge rather naturally. Given that patient values are personal life-guiding principles of the patient, which are unobservable by the physician, there is no reason to believe that patient values drive physician accommodation behavior, thus we exclude patient values from the accommodation equation.

For the estimation of the likelihood of future requests equation, which is our second "outcome" equation, we use a bivariate Probit model (Greene 2003). The future requests analysis suffers from a problem of missing values as we now use ACC_i as a covariate, which creates a situation of sample selection bias very similar to the one above for the accommodation equation (as the missing value is determined by the fact that request is either 1 or 0). The main difference between the two "outcome" equations is that we now need to use a binary Probit model, which means that the Heckit estimator is not appropriate and, instead, joint estimation of both equations should be done using a bivariate Probit model estimated by full maximum likelihood (Freedman and Sekhon 2010). The full maximum likelihood approach yields consistent and essentially unbiased estimates (see Freedman and Sekhon 2010), it is also an efficient estimator with asymptotically correct estimates of standard errors (Murphy and Topel 1985).

Let us first define the specification of the likelihood of future requests equation as:

$$FUTREQ_i = \begin{cases} 1 & if\ FUTREQ_i^* > 0 \\ 0 & if\ FUTREQ_i^* \leq 0 \end{cases} \tag{5.5}$$

where $FUTREQ_i^* = \sum_{c=1}^{C} I(c_i = c) \cdot \gamma_{3c} + \mathbf{x_{3i}}'\boldsymbol{\beta}_{\mathbf{FUTREQ}} + \boldsymbol{\delta} \cdot \mathbf{A_i} + \varepsilon_{i3}$, with $\mathbf{A_i}$ being a matrix that contains patient *i*'s answer to the accommodation question (ACC_i) and the interactions between physician accommodation and the four higher-order patient values (openness to change, conservatism, self-enhancement and self-transcendence), $\boldsymbol{\delta}$ is a 5-dimensional vector with the parameter estimates for the direct feedback effect and the four interactions discussed in H_5 and H_{8a} and H_{8b}.

Following Greene (2003, pp. 710-713), we now assume that the error terms of the requests and likelihood of future requests equations are correlated as follows:

$$\begin{pmatrix} \varepsilon_{i1} \\ \varepsilon_{i3} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_2 \\ \rho_2 & 1 \end{pmatrix}\right] \tag{5.6}$$

where ρ_2 is the correlation between ε_{i1} and ε_{i3}.

In order to construct the log-likelihood for the future requests equation we now define two auxiliary variables (i) $q_{iREQ} = 1$, if $REQ_i = 1$ and -1 if $REQ_i = 0$ and (ii) $q_{iFUTREQ} = 1$ if $FUTREQ_i = 1$ and -1 if $FUTREQ_i = 0$. Now let $w_{iREQ} = q_{iREQ} \cdot REQ_i^*$ and $w_{iFUTREQ} = q_{iFUTREQ} \cdot FUTREQ_i^*$ and $\rho_{2i}^* = q_{iREQ} \cdot q_{iFUTREQ} \cdot \rho_2$.

We can now write the model log-likelihood as:

$$\log L = \sum_{i=1}^{N} \ln\left\{\left[\Phi_2\left(w_{iREQ}, w_{iFUTREQ}, \rho_{2i}^*\right)\right]^{REQ_i} \cdot \left[\Phi\left(w_{iREQ}\right)\right]^{1-REQ_i}\right\} \tag{5.7}$$

where we follow Greene's (2003) notation, using the subscript 2 in Φ_2 to denote the cdf of a bivariate normal distribution. From Equation 5.7, it becomes clear that although we use all the sample to infer the correlation between the requests and future requests equations (allowing us to control for selection bias and obtain consistent estimates), our focal parameters of interest ($\boldsymbol{\delta}$) are estimated only from the sub-sample of patients who ever made a request in the past.

5. Results

Table 5.4 shows the estimation results of the requests and physician accommodation equations. We also estimated two models for the likelihood of future requests equation, a first model with only main effects of patient personal values and a second model following the specification in Equation 5.5.

Therapy and Health Information Acquisition Behaviors

Patients who actively search and acquire therapy and health information are, irrespective of the source of such information, more likely to request drugs by brand name, in support of H_{1a}. Yet, not all sources of therapy and health information are equally influential in driving patient requests. Therapy and health information acquired via word-of-mouth either from healthcare providers, i.e. expert word-of-mouth ($\beta_{REQ,EXP\text{-}WOM}$ = 0.12; 95% CI = [0.09; 0.15]; $stdz\text{-}\beta_{REQ,\ EXP\text{-}WOM}$ = 0.27), or from other consumers ($\beta_{REQ,WOM}$ = 0.09; 95% CI = [0.06; 0.12]; $stdz\text{-}\beta_{REQ,WOM}$ = 0.21), has a stronger influence in patient requests than health information patients acquired from mass-media sources like the Internet, direct-to-consumer ads or Television and radio programming ($\beta_{REQ,MMEDIA}$ = 0.05; 95% CI = [0.02; 0.07]; $stdz\text{-}\beta_{REQ,MMEDIA}$ = 0.11), in support of $H_{1b.}$Yet, even though the mean estimate of the effect of expert word-of-mouth ($\beta_{REQ,EXP\text{-}WOM}$) is larger than the effect of peer-to-peer word-of-mouth ($\beta_{REQ,WOM}$), the difference is not significant, which leads us to reject H_{1c}.

Turning to the accommodation equation, the first interesting finding is that ρ is very close to zero ($\rho=0.01$). This means that the error in the patient request equation is basically uncorrelated with the error in the accommodation equation, suggesting that there is no serious selection effect in this case. Furthermore R^2 = 0.13, thus the estimated model is able to explain 13% of the variance in physician accommodation requests. Next, we find that neither word-of-mouth (expert or peer) nor mass-media information influence physician accommodation of patient requests ($\beta_{ACC,MMEDIA}$ = 0.01; p = 0.29; $\beta_{ACC,EXP\text{-}WOM}$ = 0.02; p = 0.34; $\beta_{ACC,WOM}$ = -0.01; p = 0.76). Thus we reject hypotheses H_{2a} and H_{2b}. Taken together, the results from the requests and accommodation indicate that the current outrage among physicians and policy-makers against pharmaceutical firms' direct-to-consumer information and therapy and health information distributed via mass-media doesn't seem justified. In fact, therapeutic and health information distributed via mass-media seems to

have no effect in physician accommodation and, even though it drives patients' intention to voice future requests, other sources of information seem more influential.

Table 5.4 Parameter Estimates for Requests (REQ) and Accommodation (ACC)

	Patient Requests			*Physician Accommod.*		
	Param. estimate	*Stndrd. param. estimate*	*p-value (two-tailed)*	*Param. estimate*	*Stndrd. param. estimate*	*p-value (two-tailed)*
Health information sources						
Mass media	**0.05**	**0.11**	**0.00**	0.01	0.02	0.29
Word-of-mouth (other HCP's)	**0.12**	**0.27**	**0.00**	0.02	0.02	0.34
Word-of-mouth (peers)	**0.09**	**0.21**	**0.00**	-0.01	-0.01	0.76
Marketing pressure						
Sample dispensed	**0.24**	**0.24**	**0.00**	-0.01	-0.01	0.79
Promotional materials	0.04	0.03	0.21	0.02	0.01	0.54
Patient values						
Conservatism	-0.02	-0.03	0.45			
Openness	**0.04**	**0.06**	**0.06**			
Self-enhancement	**0.05**	**0.08**	**0.01**			
Self-transcendence	**-0.04**	**-0.06**	**0.09**			
Physician						
Doctor age (z-score)	0.01	0.01	0.66	**-0.02**	**-0.03**	**0.05**
Doctor gender	-0.02	-0.02	0.52	**0.06**	**0.03**	**0.02**
Patient-physician Dyad						
Doctor-initiated inf. exch.	0.00	0.00	0.94	-0.03	-0.03	0.11
Gender concordance	0.02	0.02	0.55	0.02	0.01	0.44
Patient-initiated inf. exch.	**0.13**	**0.19**	**0.00**	**0.05**	**0.04**	**0.04**
Interaction frequency	**0.06**	**0.19**	**0.00**	0.00	0.01	0.66
Relationsh. duration (z-score)	-0.01	-0.03	0.33	**0.02**	**0.03**	**0.07**
Relationsh. quality	**-0.10**	**-0.12**	**0.00**	**0.33**	**0.25**	**0.00**
Patient						
Age (z-score)	**0.05**	**0.10**	**0.00**	**0.06**	**0.07**	**0.00**
Education	**0.04**	**0.09**	**0.00**	0.01	0.02	0.28
Gender	**-0.08**	**-0.08**	**0.01**	-0.03	-0.02	0.20
Health consciousness	**-0.03**	**-0.05**	**0.10**	0.00	0.00	0.88
Health motivation	-0.03	-0.04	0.18	**0.04**	**0.03**	**0.10**
Health status	**-0.04**	**-0.07**	**0.02**	0.02	0.02	0.21
Income	0.00	-0.01	0.75	0.00	0.01	0.33
Knowledge	**0.09**	**0.16**	**0.00**	**0.03**	**0.03**	**0.05**
Self-disclosure	**0.05**	**0.11**	**0.00**	0.00	0.00	0.92
	N = 11,735; LL = -6,781			*N = 5,071; LL = -5,918*		
	AIC = 1.16			*AIC = 2.35;* $R^2 = 0.13$		
				$\rho = 0.01$; $\sigma^2_{ACC} = 0.61$		
				$\sigma_{12} = 0.01$		

Direct-to-Physician Marketing

In support of H_{3a}, we find that patients who have received free samples in the past are more likely to request drugs by brand name to their physician ($\beta_{REQ,SAMPLES}$ = 0.24; 95% CI = [0.18; 0.30]; *stdz-*$\beta_{REQ,SAMPLES}$ = 0.24). In contrast, patient exposure to branded promotion materials in a physician's office has an insignificant effect in the likelihood of patients requesting drugs by brand name from their physician ($\beta_{REQ,PROMO}$ = 0.04; 95% CI = [-0.02; 0.09]; *stdz-*$\beta_{REQ,PROMO}$ = 0.03), thus we reject hypothesis H_{3b}. It seems that samples are, as predicted, capable of making patients more vocal in the patient-physician dyad, most likely because patients receive not only the free sample but, also, valuable therapeutic information from their physician (e.g. regarding dosing and usage of the medication), who is a highly-trusted source of information for patients. Promotion materials in the physician's office, however, do not increase the likelihood that patients request drugs by brand name, contrary to our expectations. In addition, we also do not find evidence either samples ($\beta_{ACC,SAMPLES}$ = -0.01; p = 0.79) or branded promotion materials ($\beta_{ACC,PROMO}$ = 0.02; p = 0.54) increase the likelihood that physicians accommodate patient request for drugs by brand name. Thus we reject hypotheses H_{4a} and $H_{4b.}$

Physician Accommodation and Future Patient Requests

We now turn to the likelihood of future requests equation. According to the prediction of social exchange theory, we find – using a model that allows only for a direct effect of physician accommodation and patient personal values - that physician accommodation of patient requests has a psychological reinforcement effect, i.e. it leads to a higher likelihood of future patient requests ($\delta_{FUTREQ,ACC}$ = 0.24; 95% CI = [0.20; 0.29]; *stdz-*$\delta_{FUTREQ,ACC}$ = 0.44). Moreover, if we compare the standardized coefficients from this model, we find that physician accommodation of patient requests is actually strongest driver of future patient requests intention. Thus, we find strong support to our hypothesis H_5. It seems that patients may see physicians' accommodation of patient requests as a signal that it is acceptable for the patient to request drugs by brand name, leading to more future requests. However, below, when testing our hypotheses H_{8a} and H_{8b}, we explore moderating effects of patient values on this reinforcement effect, which suggest that the reinforcement effect is stronger for a specific segment of patients (those with high self-transcendence values).

Patient Personal Values

Turning to the effects of patient personal values on the likelihood that patients request drugs by brand name, the first important conclusion from our requests equation is that patient personal values matter. First, patients high in power and achievement values, i.e. with high self-enhancement ($\beta_{REQ,S\text{-}Enhanc.}$ = 0.05; 95% CI = [0.01; 0.08]; *stdz-*$\beta_{REQ,S\text{-}Enhanc.}$ = 0.08; $\beta_{FREQ,S\text{-}Enhanc.}$ = 0.07; 95% CI = [0.02; 0.11]; *stdz-*$\beta_{FREQ,S\text{-}Enhanc.}$ = 0.12) and patients high in self-direction and stimulation values, i.e. with high openness to change ($\beta_{REQ,Openness}$ = 0.04; 95% CI = [0.00; 0.08]; *stdz-*$\beta_{REQ,Openness.}$ = 0.06; $\beta_{FREQ,Openness}$ = 0.09; 95% CI = [0.04; 0.14]; *stdz-*$\beta_{FREQ,Openness.}$ = 0.16) are more likely to request drugs by brand name, which supports $H_{6a}$and H_{7a}.

Second, in line with hypothesis H_{6b}, patients high in benevolence and universalism values, i.e. who have self-transcendence are less likely to request drugs by brand name, even though the effect is only marginally significant (p = 0.09; $\beta_{REQ,S\text{-}Transc.}$ = -0.04; 95% CI = [-0.08; 0.01]; *stdz-*$\beta_{REQ,\ S\text{-}Transc.}$ = -0.14). Thus we find evidence that the concern of patients high in benevolence and universalism with the welfare of other people leads them to suppress their opinions and preferences and become less vocal in the patient-physician relationship, which supports hypothesis H_{6b}.

Third, we did not find evidence that more conservative patients (i.e. those high in security, conformity and tradition values) are less likely to request drugs by brand name ($\beta_{REQ,Conserv.}$ = -0.02; 95% CI = [-0.06; 0.03]; *stdz-*$\beta_{REQ,Conserv.}$=-0.03). It may be that patients who value security – one of the three personal values forming conservatism (the others being conformity and tradition), which emphasizes safety and threat avoidance – actually believe that requesting drugs by brand name helps them feel more secure about the treatments they follow, thus cancelling the hypothesized negative effect of conformity and tradition values on patient requests. Thus, we reject hypothesis H_{7b}.

Finally, we find clear evidence that patient values moderate the psychological reinforcement effect of physician accommodation of brand requests. We find - when we look at the estimates from the model allowing not only for a direct effect of physician accommodation but also for a moderating effect between physician accommodation and patient personal values - that the reinforcement effect postulated in H_5 is actually driven

solely by the effect of physician accommodation on the request behavior of patients high in benevolence and universalism values (i.e. high in self-transcendence). In fact, in this model the direct effect of physician accommodation on patients' request intentions is no longer significant ($\delta_{FUTREQ,ACC}$ = 0.08; 95% CI = [-0.14; 0.30]; *stdz-*$\delta_{FUTREQ,ACC}$ = 0.15). Interestingly, if we look at the coefficient of patient personal values in the likelihood of future requests, we find that patients high in benevolence and universalism (i.e. who have high self-transcendence) are significantly less likely than other patients to plan requesting drugs by brand name in the future($\beta_{FUTREQ,S\text{-}Transc.}$ = -0.42; 95% CI = [-0.69; -0.14]; *stdz-*$\beta_{FUTREQ,S\text{-}Transc.}$ = -0.73; p<0.01). The coefficients for the remaining patient personal values were not significant ($\beta_{FUTREQ,S\text{-}Enhanc.}$ = 0.15; p = 0.18; $\beta_{FUTREQ,Openness}$ = 0.11; p = 0.38; $\beta_{FUTREQ,Conserv.}$ = 0.14; p = 0.32). Looking at the moderation effects hypothesized in H_{8a} and H_{8b}, we find no support for the hypothesis that, for patients high in conservatism, physician accommodation has stronger feedback effect on their future request intentions (i.e. $\delta_{FUTREQ,Dr.Acc*Conserv.}$ = -0.03; 95% CI = [-0.10; 0.04]; *stdz-*$\delta_{FUTREQ,Dr.Acc*Conserv.}$ = -0.27, p=0.42). We thus reject H_{8a}.

Yet, in line with H_{8b}, when patients high in self-transcendence do request a drug by brand name, physician accommodation of such request results in a strong increase in their intention to voice more requests in the future ($\delta_{FUTREQ,Dr.Acc*S\text{-}Transc.}$ = 0.09; 95% CI = [0.02; 0.16]; *stdz-*$\delta_{FUTREQ,Dr.Acc*S\text{-}Transc}$ = 0.88; p = 0.02). Hence, in support of H_{8b}, for patients high in benevolence and universalism values – i.e. high in self-transcendence - physician accommodation (or non-accommodation) of patient requests sends a strong signal to the patient that requesting drugs by brand name is not (or is) disruptive of their relational exchange. The fact that we do not find the same effect for conservative patients may indicate that the suppression of a patient request is driven more by a concern with relational harmony and the welfare of the physician, than by a concern with non-violation of socially-determined roles. In such case, physicians' signals about appropriateness of patient participation are less relevant for conservative patients than for patients with high self-transcendence, who are mainly worried with physician welfare and the quality and harmony of the relationship they maintain with their physician. The strong moderation by self-transcendence of the effect of physician accommodation of patient requests may explain why physicians' accommodation of drug requests tends to trigger more patient

requests in certain countries but not in others[34], a finding that can have important consequences for pharmaceutical firms' marketing strategies.

Control Variables

We also included several control variables in our models. The results indicate that our model has high face-validity. First, in terms of patient characteristics, patients are more likely to request drugs by brand name when they perceive their health status to be worse ($\beta_{REQ,H.Status}$ = -0.04; 95% CI = [-0.07; -0.01]; *stdz-*$\beta_{REQ,H.Stauts.}$ = -0.07) or when they believe they have higher knowledge and experience concerning medical treatment of diseases ($\beta_{REQ,Pat.Knowl.}$ = 0.09; 95% CI = [0.06; 0.12]; *stdz-*$\beta_{REQ,Pat.Knowl.}$ = 0.16). Chronically-ill patients are typically more knowledge about their illness and therapies they take, so both effects were expected. Patient self-disclosure (trait) is associated with higher likelihood to request drugs by brand name ($\beta_{REQ,SDisc.}$ = 0.05; 95% CI = [0.03; 0.07]; *stdz-*$\beta_{REQ,SDisc.}$ = 0.11). Patient income is not a significant predictor of patient likelihood to request drugs by brand name (p=0.75), but patients with higher education are more likely to request drugs by brand name ($\beta_{REQ,Education}$ = 0.04; 95% CI = [0.02; 0.06]; *stdz-*$\beta_{REQ,Education}$ = 0.09).

Second, in terms of patient-physician dyad characteristics, doctor-initiated information exchange has no effect on the likelihood that patients request a drug by brand name (p = 0.94). In addition, it seems that the more frequently and deeply patients interact with their physician, the higher the likelihood that patients request drugs by brand name, as we can see from the effects of interaction frequency ($\beta_{REQ,IntFreq.}$ = 0.06; 95% CI = [0.04; 0.08]; *stdz-*$\beta_{REQ,IntFreq.}$ = 0.19) and patient-initiated information exchange ($\beta_{REQ,PatInit}$ = 0.13; 95% CI = [0.09; 0.18]; *stdz-*$\beta_{REQ,PatInit}$ = 0.19). Yet, if the patient feels he maintains a high quality relationship with the physician (high trust, satisfaction, commitment and good communication), then she is less likely to request drugs by brand name ($\beta_{REQ,RelQual.}$ = -0.10; 95% CI = [-0.16; -0.04]; *stdz-*$\beta_{REQ,RelQual.}$ = -0.12).

[34] We find that physician accommodation leads to more future patient requests in Belgium, Brazil, Canada, India, Italy, Poland, Portugal, Switzerland, The Netherlands and United Kingdom but not in Denmark, Estonia, France, Germany, Japan, United States of America and Singapore. This discrepancy can be driven by the prevalence of self-transcendence values in these countries, a question that may deserve future scrutiny.

Third, physician accommodation of patient requests, contrary to patient requests per se, is influenced by physician age and gender. Older physicians, presumably more experienced and more used to a white-coat model, are less likely to accommodate patient requests ($\beta_{ACC,Dr.Age}$ = -0.02; 95% CI = [-0.05; 0.00]; *stdz-*$\beta_{ACC,Dr.Age.}$ = -0.03) and male physicians are more likely than female physicians to accommodate patient requests ($\beta_{ACC,Dr.Gender}$ = 0.06; 95% CI = [0.01; 0.11]; *stdz-*$\beta_{ACC,Dr.Gender.}$ = 0.03).

Fourth, physicians are more likely to *accommodate* requests from patients who take more initiative to ask questions and interact with their physician during medical encounters ($\beta_{ACC,PatInit}$ = 0.05; 95% CI = [0.00; 0.10]; *stdz-*$\beta_{ACC,PatInit.}$ = 0.04), from patients with whom they have a longer relationship ($\beta_{ACC,Rel.Dur.}$ = 0.02; 95% CI = [-0.00; 0.05]; *stdz-*$\beta_{ACC,Rel.Dur.}$ = 0.03), from patients with whom they maintain a relationship with higher quality ($\beta_{ACC,Rel.Qual.}$ = 0.33; 95% CI = [0.28; 0.39]; *stdz-*$\beta_{ACC,Rel.Qual.}$ = 0.25), from older patients ($\beta_{ACC,Pat.Age.}$ = 0.06; 95% CI = [0.03; 0.08]; *stdz-*$\beta_{ACC,Pat.Age.}$ = 0.07) or from patients with higher perceived knowledge and experience regarding medical treatment of diseases ($\beta_{ACC,Pat.Knowl.}$ = 0.03; 95% CI = [-0.00; 0.06]; *stdz-*$\beta_{ACC,Pat.Qual.}$ = 0.03). All these findings seem to (i) add to the face-validity of our model and (ii) be sensible from a patient-centered care perspective, potentially reducing concerns of physicians and policy-makers regarding physician accommodation of patients' requests.

6. Conclusion

In this study we rely on social exchange theory (Blau 1964; Baumeister and Vohs 2004) and Schwartz's (1992) values theory to test a culturally-sensitive theory of patient requests and physician accommodation of such requests. We view the dyadic negotiation between a patient and a physician – needed for prescription choices to be made – as a values-shaped transaction between the two parties where the "share-of-voice" of each party depends on the value of the knowledge each party brings to the negotiation. Patients acquire knowledge from three main sources: word-of-mouth with peers, word-of-mouth from expert consumers (i.e. other healthcare professionals) and mass-media (which includes direct-to-consumer ads, but also therapeutic and health information broadcasted via the Internet, TV, radio, newspapers or magazines…). We show that even though mass-media information is indeed associated with more patient requests, word-of-mouth (from peers or

experts) is a significantly stronger driver of patient requests than mass-media, which may help reducing concerns by physicians and policy-makers regarding the effects of health and therapy information disseminated through mass media.

Moreover, the fact that patients learn about a certain therapy by gathering information through mass-media (or through any other source) doesn't seem to influence physician accommodation of patient requests. Interestingly, we find that samples dispensed by physicians (but not promotion materials visible in the physician's office) lead to more patient requests, but not to more physician accommodation of patient requests. The reason may be that samples dispensed to patients are a good opportunity for the physician to explain how the therapy works (dosing, usage…), which results in patients being able to gather information from a highly-trusted source by receiving a free sample. The additional knowledge patients acquire from a free sample dispensed by their physician thus seems to empower the patient in the patient-physician relationship, making her more likely to request drugs by brand name.

For policy makers, these results suggest that instead of investing most monitoring resources to screen advertising and therapeutic information online, regulatory agencies like FDA should be more worried with regulating what happens in channels where word-of-mouth is generated (like social media) and with the spillover effects of direct-to-physician marketing, namely free samples, on patient likelihood of requesting drugs by brand name. For marketers, these results suggest that direct-to-patient marketing strategies should be more focused in facilitating patient-to-patient and patient-to-expert interaction (including brand-focused interactions with their physician, which needs to occur when free samples are dispensed) and in increasing the quality and credibility of health and therapeutic information broadcasted via the mass-media.

Importantly, we also find that patient values matter. Patients who hold stronger values of openness to change (i.e. people who value self-direction and a higher level of stimulation) or self-enhancement (achievement and power) are more likely to request drugs by brand name from their physician, in contrast with patients who hold stronger self-transcendence values (benevolence and universalism), who are less likely to request drugs by brand name. Physicians' accommodation of drug requests provides a strong

psychological reinforcement to patients, in the sense that it motivates patients' intentions to request a drug in the future, as predicted by social exchange theory.

Interestingly, this "psychological reinforcement" effect seems to influence exclusively the request behavior from patients who have high self-transcendence values. These patients, who are by definition highly concerned with the welfare of other people, seem to need a signal from their physician that it's appropriate to request a drug by brand name, which may explain why the prevalence of patient requests – and the effect of physician accommodation in patient requests – is very different across countries. For marketers this suggests that direct-to-patient marketing efforts aimed at triggering patient participation in prescription choice may need to be complemented by direct-to-physician marketing efforts. Our study shows samples and gifts do not seem to influence physician accommodation behavior. Therefore, firms may need to consider engineering their sales calls in order to motivate physicians for the importance of patient empowerment and the need to not only allow but actually motivate patients to request drugs by brand name[35].

Limitations and directions for future research

A first limitation of our study is that we rely solely on patient self-reported data. Even though self-reported data is commonly used in medicine and public health research (e.g. Haynes et al. 1980; Osterberg and Blaschke 2005; Walsh, Mandalia and Gazzard 2002), ideally we would not only survey patients but also their physicians for an even deeper understanding of patient requests and subsequent physician accommodation of such requests. Given that a major goal of our study was to ensure that our results were culturally and cross-nationally generalizable, we collected self-reported data from 17 countries which makes the dyadic-response approach infeasible. Yet, it would be interesting if future research, using a more limited set of countries, could test whether our results are robust under such a paradigm.

[35]The challenge, if we consider the results from Chapter 4 on the effects of patient empowerment on therapy adherence, is to facilitate patient empowerment while avoiding overwhelming the patient with information and while alerting patients for the risks of overconfidence regarding health and therapy decision-making. A solution may be to make these risks salient to the patient in order to persuade her to follow the treatment as prescribed by the physician, and for its full duration, even when patients were asked to participate in treatment choice.

Second, we model patient (past and future) requests as driven by three sources of health and therapy information only: mass-media, expert word-of-mouth and word-of-mouth. Moreover, patients report the extent to which they use these sources of information to gather information capable of leading to a patient requests. Future research could test a model with a more fine-grained distinction between alternative information sources. For instance, including different types of direct-to-consumer information, information provided by different sources and possibly manipulating source credibility are all interesting avenues for future research. In addition, behavioral (i.e. secondary) data on consumer usage of information and subsequent patient requests, if available, could be used to test the robustness of our findings with a different type of data.

Third, we assume that the patient-physician relationship is well-captured by a social exchange paradigm. Even though social exchange theory is very well-supported by applications in many different contexts, it would be interesting to use observational or qualitative research to test whether, in real medical practice, physicians and patients understand their relationship, and engage in therapy negotiation, in terms of cost-benefit analyses and if they see their relationship as a simple or a productive exchange. Collecting more evidence about how patients and physicians view their relational interactions could perhaps help researchers developing more informed, process-based models of this very important dyadic exchange.

Finally, although we control for observed heterogeneity at the patient and physician level (including patient personal values), other sources of unobserved heterogeneity could also be modeled. Given our large set of controls, we don't expect this assumption to bias any of our results. Still, future research could propose an extended version of our model which could account for unobserved heterogeneity and thus be usable with less rich data.

In general, this study shows that the current outrage of policy-makers and physicians against therapy and health information distributed via mass-media channels may be exaggerated and that other sources of health information, including direct-to-physician marketing efforts, seem more influential in driving patient requests. For managers, this study highlights that sample-dispensing is a powerful marketing tool, probably because it motivate patients and physicians to engage in meaningful therapy-related information exchange, allowing brand-related information to be transferred to the patient from a very

credible and highly trusted source their physician. Finally, patient personal values matter. Given that the prevalence of different personal values is very different in different regions of the Globe, both managers and policy-makers willing to increase patient requests (marketing) or to control either patient requests or physician accommodation of such requests (policy-making) need to devise culturally sensitive strategies to achieve their goals.

Appendix V.A

Table A.5.1 - Patient Characteristics

Variable	*Operationalization (items)*	*Relia-bility*	*Source*
Age	"How old are you?" *We use the standardized score of the patient's age.*		SSI
Education	"Which of these best describes your highest level of education?" *1 = "no formal education," 2 = "education up to age 12," 3 = "education up to age 14," 4 = "education up to age 18," 5 = "higher education," 6 = "university."*		Steenkamp, Van Heerde and Geyskens (2010)
Gender	"What is your gender?"; *Dummy: 1 = men, and 0 = women.*		SSI
Income	"Please indicate the total yearly income of all wage earners in your household before taxes, from all sources including salaries, rents, dividends, self-employment income, etc."; *1 = "up to [$2,000] per year," 2 = "between [$2,000] and [$4,999] per year," 3 = "between [$5,000] and [$9,999] per year," 4 = "between [$10,000] and [$19,999] per year," 5 = "between [$20,000] and [$39,999] per year," 6 = "between [$40,000] and [$74,999]*		Own developme nt
Health status	"In general, would you say your health is…" *1 = "poor," 2 = "fair," 3 = "good," 4 = "very good," 5 = "excellent."*		Safran et al. (1998)
Health motivation and confidence (HM)	I try to prevent health problems before I feel any symptoms. I try to protect myself against health hazards I hear about. I have a lot of confidence in my ability to cure myself once I get sick. There is a lot I can do to prevent illness.	0.61	Moorman and Matulich (1993)
Health consc. (HC)	(1) I consider myself as very health conscious... / (2) I think I do very much for my health... / (3) I value my health so much that I sacrifice many things for it...	0.79	Oude Ophuis (1989)
Self-disclosure (SD)	*Think now about a very good friend you now have, or ever had. Please indicate to what extent you have discussed the topics below with him or her. I have discussed with my friend…* (1) …things I have done or thought that I feel guilty about / (2) ...my deepest feelings / (3) …what things I don't like about myself / (4) …what is important for me in life / (5) …my biggest fears / (6) …my deep relationships with other people/ *Response scale: from 1 = "not discussed at all," to 5 = "discussed it completely."*	0.93	Based on Miller, Berg, and Archer, (1983)
Patient knowledge (PK)**	Regarding medical treatment of diseases you consider yourself… *The response scale for the first question ranged from 1 = "not at all knowledgeable," to 5 = "very knowledgeable."; The response scale for the second question ranged from 1 = "not at all experienced," to 5 = "very experienced."*	0.76	Adapted from Stremersch et al. (2003)

* Unless otherwise noted, all items were measured using the scale *1 = "strongly disagree," 2 = "disagree," 3 = "neither agree nor disagree," 4 = "agree," 5 = "strongly agree."*

** This construct was measured with two items, hence reliability is measured using two-tailed Spearman's correlation between these two items

Table A.5.1. (Cont.) – Physician and Dyad Characteristics

Variable	*Operationalization (items)*	*Reliab.*	*Source*
Physician Age	"What is approximately your doctor's age?" *Respondents tended to round their doctor's age around 5-year intervals (i.e. 30, 35, 40, 45…). We use the standardized score of the physician age as reported by the patient.*		SSI
Physician Gender	"What is your doctor's gender?"; *Dummy: 1 = men, and 0 = women.*		SSI
Patient-initiated information exchange (PI)	(1) I ask my doctor to explain to me the treatments or procedures in detail / (2) I ask my doctor a lot of questions about my medical symptoms / (3) I give my opinion (agreement or disagreement) about the types of test or treatment that my doctor orders / (4) I am typically involved in treatment decisions.	0.78	Lerman et al. (1990)
Doctor-initiated information exchange (DI)	(1) My doctor asks me about how my family or living situation might affect my health / (2) My doctor shares with me the risks and benefits associated with alternative treatment options / (3) My doctor asks me what I believe is causing my medical symptoms / (4) My doctor encourages me to give my opinion about medical treatments.	0.83	Kao et al. (1998) Lerman et al. (1990)
Relationship Quality (RQ)	(1) I trust my doctor's judgment about my medical care / (2) I trust that my doctor performs necessary medical tests and procedures regardless of cost / (3) I trust that my doctor performs only medically necessary tests and procedures / (4) The relationship I have with my doctor is something I am very committed to / (5) The relationship I have with my doctor is something I intend to maintain indefinitely / (6) I am satisfied with my doctor's caring and concern for me / (7) I am satisfied with my doctor's social skills (interactions with your doctor are fulfilling, gratifying and easy) / (8) I am satisfied with my doctor's professional skills (medical expertise / (9) quality of treatment decisions) / (10) I am satisfied with the thoroughness of my doctor's physical examinations when checking a health problem I might have / (11) My doctor gives me enough time to explain the reasons for my visit / (12) When I ask questions to my doctor, I get answers that are understandable / (13) My doctor takes enough time to answer my questions / (14) I get as much medical information as I want from my doctor / (15) I trust my doctor's judgment about my medical care / (16) I am satisfied with my doctor's caring and concern for me / (17) I am satisfied with the thoroughness of my doctor's physical examinations when checking a health problem I might have	0.94	Kao et al. (1998) Morgan and Hunt (1994) Geyskens and Steenkamp (2000)

* Unless otherwise noted, all items were measured using the scale *1 = "strongly disagree," 2 = "disagree," 3 = "neither agree nor disagree," 4 = "agree," 5 = "strongly agree."*

Table A.5.1. (Cont.) –Dyad Characteristics

Variable	***Operationalization (items)***	***Source***
Age homophily	-1*ZAgeDiff; *where ZAgeDiff = Standardized score of the difference, in absolute value, between the patient and the physician's age.*	Own development
Gender homophily	*Dummy: 1 = patient and physician of the same gender, and 0 = otherwise.*	Own development
Relationship duration	"For how long have you been seeing your doctor? (please indicate the number of years; if you have been seeing your doctor for less than a year please indicate 1)".	Own development
Interaction frequency	"How regularly do you visit your doctor?" *1 = "Usually less than once every two years," 2 = "At least once every two years," 3 = "At least once a year," 4 = "Usually once every six months," 5 = "Once every three months," 6 = "Once every month," 7 = "Every other week," 8 = "Once a week or more."*	Own development

CONCLUSION AND SUMMARY

In this dissertation I have explored important topics in health marketing. My main goal was to study key issues in the consumer side of healthcare industry. Studying the process leading to consumer decisions and building theory-rich models and hypotheses allows us to better understand not only consumer behavior but, importantly, key industry and market dynamics. To quantify such dynamics, and guarantee generalizability of our findings, decision-making models need to be calibrated in real world individual-level data. Moreover, we also need robust theoretical roots and knowledge of the institutional context surrounding the decisions under study for the hypothesized processes to be descriptively valid (i.e. for internal validity). Hence, in an effort to combine external and internal validity, I have used theories from cognitive, social and cross-cultural psychology to develop econometric models to be calibrated in real world data: a patient-level panel of prescription behavior in Chapter 2 and a very large international survey conducted among 11,735 patients in 17 countries in Chapters 4 and 5. In each of the chapters and especially in Chapter 3, I also critically reviewed medical decision-making literature in order to better understand current trends and dynamics on patient and physician decision-making. I now very briefly summarize the results from each chapter.

2. Summary of Main Findings

In Chapter 2, I investigated physician learning about the quality (and adoption) of a new drug (in our case, AstraZeneca's Symbicort). By collaborating with the Erasmus Medical School, I had access to a physician- and patient-level panel of prescription behavior in the asthma and COPD category. Physicians in this panel use paperless offices, meaning that all their prescription behavior gets registered in the data, creating a very rich dataset for the study of consumer learning. I show that salience effects interfere with physician learning, which is reflected in the fact that switching patients (those who abandon a treatment) are 7 to 10 times more influential during physician's quality belief formation than patients that refill their therapy. I extend the Bayesian learning model to account for these salience effects and show that salience slows down adoption of new drugs, which makes the finding important for pharmaceutical firms but also public policy officials.

In Chapter 3, I have critically reviewed current trends in patient-physician decision-making. One of the main conclusions of the chapter is that patient empowerment – a movement that defends more active patient participation in medical decision-making – is an emerging paradigm in medicine. The chapter reviews evidence showing that the vast majority of medicine and public health scholars currently believe that patient empowerment is a desirable goal for patient-physician relationships. The benefits accredited to patient empowerment include increased patient trust in the physician, patient satisfaction with care and therapy adherence. However, the definition of patient empowerment is fragmented over the literature and needs to be systematized. Perhaps as a consequence of this gap, empirical evidence demonstrating the benefits of patient empowerment is still rare, especially with respect to tangible health outcomes, like therapy adherence or improvements in health status. In this Chapter I review the antecedents of this trend, and the consequences for firms and policy-makers. For example, I discuss why patient needs and preferences regarding participation in medical decisions need to be taken into account (some patients are better prepared to be empowered than others…) and why they are a promising variable for patient-level segmentation. Finally, the current trends in medical decision-making and patient-physician relationships suggest that the patient may become increasingly central in pharmaceutical marketing strategies (increased focus on preventive medicine, niche-marketing strategies, etc) and in medical decision-making research. I discuss a major implication of this trend for life sciences firms: the need to put the patient at the center of marketing strategies.

In Chapter 4, I have studied the relationship between patient empowerment and therapy adherence. I develop a decision-making model for therapy adherence and discuss the influential role of self-determination theory – which defends that people persist more and have better performance in behavior that is based on a true sense of volition - in fostering the currently widely held belief that patient empowerment increases therapy adherence. This belief persists despite very scarce empirical evidence attesting its validity. I rely on psychological theories to make predictions regarding the effects of different forms of patient empowerment (doctor-initiated informational empowerment, patient-initiated informational empowerment and decisional empowerment) on therapy non-adherence. I find support for many of the hypotheses, many of which in direct contradiction to self-

determination theory. Specifically, I show that only patient-initiated informational empowerment leads to lower therapy non-adherence and that decisional empowerment and doctor-initiated informational empowerment actually lead to higher therapy non-adherence. I discuss the implications of these findings for managers and policy makers willing to reduce therapy non-adherence.

Finally, in Chapter 5, I study dyadic therapy choice, in particular the drivers of patient requests of medications by brand name and physician accommodation of such requests. I show that even though health and therapy information disseminated via mass-media - typically indicated by policy-makers as the culprit for patient requests and physician accommodation of such requests (and consequent rise in prescription costs) - is indeed associated with more patient requests, word-of-mouth (from peers or experts) is a clearly stronger driver of patient requests. Moreover, the fact that patients learn about a therapy through mass-media (or through any other source) doesn't influence physician accommodation of patient requests.

Looking to direct-to-physician marketing efforts, I show that a major driver of patient requests are free samples dispensed by physicians. Samples need to be dispensed by physicians to their patients, which affords an opportunity for the physician to explain to the patient how the therapy works (dosing, usage…). Thus, most likely this effect occurs because samples result in patients receiving brand-related information from a highly-trusted source (their physician), which has a stronger effect in patient request behavior than other, direct-to-patient, sources of therapy-related information. Importantly, I also find that patient values matter. Patients who are more open to change and have more power and achievement ambitions are more likely to request drugs by brand name. In contrast, patients who care more about the welfare of others (benevolent and universalistic patients), are less likely to request drugs by brand name.

For policy makers, these results suggest that mass-media information may not be the best focus of their attention, if the goal is to reduce patient requests for medications by brand name. Instead, monitoring resources should be invested in better understanding what happens in channels where word-of-mouth is generated (like social media) and with the spillover effects of direct-to-physician marketing, in particular free samples, on patient likelihood of requesting drugs by brand name. For managers, this chapter suggests that

direct-to-patient marketing strategies should be more focused in facilitating patient-to-patient and patient-to-expert interaction and increasing the quality and credibility of health and therapeutic information broadcasted via the mass-media. Moreover, such strategies need to be culturally-sensitive.

3. Future Research in Health Marketing

Future research in health marketing and in patient and physician-decision-making is very promising. Three factors combine to make this period particularly exciting for scholars interested in developing models of consumer decision-making, especially for health marketing: (i) the exponential growth in the availability of individual-level datasets (e.g. prescription data, Internet clickstream data…), (ii) recent developments in econometric methods and computers' computational resources (allowing the estimation of heavy Bayesian or simulation-based algorithms) and (iii) the consolidation of the body of knowledge of behavioral economics (allowing a richer exploration, using revealed preference data, of patient or physician behavior). At the same time, important trends reviewed in this thesis (see Chapter 3) - like population aging, increasingly participatory consumers in their health decisions and connectedness of patients and healthcare professionals - ensures that there is no shortage of questions to be answered. I believe that this journey is still in its infancy and I now suggest some future research topics.

Who is the customer for therapeutic offerings?

Traditionally, pharmaceutical marketers have focused on the physician as their key customer. Under the traditional model, a pharmaceutical company seeks to develop a new therapy, market it as the new best-in-class (the search for a blockbuster drug), determine its pricing and push it via direct-to-physician marketing. Important topics to inform managerial decisions in this traditional model include understanding key physician opinion leaders and developing models to segment the physician population and optimally allocate detailing and samples. These may be, today, mature areas in terms managerial and academic interest, but that doesn't mean that we fully understand therapy consumption and marketing. In fact, this traditional model is endangered by many of the trends revisited in this dissertation, namely the trend towards patient empowerment, widespread availability

of therapy and health information and the emergence of new stakeholders. Future research is needed to better understand therapy consumption in this new environment.

First, in many situations the customers are not limited to the patient and the physician and therapy choice is influenced by other parties. For example, when in 1998 Eli Lilly partnered with ICOS, a biotech startup, to launch the erectile dysfunction drug *Cialis*, it opted to target both sufferers of the disease and their partners, in a strategic marketing approach aimed at triggering the *couple's* interest in the therapy. This was a very elegant marketing move. Eli Lilly started by identifying that a major hurdle in the adoption of erectile dysfunction therapies is the tendency of male patients to deny, often for a long period, that they suffer from the disease. Using the drug's 36-hour effectiveness as an important point-of-difference, Lilly targeted its communications to the couple, promising them they would enjoy *"tender moments."* Such an approach gained the acceptance of patients' partners, contributing to the drug's successful penetration in the erectile dysfunction market[36].

Marketing models to better understand triadic decision-making contexts, like the one suggested by the *Cialis* example, are a fruitful area of research. Other important examples of triadic choices include therapy choice for elderly patients (who often bring their younger relatives to the clinical encounter), pediatric patients (who depend on parent's judgment, but also the child's cooperation) and patients suffering from psychiatric conditions and stigma-related conditions (like alcoholism and other addictions, which, like erectile dysfunction, often trigger denial effects). In these contexts, firms need to better understand which customers they should target and how should they streamline marketing actions to influence different decision-makers. Thus, both new models and substantive results are needed.

Even within the traditional patient-physician dyad there are many open questions. For instance, relationships often get sour, ultimately culminating in legal battles between patients and their physicians (see Gawande 2005). This liability climate, as discussed in Chapter 3, severely impacts patient-physician relationships and the behavior of both patients and physicians. For instance, antecedents and consequences of defensive medicine

[36]See for example Elie Ofek's (2004) case study HBR 505038, "Product Team Cialis: Getting Ready to Market."

- the practice of medical care with the primary purpose of avoiding malpractice liability, rather than maximizing patient health – are very important topics for future research. Moreover, within the patient-physician relationship it is important to better understand drivers of perceived quality of medical care, and whether supposedly irrelevant patient characteristics or patient-physician attitudes, influence physician or patient therapy and health decisions. For instance, do patients disclose more to physicians whom they like more? And would they also adhere more to therapy? All these questions deserve future scrutiny.

Beyond Blockbuster Rx's

Most research in pharmaceutical marketing focus on prescription drugs from blockbuster categories like pulmonology, gastrointestinal drugs, cardiology, hypertension, antidepressants, erectile dysfunction, etc. Less attention has been devoted to more complex therapies and treatments, for example those indicated for oncology and central nervous system (CNS) patients. Given their magnitude and welfare consequences, it is important to devote research attention to the study of therapy development, launch and promotion in these more complex disease areas.

On the other side of the therapy-complexity spectrum we have over-the-counter (OTC) drugs, for which patients do not need a physician prescription. Thus, OTC also pose their unique challenges to firms, patients and regulators. Although some research exists on OTC markets, I believe that there are many research opportunities in this area. For instance, we can certainly learn from our current knowledge on consumer behavior in other categories (e.g. high-involvement brands) and test whether it is also applicable to OTC drugs. For example, what is the role of the retailer and of the pharmacist in promoting OTC brands? Do patients trust more their pharmacist's or retailer's recommendations than information available via mass-media (e.g. direct-to-consumer advertising)? What about pricing – what drives consumers' willingness to pay for OTC brands?

In addition, given the macro-trend towards population aging, preventive medicine and patient empowerment (see Chapter 3), research focusing on drivers of self-medication may provide valuable insights for producers of OTC drugs, and even for marketing of

prescription drugs (as self-medication may lead to drop-out or brand switching without consultation of the physician).

In many countries, notably in the U.S. and U.K., there is also a trend away from traditional brands (e.g. Losec) towards either pure generics (e.g. Omeprazole) or branded generics (e.g. Omeprazole Ratiopharm), which creates important challenges for pharmaceutical firms[37]. This shift is often related to a shift of power, in therapy choice, away from the physician and to other stakeholders, like the pharmacist. Indeed, in many countries, pharmacists are not only allowed but incentivized to replace physicians' prescriptions of branded drugs by generic bioequivalents, which suggests that research needs to address the decision-making process of these stakeholders. Moreover, questions like how well do patients adhere to generic therapy and whether there are differences in the perceived performance of generics (vis-à-vis branded generics and branded medications), despite their bioequivalence, are important and currently largely unaddressed[38].

Social Interactions and Therapy Choice

The exploding ease-of-interaction among patients, physicians and other stakeholders (pharmacists, regulators or even payers), for example using web 2.0, also brings substantial challenges to firms. These, in turn, tend to translate into ample opportunities for research. For example, many pharmaceutical firms are trying to understand how to leverage the power of social-media. Yet, patient behavior and motivations on these social networks is, at present, poorly understood. As a consequence, firms are often slow and even sloppy in their reactions to customers in social media. For example, a well-known case in pharmaceutical companies' social media efforts is the story of Shirley Ledlie, a patient who suffered from permanent baldness - a rare side effect of Sanofi-Aventis' chemotherapy drug Taxotere - and who decided to share her experience in one of Sanofi-Aventis' pages on Facebook. Sanofi-Aventis was slow to react to Ledlie's initiative. First,

[37]McKinsey. 2007. *India Pharma 2015-Unlocking the Potential of the Indian Pharmaceutical Market: http://www.mckinsey.com/locations/india/mckinseyonindia/pdf/India_Pharma_2015.pdf*

[38] For an example of a laboratory experiment that could shed light in some of these processes see: Waber, R.L., B. Shiv, Z. Carmon, D. Ariely. Commercial Features of Placebo and Therapeutic Efficacy. *Journal of the American Medical Association***299**(9) 1016-1017.

it seemed to ignore her comments. Later, the company overreacted by cancelling the patient's account and all her comments in their Facebook pages. The consequence of Sanofi-Aventis strict reaction was a militant campaign initiated by Shirley Ledlie against the company in social media (including Twitter, Facebook, blogs…) and intense reactions from the patient community. The story is now widely known among pharmaceutical circles and patient community. Pharmaceutical firms need answers regarding how to deal with patient-generated content and with health and therapy information distributed and discussed in social media. Immediate concerns include how to detect and deal with influential patients, with adverse events reported by patients in social media platforms and with the regulatory implications of such reporting[39]. Thus, questions that need to be urgently addressed include: What can firms do to better understand and promptly respond to the voice of the patient in social media? How to avoid the substantial damage to public image that they can create?

Consumer-generated content deserves a special mention. Many consumers (both patients and physicians) invest their time and energy in filtering, creating and sharing information regarding their diseases on web 2.0 (blogs, forums, social media platforms…). This effort has been facilitated by the emergence of health-related social networks like *patientslikeme.com* (where patients share experiences with each other) and *sermo.com* (where physicians interact with each other). It is important to understand how physicians deal with this information, who are the key online opinion leaders and how to interact with them. Moreover, on the patient side, some of the most vocal consumers become "patient opinion leaders", i.e. very respected opinion-makers who can radically influence other patients with their opinions. Research on how patients (or physicians) learn from the experiences of others can thus have wide applicability in the near future. The pharmaceutical industry is already well-versed in the targeting and usage of physician opinion leaders. Yet, new research needs to be conducted to better understand the formation and the influence of these "patient opinion leaders."

To clarify what I mean by patient opinion leader, let me give you the example of Leighann Calentine. Leighann is the founder and main author of D-Mom Blog (http://www.d-mom.com/), a weblog where Leighann gives advice and shares her own

[39]http://www.doseofdigital.com/2009/01/myth-adverse-event-reporting/

experiences on parenting children with Type 1 diabetes. In her blog, Leighann frequently voices her opinion about different therapies and devices. For firms, it is crucial to monitor this type of content (e.g. via blog sentiment analysis), as it can bring very important and timely information on brand buzz and market dynamics. Yet, it is also crucial to understand how other consumers use patient opinion leader's information, and how influential are their opinions in patient behavior.

Marketing Resource Allocation

Pharmaceutical companies also need better tools, i.e. models and metrics, to facilitate optimal allocation of marketing dollars to different stakeholders. There is a growing belief, within the pharmaceutical industry, that effectiveness of targeting physicians with detailing efforts is decreasing, making it a less attractive investment[40]. The challenge is to understand which stakeholders firms should target, and which marketing channels are more appropriate for each stakeholder.

There are many important stakeholders besides physicians and patients. In fact, any agent who has a direct influence in therapy choice may be considered a possible target for pharmaceutical firms' marketing strategies. These stakeholders include regulators (e.g. regulatory agencies like FDA and EMEA), policy-makers (including local regulators and producers of medical guidelines), payers (including health insurance companies and health maintenance organizations), pharmacists (can be a very important stakeholder, especially with respect to generic drugs and OTC brands), nurses (can be pivotal in promoting therapy comprehension, persuasion and adherence) or hospital administrators (a very large market for pharmaceutical drugs involves drugs supplied to hospitals, where the decision-making process is heavily influenced by administrators; there is still little research in this domain).

Research highlighting how to better interact with these stakeholders, many of which are increasingly powerful, can thus be very valuable. For example, a very important topic that has not received enough attention in marketing is the definition of pre-launch negotiation strategies. How can pharmaceutical firms be better prepared to negotiate with regulators, present evidence in favor of their new therapies and influence pricing and

[40]BusinessWeek. 2007. *The Doctor Won't See You Now*. A. Weintraub, Feb. 5.

reimbursement decisions? Research in this area will fall in the intersection between marketing, decision-making and legal studies.

Health Marketing Research Related to Current Macro-Trends

Finally, there are many research topics in health marketing that can address current macro-trends like the colossal growth in therapy consumption in emerging countries like the BRIC (Brazil, Russia, India and China). A recent report by McKinsey, for example, estimates that – due to an explosive growth of its middle class - the Indian pharmaceutical market alone will demand US$ 20 billion in pharmaceutical drugs by 2015, becoming the 10th largest market in the world[41]. Many issues need to be researched in these markets. First, unique cultural values may influence the way physicians and patients see medicine and, hence, change therapy choice and consumption patterns. A better understanding of these emerging consumers is therefore urgently needed. Second, the specific context in these countries may create both threats and opportunities to firms that need to be studied. For example, the level of counterfeiting, especially for generics (whose brands are unfamiliar) is much higher in these markets than in the Western world. This creates both a public health problem, and a trust issue – with consumers having low trust in the efficacy and safety of generics and be willing to pay a premium for branded generics, which garner consumer trust[42].

Marketing scholars can also contribute with research in health marketing that goes beyond therapy choice. The study of nutrition and obesity, addiction, behaviors that may increase the risk of sexually-transmitted diseases and the effects of marketing in health-threatening (e.g. violence in movies and computer games) or health-improving behaviors (e.g. lifestyle changes introduced by products like *wii* fitness) are just a few examples of exciting topics for which marketing scholars can contribute with their knowledge and methods. These topics have, in recent years, garnered the attention of researchers in the

[41]McKinsey. 2007. *India Pharma 2015-Unlocking the Potential of the Indian Pharmaceutical Market: http://www.mckinsey.com/locations/india/mckinseyonindia/pdf/India_Pharma_2015.pdf*

[42]New York Times. 2010. *Drug Firms Apply Brand to Generics*, by N. Singer: http://www.nytimes.com/2010/02/16/business/16generic.html?_r=1

area of *transformative consumer research*[43], who have mainly taken a consumer behavior approach, namely by using laboratory experiments. Yet, if data from recent services like Philips DirectLife (http://www.directlife.philips.com/) - an activity program by Philips where consumers, with the help of a counselor, set goals for 12 week activity plans and record their daily activity using a specialized device – becomes available to researchers, this represents a fantastic opportunity to build models to study many of these health-related behaviors using secondary data. For example, building a psychologically-grounded structural model of motivation, goal-setting and achievement using this type of data would certainly be a valuable topic of future research. Other topics on self-control issues, adherence to exercise and preventive health behaviors can also be studied in depth with this type of data or even with scanner panel data (e.g. eating habits over time).

Finally, other non-therapy related topics in health and marketing that I can think of include: (i) data and privacy-related issues – how are consumers reacting to the increasing levels of health data available to them? Is it changing their health behaviors?, (ii) how do patients choose between physicians, clinics and hospitals?, (iii) How will the current trend towards home-based care (triggered by technological advances and increased cost of care) interfere with patients' treatment decisions?

Another topic that deserves further research is how to streamline communication of public health concerns by governments and public health officials. For example, in pandemics there is often a paradoxical tension between creating enough awareness for a certain health risk and guaranteeing effectiveness of the government's health risk communications in the long run. That is, if a campaign is very successful raising awareness and motivating patients to engage in active prevention of a certain health threat, then such threat may never materialize, or materialize in much smaller scale. Yet, if risks don't materialize consumers may not pay sufficient attention or even trust future warnings – a dynamic model quantifying this effect would be a good contribution to the literature.

I hope my dissertation has, on top of the substantive and methodological contributions presented in Chapters 2-5 achieved three goals: (i) demonstrated the importance of

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[43]Mick, D.G. 2006. *Meaning and Mattering Through Transformative Consumer Research*. Presidential address to the Association for Consumer Research, in *Advances in Consumer Research***33** C. Pechmann, L.L. Price. Eds. Provo, UT: Association for Consumer Research, 1–4.

developing models and theories to study health-related consumer decisions, (ii) stimulated interest among marketing scholars to examine health topics, including therapy choice but also other health-related topics and even health consequences of marketing actions and (iii) emphasized the importance of developing models of consumer decision-making for better understanding of market dynamics. Despite considerable progress made in the literature on pharmaceutical and health marketing in the last years, many interesting and highly-influential topics in health marketing remain unexplored, making this area a promising area for future scholarly work in marketing. I trust the next few years will bring many novel contributions, by marketing scholars, to the health field.

SUMMARY IN ENGLISH

In this dissertation, I focus on physician and patient behavior. I model patient and physician decisions by integrating robust insights from different behavioral sciences (e.g. economics, psychology and sociology) in econometric models calibrated on individual data. This approach allows me to bring novel insights for managers, policy-makers and patients on three main topics. First, when studying physician learning from patient feedback about the quality of a new drug, I find that switching patients are 7 to 10 times more salient, in physicians' memory, than patients who refill their medication. Second, when studying the relationship between patient empowerment and patient non-adherence to physician advice, I show that it is important to go beyond the logic of self-determination theory, which predicts that empowering patients during medical encounters is always beneficial, and consider side effects like patient overconfidence. In the case of therapy adherence, these side effects actually make patient empowerment undesirable, as it decreases therapy adherence. Third, when studying the main drivers of patient drug requests by brand name and the physician's accommodation of such requests, I find that health information obtained via mass-media is less important than patient values, word-of-mouth from other patients and word-of-mouth from expert consumers (e.g. other healthcare professionals).

NEDERLANDSE SAMENVATTING (SUMMARY IN DUTCH)

In dit proefschrift richt ik me op het gedrag van de arts en patiënt. Ik modeleer beslissingen van de arts en patiënt door belangrijke inzichten vanuit verschillende gedragswetenschappen (b.v. economie, psychologie en sociologie) te integreren in econometrische modellen die zijn ontwikkeld op basis van werkelijke individuele data. Deze aanpak maakt het mogelijk om nieuwe inzichten voor managers, beleidsbepalers en consumenten te verkrijgen betreffende drie belangrijke onderwerpen. Ten eerste, tijdens het bestuderen van hoe een arts leert van opmerkingen van een patiënt met betrekking tot de kwaliteit van een nieuw medicijn, is aangetoond dat volgens de arts, patiënten die wisselen van medicijn 7 tot 10 keer meer tevreden zijn dan patiënten die niet wisselen van medicijn. Ten tweede, tijdens het bestuderen van de relatie tussen een patiënt die actief participeert en een patiënt die niet zich niet aan het advies van de arts houdt, toon ik aan dat het belangrijk is om verder te gaan dan de vanzelfsprekende zelfbeschikkingstheorie, welke voorspelt dat een patiënt die actief participeert tijdens een medische ontmoeting daar altijd baat bij heeft, en rekening houdt met andere factoren zoals een overmoedige patiënt. In het geval dat een patient zich aan de voorgeschreven therapie houdt, maken deze andere factoren een actieve patiënt participatie ongewenst, omdat het de kans dat de patient zich aan de therapie houdt verlaagd. Ten derde, tijdens het bestuderen van de belangrijke aspecten van het aanvragen van een medicijn met een merknaam en de bereidheid van de arts om aan deze aanvraag te voldoen, heb ik aangetoond dat informatie verkregen via massamedia minder belangrijk is dan patiënt waarden, mond-tot-mond informatie van andere patiënten en mond-tot-mond informatie van experts (b.v. professionals actief in de gezondheidszorg).

RESUMO EM PORTUGUÊS (SUMMARY IN PORTUGUESE)

A presente dissertação debruça-se sobre o comportamento do médico e do paciente. Nela desenvolvo modelos que integram resultados robustos provenientes de diferentes ciências sociais e comportamentais (nomeadamente economia, psicologia e sociologia) em modelos econométricos calibrados em dados não-laboratoriais recolhidos ao nível individual (um painel com dados de prescrições médicas e dados recolhidos através de questionários). Esta combinação de modelos e dados permitiu-me obter resultados generalizáveis que descrevem factos novos para gestores, legisladores, médicos e pacientes em três áreas principais. Em primeiro lugar, estudo como aprendem os médicos – através das suas interacções com os seus pacientes - acerca da qualidade de um novo medicamento. Neste estudo, demonstro que o *feedback* de pacientes que abandonam o novo medicamento fica entre 7 e 10 vezes mais saliente na memória do médico do que o feedback de pacientes que persistem no novo medicamento. Dado que estes pacientes são exactamente os que tiveram experiências menos felizes com o novo medicamento, este fenómeno comportamental traduz-se num pessimismo prolongado dos médicos acerca desse medicamento. Em segundo lugar, estudo a relação entre poder do paciente na escolha de tratamentos e aderência às recomendações de tratamento do médico. Neste estudo, demonstro a importância de considerar argumentos para além da teoria de auto-determinação que prevê que transferir poder para os pacientes é sempre benéfico. Por exemplo, ao incorporar fenómenos psicológicos como sobre-confiança, demonstro que a transferência de poder para o paciente pode ser indesejável, pois resulta em menor adesão do paciente à terapêutica recomendada pelo médico. Em terceiro lugar, estudo os principais antecedentes da decisão de pacientes em diversos paíes de pedirem medicamentos ao seu médico utilizando a marca, e da decisão do médico de acomodar tais pedidos. Neste estudo, demonstro que a informação acerca de saúde distribuída via *mass-media* tem menor impacto nesses pedidos que o contacto com outros pacientes, com profissionais de saúde e do que os valores culturais do próprio paciente.

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ABOUT THE AUTHOR

Nuno was born on November 5, 1977 in Coimbra, Portugal. He obtained his undergraduate degree, a *Licenciatura* (a 5-year degree) in Economics, from University of Porto, Portugal in 2001. Before finishing his first degree, Nuno studied as an exchange student at Lund University in Sweden, in a program that combined insights from different social sciences, in particular Economics and Sociology. In October 2000 he also started, together with some of his colleagues, a multimedia and digital marketing start-up. The company maintains a business performance until today. After finishing his undergraduate degree, Nuno worked as a business intelligence analyst for the largest retailer operating in Portugal – Sonae Retail – until July 2004. In 2004, Nuno decided to move to Rotterdam and completed a Master of Science in Economics and Business, majoring in Marketing, at the Erasmus University Rotterdam (cum laude).

In October 2005, Nuno started his Ph.D. at the department of Economics and Business (Marketing) of the Erasmus School of Economics. During his Ph.D., Nuno taught Marketing and Innovation and Marketing Strategy at the Erasmus School of Economics. In 2009 and 2010, he was also a visiting doctoral student at IESE Business School in Barcelona. Nuno's research interests include behavioral modeling and behavioral economics of consumer decision making. In particular, Nuno applies econometric models to understand patient and physician behavior, as well as to study individual and joint consumer decision processes. In terms of substantive focus, he is working on topics in the life sciences industry and is interested in new product adoption, in cross-cultural differences and social influences in decision-making.

Nuno's work has been published in the book *The Connected Customer: The changing nature of consumer and business markets* (edited by Stefan Wuyts, Marnik G. Dekimpe, Els Gijsbrechts and Rik Pieters) and in *Marketing Science*. Nuno has presented his work at various conferences, such as the *INFORMS Marketing Science* the *Marketing Dynamics*

Conference and the *European Marketing Academy Conference.* In 2008, Nuno was invited to be a consortium fellow at the American Marketing Association Sheth Foundation Doctoral Consortium, in University of Missouri. Next to his academic activities, Nuno maintains a strong passion for music and regularly plays guitar at home and occasionally with friends. In July 2011, Nuno starts his tenure track position as Assistant Professor of Marketing at the Erasmus School of Economics.

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ESSAYS ON PHYSICIAN AND PATIENT DECISION-MAKING

In this dissertation, I focus on physician and patient behavior. I model patient and physician decisions by integrating robust insights from different behavioral sciences (e.g. economics, psychology and sociology) in econometric models calibrated on individual data. This approach allows me to bring novel insights for managers, policy-makers and patients on three main topics. First, when studying physician learning from patient feedback about the quality of a new drug, I find that switching patients are 7 to 10 times more salient, in physicians' memory, than patients who refill their medication. Second, when studying the relationship between patient empowerment and patient adherence to physicians' therapy advice, I show that it is important to go beyond the logic of self-determination theory, which predicts that empowering patients during medical encounters is always beneficial, and consider side effects like patient overconfidence. In the case of therapy adherence, these side effects actually make patient empowerment undesirable, as it decreases therapy adherence. Third, when studying the main drivers of patient drug requests by brand name and the physician's accommodation of such requests, I find that health information obtained via mass-media is less important than patient values, word-of-mouth from other patients and word-of-mouth from expert consumers (e.g. other health-care professionals).

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