Switching Costs, Brand Premia and Behavioral Pricing in the Pharmaceutical Market*

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November 8, 2019

Abstract

This article examines the market power of branded prescription drugs faced with generic competition. Using prescription-level and matched socioeconomic panel data of the entire Swedish population between 2010 and 2016, I provide evidence for the key role of switching costs. A discontinuity surrounding patent expirations establishes that the effect is causal. Further, by comparing patients with and without medical education, I show that those without medical education experience higher brand premia. A unique feature of the Swedish market allows me to rule out patients' inattention due to information costs as a source of market power. Therefore, switching costs and perceived quality differences are the key determinants of market power. I then estimate a dynamic oligopoly model with forward-looking firms which is used in counterfactual studies of the effect of switching costs and perceived quality differences on prices. First, an increase in the length of procurement mimics a reduction of switching costs and increases prices. While the effect of switching costs on prices in theory is ambiguous, moderate switching costs and sufficient competition for new patients increase competitive pressure. Second, if everyone acts as a medical expert and experiences fewer brand premia, prices decrease.

Keywords: Switching Costs, Brand Premia, Behavioral Pricing, Pharmaceuticals

JEL Codes: D12, I11, L13

*I am grateful to Richard Friberg and Michelle Sovinsky for detailed feedback. I thank Andreas Born, Francesco Decarolis, Anna Dreber Almenberg, Liran Einav, Michele Fioretti, Matthew Grennan, Magnus Johannesson, Johannes Kasinger, Matthew Leisten, Erik Lindqvist, Elle Parslow, Matthew Shapiro, and Giancarlo Spagnolo as well as seminar participants at the Stockholm School of Economics, the Universidad Carlos III de Madrid, the XXXIII Jornadas de Economía Industrial, the Research Institute of Industrial Economics, the University of Gothenburg, the Empirics and Methods in Economics Conference at Northwestern University, the MicroWave at the IIES, the University College London, the University of Bern, the IO workshop in St. Gallen, the University of Umea, the Norwegian School of Economics, the European Winter Meeting of the Econometric Society, the 43rd Simposio de la Asociación Española de Economía-Spanish Economic Association, the Copenhagen Business School, the Hanken School of Economics, the National University of Singapore, the Singapore Management University, the University of Sydney, the University of Melbourne, the Ecole Polytechnique, the Instituto Tecnológico Autónomo de México, and the IIOC 2019 in Boston for helpful comments. I also thank Lars Näsström at Kantar Sifo for providing the advertisement data. Financial support from the Jan Wallander and Tom Hedelius Foundation is gratefully acknowledged.

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1 Introduction

Consumers in various markets stick to products they have purchased before and prefer to buy known brands even when cheaper alternatives of similar quality are available. Previous research has put forward a number of possible reasons for such habit persistence and brand premia: switching costs, inattention due to information costs, risk aversion, quality uncertainty, quality misconceptions or prestige effects of consuming a particular brand.[1] Such behavior is especially surprising when it comes to the consumption of prescription drugs in developed markets where fraud is not an issue.[2] Consumers often prefer branded and familiar products even though regulations require generic products to be medically equivalent to the branded product, and pharmaceuticals do not generally carry any value except for their treatment abilities. In addition, these markets are characterized by high prices and odd price patterns despite the generic competition that, according to economic theory, should serve as an important tool to reduce prices.[3]

In comparison to the United States, where the share of generics exceeds 80% of the total pharmaceutical market volume in 2018, most European countries have a penetration of less than 50% (OECD, 2017).[4] Even among generics, branded generics play a crucial role. Manufacturers that are different from the originator will market an off-patent product under a new trade name.[5] Branded generics are more expensive than generics without a brand name.

In this article I answer the question of whether consumers' behavioral frictions can explain the market power of branded prescription drugs. This study uses individual choice data for prescription drugs covering the entire Swedish population from 2010 to 2016 to examine the underlying cognitive reasons why consumers are willing to pay a higher price for pharmaceuticals with the same ingredients. The unique institutional setting and data sources allow me to identify important determinants of consumer choice: switching costs and perceived quality differences. The article

[1] The importance of switching costs in the retail market has been documented by Erdem and Sun (2001), Dubé et al. (2009), Shcherbakov (2016), Shy (2002), Viard (2007) and Rickert (2016). There is a substantial economic and marketing literature on brand premia and the general concept of brand equity. Following Handel and Schwartzstein (2018), one may distinguish mental gaps from behavioral frictions that are in line with the neoclassical assumption of correct beliefs. For the latter, see Hortaçsu and Syverson (2004) for an example of risk-index funds and a discussion of risk aversion and possible information costs. Ackerberg (2001) discusses the importance of prestige effects. The other possibility is that consumers have mental gaps or psychological distortions (Handel and Schwartzstein, 2018). Consumers can have wrong beliefs. Early marketing work, such as that of Braithwaite (1928) and Frederic and David (1990), contends that misleading information comes from advertisements. Bronnenberg et al. (2015) demonstrate an example of a brand premium that is not due to real quality differences. Also, the media has covered habit persistence and brand premia; see, for example, Mullainathan (2017) for the *New York Times*.

[2] Counterfeit pharmaceuticals are a problem in large parts of the developing world. According to an OECD report (OECD, 2009) the incidence of counterfeit medicine is 1% across all medications but an increasing problem in some Asian and African countries. Because of the increase of the black market and personal prescription drug importation, counterfeit medicine is also an increasing problem in the United States (Zullo et al., 2015). Patients may face insecurity due to counterfeit medicine and rely on brand names. The problem of counterfeit medicine in the legal pharmaceutical industry in the European Union is less severe. Especially in Sweden, counterfeit medicine in the legal distribution networks has not received attention.

[3] In the US, prices of generic pharmaceuticals often rise unpredictably. In 2014 and 2015 several producers increased prices of generic products drastically (e.g., Ursodiol), see Reinhardt (2016) for a discussion. More recently, in July 2018 Pfizer announced plans to increase the price of a number of generics (LaVito, 2018). In the United Kingdom, manufacturers of generic competitors have been accused of differentiating generic pharmaceuticals to increase prices (Hyde, 2016). In Sweden, price cycles, in which competing producers take turns setting a high price each month, have been observed (Janssen, 2018).

[4] Within the US, adoption of generics was fast. See Aitken et al. (2018) for a general historical discussion.

[5] Note that manufacturers often use an umbrella brand name for several generic products. For industry reports concerning the profitability of branded generics, see, for example, Accenture (2012).

first documents patterns of the behavioral phenomena in the data and then proceeds to the structural estimation of a dynamic oligopoly model to allow for a systematic evaluation of the welfare effects of counterfactual policies. In the counterfactual analysis I show that prices in equilibrium are dependent on consumers' behavioral frictions. Behavioral pricing incorporates the idea that the pricing of a product is based on the behavior of potential customers and explains the high prices as well as price dynamics of pharmaceuticals under generic competition.[6] I make contributions to three literatures: industrial organization, behavioral economics and health economics.

First, the panel structure of the individual choice data allows the identification of consumers' switching costs after starting a medical treatment with a specific product. Crucially, switching costs are not apparent in all prescription markets.[7] I show that patients are 17.75% (3.22 percentage points) more likely to pay premia for painkillers and 12.35% (1.16 percentage points) more likely to pay premia for antibiotics if they have consumed the identical product in the preceding month. There is no evidence of this habit persistence in markets for antiepileptics. The results withstand several robustness checks in which I explore identification strategies beyond panel data methods. For example, I compare repeated purchases by patients briefly before and after the patent for a substance has expired, showing that the estimates of habit persistence due to switching costs are robust. This clean evidence for switching costs over a wide range of pharmaceuticals is novel.[8]

Second, the regulatory background of the Swedish prescription drug market, as well as the registry data, allows the identification of mechanisms behind the brand premia. There are three different kinds of products in the market: original products, branded generics and other generics. Branded generics may differ from other generics as consumers know about the specific brands even though the products are not originals. However, brand premia are relevant for originals as well as branded generics. In general, the explanation for brand premia is that either some brands carry a higher quality (in real terms or caused by psychological effects, i.e., prestige effects) or consumers perceive quality differences, for example, due to uncertainty of the medical equivalence between products. I can exclude the possibility that brand premia are due to real quality differences for two reasons. First, the market for prescription drugs is ordered into groups of exchangeable products that are medically equivalent.[9] Second, I exclude real quality differences by comparing purchasing behavior between experts (patients with medical education as a physician) and non-experts (patients without such medical education) in an approach similar to that of Bronnenberg et al. (2015).[10]

[6] The term *behavioral pricing* has been used in the marketing literature. See Gannett (2012) for a general definition. Note that the term incorporates the dynamic as well as simultaneous connection between the behavior of consumers and prices. Indeed, prices shape the choice as well as future behavior of firms. However, past choices, behavior, and general brand preferences also shape demand and therefore prices.

[7] Klemperer (1995) differentiate between five cost types: (1) need for compatibility with existing equipment, (2) transaction costs of switching suppliers, (3) costs of learning to use new brands, (4) uncertainty about the quality of untested brands and (5) discount coupons and similar devices.

[8] Only Feng (2017) identifies switching costs for anticholesterol drugs using a similar strategy of identifying a discontinuity surrounding patent expiration.

[9] The Swedish Medical Product Agency (2010) states that the 'basic principles for substitution are that the products have the same active substance in the same amount and are otherwise medically equivalent'. Non-medical ingredients of drugs could differ.

[10] In this article, I use the term 'medical education' to refer specifically to the academic training of physicians.

While the comparison of experts to non-experts allows me to exclude real quality differences as a reason for brand premia, it is often not possible to differentiate between situations in which consumers are inattentive and situations in which the consumer perceives quality differences (Handel and Schwartzstein, 2018).[11] In the former, information costs prevent consumers from accessing all the relevant information.[12] In the latter case, even when consumers have information, uncertainty about the products' equivalence drives the choice.[13] There is a growing literature that tries to isolate inattention (and switching costs) in markets of insurance and pension choices (e.g., Ho et al., 2017). Handel and Schwartzstein (2018) argue that also in the case of insurance choices the underlying mechanisms are still based on assumptions of the authors.[14] Given the institutional setting, this study is unique in that I can credibly rule out inattention as a possible reason for brand premia. In Sweden, not only are patients with a prescription from a primary health care provider financially incentivized to consume the cheapest available product from a predefined group of equivalent drugs, but also the pharmacist is obliged by law to tell the patient about the cheapest product as well as its equivalence (Sveriges Riksdag, 2002). Given that the information about equivalence is provided at the time of purchase and the cheapest equivalent pharmaceutical is always presented as a default option, inattention is not an explanation for brand premia.[15] Therefore my approach differs from the existing literature on insurance choices (Abaluck and Gruber, 2016; Bhargava et al., 2017; Handel, 2013; Handel and Kolstad, 2015; Ho et al., 2017; Ketcham et al., 2015; Marzilli Ericson, 2014; Miller, 2019), not only because I investigate consumer choices of physical consumption products but also because inattention is not an option. Instead, compared with experts, non-experts are 26.1% (4.88 percentage points) more likely to purchase painkillers that carry additional costs compared to the cheapest available product. For antibiotics, non-experts are 26.06% (2.45 percentage points) more likely than experts to pay an additional price difference, and for antiepileptics, non-experts are 38.21% (1.07 percentage points) more likely to oppose substitution to the cheapest available option. Controlling for switching costs, non-experts usually pay a brand premium for originals as well as branded generics. While inattention is not a source of the brand premia, it may be that consumers do not trust non-branded generics or, more likely, they may be uncertain about the equivalence.

Third, I quantify the effect of switching costs and brand premia on firms' pricing strategies. Theory predicts that

[11] Handel and Schwartzstein (2018) report numerous examples where both phenomena may play a role. For example, the difference in purchasing behavior of over-the-counter (OTC) drugs between pharmacists and the general population in Bronnenberg et al. (2015) could be caused by the lower information costs of pharmacists (who have lower search costs when comparing products) or by differences in perceived quality. The authors report that pharmacists have better knowledge about the ingredients of drugs, which is in line with lower information costs as well as fewer perceived quality differences. Note also that I explore behavior only within specific substitution groups. The products within a substitution group are equivalent from a medical perspective. Exploration and learning, as described by Crawford and Shum (2005), are not important within but solely between substitution groups.

[12] Information costs are defined as the time, monetary and other resource costs of gathering information.

[13] Handel and Schwartzstein (2018) speak of 'mental gaps'. Indeed, their definition of a mental gap is broad: 'there is a gap between what people think and what they should rationally think given costs'. Mental gaps are psychological distortions.

[14] For example, Handel (2013) uses similar data and mechanisms to Ho et al. (2017) and acknowledges that underlying mechanisms could include true switching costs, search costs or miscalibrated beliefs.

[15] In a series of robustness checks I investigate whether the Swedish substitution system works as intended. See Sections 4 and 5 for detail.

switching costs affect the price-setting behavior of firms.[16] Firms have an incentive to decrease prices sporadically and set higher prices in subsequent periods to harvest consumers (the 'lock in and harvest' strategy). Furthermore, switching costs may lead to collusion schemes in which firms alternate systematically in prices (Janssen, 2018). Prices in the pharmaceutical market show cyclical price patterns. Firms with a high market share due to a period of low prices increase their prices in forthcoming months. The patterns can be explained by behavioral pricing. A structural estimation of the market allows me to extend the analysis of market equilibria and quantify the effects of switching costs and brand premia. I estimate the demand for pharmaceutical products from experts as well as non-experts, incorporating switching costs. I show that switching costs in a representative substitution group of high-dosage paracetamol account for 11% to 28% of the retail price, while brand premia for this specific drug group are 5% to 16% of the retail price. I use a two-step estimator similar to that of Bajari et al. (2007) to recover firms' cost parameters under the assumption that firms compete in an infinite horizon setting.

I use the structural model to investigate two counterfactual scenarios that highlight the importance of consumers' behavioral frictions for price equilibria in an applied industrial organization setting. The first counterfactual evaluates effects on prices and consumer welfare by changing the procurement procedure for prescription drugs in the Swedish health care system. Under the hypothetical policy, firms are allowed to change the price of a product every twelve months instead of each month. Under this scenario, firms have a lower incentive to engage in behavioral pricing because it is more costly to lock in patients and less profitable to harvest them. In other words, switching costs are less important. I choose to increase the length of procurement contracts instead of decreasing the switching costs directly because this approach represents a realistic policy intervention.[17] Nevertheless, the policy is well suited to explore the effects of switching costs on market equilibria.[18] Intuitively one might think that switching costs make a market less competitive and that a policy lowering their importance would result in reduced prices. In contrast, the results show that prices increase and patients' welfare decreases (consumers pay on average 2.08% more) under the alternative regime with only annual procurement. The results are in line with theoretical (Cabral, 2016; Rhodes, 2014) and empirical (Dubé et al., 2009) research that shows that moderate switching costs may lower prices. The basic reasoning is as follows. Switching costs always have two effects. On the one hand, they increase the market power of firms with locked-in consumers. On the other hand, they increase competition for new customers. If switching costs are moderate in size and there are enough new customers, then an increase in switching costs is associated with

[16] Klemperer (1987a) and Klemperer (1987b) provide insights regarding the impact of switching costs on the competitive outcome in a duopoly. Note also the existence of similar models in monopolistic competition (e.g., Conlisk et al., 1984; Sobel, 1984; Villas-Boas, 2006). Specifically, it may even be possible that monopolists under some conditions (e.g., durable goods) play a 'lock in and harvest' strategy. Multi-period environments (Anderson et al., 2004; Anderson and Kumar, 2007; Beggs and Klemperer, 1992; Padilla, 1995; see also the survey in Farrell and Klemperer, 2007) have extended the theoretical literature on the competitive effect of switching costs in duopolies.

[17] A policy of a longer contract time has been proposed by Granlund and Rudholm (2018). The authors suggest that it decreases the possibility of coordination in the form of price cycles, empirically described in Janssen (2018).

[18] In *Online Appendix I.3* I confirm that the result is similar when decreasing switching costs on the demand side directly.

higher competitive pressure and lower prices in equilibrium. The results of this study add to the discussion about the competitive pressure of switching costs.[19] Firms have a lower incentive to reduce prices in order to lock in consumers, and moderate switching costs prevent prices from becoming too high in the harvest periods. Further, not every patient is a frequent consumer. New incoming patients and those that do not experience switching costs profit from behavioral pricing as firms decrease their prices sporadically to lock in patients. The results are important for the interpretation of switching costs from an industrial organization perspective as well as for policymakers: First, switching costs are empirically important when it comes to evaluating firms' price incentives. Second, switching costs do not necessarily increase prices in equilibrium. Policymakers must carefully evaluate the size and effect of switching costs in a pricing equilibrium.

The second counterfactual investigates the situation in which all consumers are medical experts, limiting the role of brand premia in patients' choices. The hypothetical situation is closely related to directly targeting consumers' perceptions of quality differences or a reform that makes prescription by physicians mandatory. In such a situation, substitution is mandatory if not opposed by a physician. Limiting brand premia to 5% of the retail price is associated with price decreases of 2.7% and an increase in patients' welfare (costs for consumers decrease by 3.0%). With less scope for brand premia, firms have less opportunity to take advantage of patients. A decrease in brand premia is profitable for the consumers through a direct effect of lower absolute payment and an indirect effect caused by an increase in competition as firms cannot rely on brand premia.

The paper is organized as follows. In Section 2 I examine the behavioral phenomena in a stylized choice model. Section 3 presents the institutional background, and Section 4 describes the data sources as well as the markets of the studied substances. In Section 5 I identify switching costs and perceived quality differences. I develop the model in Section 6 and describe the estimation techniques in Section 7. The results of the model are presented in Section 8, and the counterfactuals are presented in Section 9. Section 10 concludes the paper.

2 Stylized Choice Model

To frame the definitions of consumers' switching costs and perceived quality difference in the prescription drug market, I outline a stylized choice model.[20] The model intends to solely capture the basic intuition of the behavioral features.

[19] Recent theoretical literature includes discussion of the possibility that lower switching costs may increase competitive pressure (Arie and Grieco, 2014; Cabral, 2016; Dubé et al., 2009; Fabra and García, 2015; Rhodes, 2014). A detailed discussion of previous literature and an analysis of when switching costs make markets more or less competitive can be found in Ruiz-Aliseda (2016).

[20] The model shares some similarities to that of Bronnenberg et al. (2015); however, it extends the basis to switching costs and a multiple-product environment.

Let there be i patients. Each patient chooses between $j = 1, ..., N$ products. Prices of products are denoted by p_j. There are two kinds of patients in the market, experts (with a medical education) and non-experts (all others). Let us consider a patient i: The utility that experts attach to a product is denoted by u_j^E, whereas the non-experts attach a utility of u_j to a product. Drugs are used for treatment of a disease such that there is no outside good. Experts choose a product j_E^* that maximizes net utility, $\max_j\{u_j^E - p_j\}$. Non-experts choose j^* such that $\max_j\{u_j - p_j\}$. Experts and non-experts may make the same product choice, so $j_E^* = j^*$, or the product choice may differ, that is, $j_E^* \neq j^*$. Behavioral phenomena may affect (1) the product choice in general, that is, j^*, and (2) the difference in product choice between experts and non-experts. In the following I briefly describe possible factors that influence a patient's choice.

1. *Switching Costs:* Switching costs affect a patient's utility, independently of whether the patient is an expert or not. The utility of product j is defined not only by the quality of usage $\underline{u}_j$ but also by the previous usage of j, which affects utility by a factor of β_j. So, if j was used in previous treatment, utility increases by β_j to $\underline{u}_j + \beta_j$. Switching costs influence the decisions of non-experts and experts, $\max_j\{u_j - p_j\}$ and $\max_j\{u_j^E - p_j\}$, and result in habit persistence/state dependence, which means that consumers tend to purchase the same product/brand on subsequent occasions even though the environment, such as prices or choice sets, has changed.

2. *Real Quality Differences:* Even though the products are medically equivalent and counterfeit pharmaceuticals are not a problem in the Swedish market, the model allows for quality differences among drugs, that is, it may be possible that $\underline{u}_j \neq \underline{u}_k$ for $k \neq j$. Naturally, quality differences affect product decisions, that is, $\max_j\{u_j - p_j\}$. Note that real quality is the same for experts and non-experts.

3. *Perceived Quality Differences:* Perceived quality differences lead to a divergence between the real quality of a product, $\underline{u}_j$, and the perceived quality, $\underline{u}_j + \rho_j$. Patients may be uncertain about the real quality and attach an erroneous higher quality to a prescribed product. It is also possible that patients have a higher trust in some products. Note that experts, compared with non-experts, have less uncertainty and more correct beliefs about products. Therefore, the perceived quality differences influence the choice $\max_j\{u_j - p_j\}$ and may lead to different choices between experts and non-experts, that is, $j_E^* \neq j^*$.

4. *Inattention:* Inattention can result in a mistaken quality or price. Inattentive consumers may fail to evaluate quality or prices correctly, such that the perceived quality is $\underline{u} + \varepsilon_j$ and perceived prices take the form of $p_j + \varphi_j$. When consumers do not know the true quality or price of a product, they may rely on heuristics or expectations in their perceptions of quality and prices. In comparison to perceived quality differences, inattention can be reduced with informational treatment. In some situations, there may be a divergence between experts and non-

experts, as experts are able to access information more easily. Inattention does *not* exist in the institutional setting studied in this paper, because patients get information about the quality of products directly from the pharmacist.

Overall, the utility of j for a non-expert is defined as $u_j = \underline{u}_j + \rho_j + \beta_j$, where $\underline{u}$ represents the real quality, ρ_j is the perceived quality difference and β_j is the switching cost that exists if i has consumed j before. If i is an expert, the utility of j is $u_j^E = \underline{u}_j + \beta_j + \alpha\rho_j$ with α adjusting the perceived quality. The institutional setting allows for quality differences and excludes inattention, as patients get information about quality and prices.

I identify switching costs β_j through panel data for patients who start, finish or restart a treatment at a different time in a different price or choice environment. Treatment with prescription drugs is exogenous, as patients do not begin treatments as a result of the choice environment. In additional robustness checks, I use quasi-experimental settings to show switching costs. Further, I identify perceived quality differences ρ_j by comparing experts with non-experts. Experts have better knowledge about quality differences, that is, $\underline{u}_j \neq \underline{u}_k$ for $k \neq j$. The rationale is that the experts' choice approximates the real quality. The exclusion restriction for the identification of perceived quality differences is that experts and non-experts experience the same quality from a drug.

3 Pharmaceuticals in the Swedish Health Care System

Health care coverage in Sweden is universal and mainly publicly funded. Prescription drugs are reimbursable.[21] I show the co-payments of patients in Table I.[22] Patients' co-payments depend on the yearly costs for pharmaceuticals. Costs above a ceiling are entirely covered.[23] Almost half of the revenue from prescription pharmaceuticals is from coverage for patients that have reached the cost ceiling (Bergman et al., 2012).

[Table I about here.]

The market for off-patent drugs is arranged into substitution groups (groups of pharmaceuticals with the same substance, size and strength) that are determined by the Medical Product Agency (MPA). Each product within a substitution group is medically equivalent. Only nonactive ingredients such as coloring or sugar content may differ; however, medical equivalence is tested (Swedish Medical Product Agency, 2010). In the case of pharmaceuticals with

[21] Note that the exact product reimbursement is subject to the decision of the Dental and Pharmaceutical Benefits Agency (TLV). Some products are only partly reimbursed. TLV (2016e) provides detailed information.

[22] Note that the co-payment covers all prescription drugs. Costs for pharmaceuticals that are not in the benefit scheme are not covered. OTC drugs are not subsidized. Specific pharmaceuticals for children (younger than 18 years), pharmaceuticals against communicable diseases, insulin and pharmaceuticals for persons lacking perception of their own illness are fully subsidized.

[23] If patients' pharmaceutical costs exceed 2200 SEK (approx. 220 USD), additional costs are covered without out-of-pocket expenses.

generic competition, patients with a prescription for a product in a substitution group are incentivized to acquire the cheapest available generic in the substitution group. Substitution for the cheapest product happens at the pharmacy level (TLV, 2016c; Sveriges Riksdag, 2002).[24] However, not every patient receives the cheapest available product. Three possible reasons may prevent a substitution. First, patients may oppose substitution. In this case, patients have to pay the price difference between the cheapest available generic and the prescribed product out of pocket. Only the price of the cheapest available product is subject to the co-payment structure. Second, a physician or health care provider has the option to oppose substitution.[25] Third, the cheapest available product may not be in stock at the pharmacy. In such a case, the second cheapest product is dispensed. In the latter two cases, patients have the same co-payment structure as in Table I.

The pharmaceutical market had a market capitalization of $4.15 billion in 2015, with $3.08 billion due to prescription drugs; patients' co-payments account for $0.64 billion (TLV, 2016a). Since 2002, a tendering system determines prices of off-patent drugs in each substitution group.[26] In Figure I I show the details of the sealed-bid first-price auction. Timing is as follows. A pharmaceutical company that wishes to sell a product submits a price at the end of a month (Month A) for the month after the next (Month C).[27] Companies have to bid a lower price than the specified ceiling.[28] The auctioneer publishes a preliminary list of prices in the middle of the next month (Month B). After the supplier of the cheapest product confirms the ability to service the entire Swedish market, prices are implemented.[29] Note that the pharmaceutical companies see the preliminary list for Month C before bidding for the month after that (TLV, 2016c).

[Figure I about here.]

Retail prices are regulated and dependent on the prices in the auction as an almost linear function of pharmacy purchasing prices. The difference between the retail and pharmacy purchasing prices provides the pharmacy's trade

[24] A pharmacist is obliged to recommend the cheapest available generic to patients. Further, pharmacists are required to explain the medical equivalence of the products.

[25] One may ask why this possibility exists if products are equivalent. Historically, pharmacists were required to follow a physician's prescription exactly, including the choice of brand. Since the reform, substitutions are possible, but doctors can oppose them. However, physicians seldom oppose substitution.

[26] Before 2012, the system determined only the cheapest product in a substitution group each month. Since 2012, the system also determines the second and third cheapest products. The reason for the change is that pharmacies experienced difficulties in dispensing the single cheapest product of the month.

[27] Note that in case of default, the price of the previous month is taken as a bid.

[28] The usual ceiling is 35% of the original brand product price before expiration of the patent. In detail, a price ceiling exists if a branded drug has had generic competition for at least four months and the prices of the drug have fallen by 70% of the original price 12 months prior to patent expiration. If no price ceiling exists, the most expensive product of the month will form the price ceiling. If an original product does not have sufficient generic competition, prices may also be reduced (7.5% reduction) if its market authorization was at least 15 years ago (TLV, 2016b).

[29] If a firm confirms delivery but fails to do so, it is subject to a penalty fee. Before 2014 the confirmation was not part of the process.

margin.[30] Although some pharmacies were privatized in 2009, pharmacists are required to dispense the cheapest available generic (Sveriges Riksdag, 2002).[31] As noted, the pharmacy can dispense the second cheapest generic if the cheapest product is not in stock.[32]

4 Data

I use data for painkillers (ATC code N02), antibiotics (ATC code J01) and antiepileptics (ATC code N03) from January 2010 through June 2016 in Sweden.[33] The data are provided by Socialstyrlsen, the Swedish governmental agency for health and welfare. To restrict the data to reimbursable pharmaceuticals, I connect the choice data to monthly prices/bids for outpatient pharmaceuticals under generic competition, provided by the TLV. Each individual who is covered by the universal health care system and purchases a product at a pharmacy with a prescription from a health care provider is observable.[34] The data include a personal identifier, the dispensed product, the time of the transaction and whether the individual, physician or pharmacy opposed substitution. In cases where a patient opposed substitution, one can further identify the initially prescribed product. By connecting the choices to Swedish registry data provided by Statistics Sweden (SCB), I observe the patient's place of residence (county and municipality) and some socioeconomic characteristics. The socioeconomic data consist of yearly income and length, degree and subject area of education. Finally, for non-prescription drugs, I use advertisement expenditure data provided by Kantar Sifo. These data include advertisement expenditures for non-prescription drugs by pharmaceutical brands between 2010 and 2016.

Table II shows a basic market description. In terms of substances, the market for antibiotics (24 substances) is greater than the market for painkillers (10 substances) and the market for antiepileptics (4 substances). However, the number of substitution groups and the number of products are highest for painkillers (158 substitution groups, 566 products). In the study period, the average number of products per substitution group was 1.95 for painkillers, 1.61 for antibiotics and 1.38 for antiepileptics. For all three therapeutic groups, the majority of products are generics (70% of painkillers, 75% of antibiotics and 76% of antiepileptics); 30% of painkillers and 19% of antibiotics are originals. For antiepileptics no originals are included, but parallel imports are observable. The average product prices vary: 255

[30] I describe the exact relationship between purchasing and retail prices in *Online Appendix A*. It has changed slightly in recent years (TLV, 2016d).

[31] Two-thirds were privatized, and one-third remain under public control.

[32] Additionally, a pharmacy can sell the remainder of the previous month's cheapest product in the first two weeks of a new month. After these two weeks, pharmacies can sell the products at the pharmacy's purchasing price without profit. Thus, the pharmacy has no incentive to overstock the product. In *Online Appendix D* I provide tests to show that the system is working as intended and pharmacies do substitute.

[33] The ATC code describes each pharmaceutical substance and is ordered according to five levels. The first level describes the anatomical main group (e.g., nervous system); the second level, the main therapeutic group (e.g., analgesics/painkillers); the third level, the pharmacological subgroup; the fourth level, the chemical subgroup; and the fifth level, the exact chemical substance.

[34] Note that reimbursement of pharmaceutical expenses requires a prescription. The majority of the products are pharmaceuticals that require a prescription.

SEK (approx. 25.5 USD) for antibiotics, 333 SEK (approx. 33.3 USD) for painkillers and 393 SEK (approx. 39.3 USD) for antiepileptics. Originals are on average more expensive than generics.

[Table II about here.]

4.1 The Markets for Painkillers, Antibiotics and Antiepileptics

The upper part of Table III shows basic demand characteristics for all three markets. The number of purchase occasions is the number of prescriptions that were filled during the 6.5-year period. The number of purchase occasions is much higher for painkillers (approximately 38.5 million) and antibiotics (approximately 13.8 million) than for antiepileptics (0.57 million). Also, the number of unique patients who received an antiepileptic is much lower than for painkillers or antibiotics (approximately 60,000 for antiepileptics, compared with approximately 3.2 million for painkillers and 4.7 million for antibiotics).[35] Whereas painkillers and antiepileptics are often repeatedly purchased by the same individual (the average number of purchase occasions in the 6.5-year period is 12.1 for painkillers and 9.4 for antiepileptics), antibiotics have a much lower average number of purchase occasions (2.9). Note, also, that a large variability exists among painkillers (standard deviation of 26.3). The heterogeneity in frequency of purchase occasions is not surprising from a medical point of view because painkillers and antiepileptics may be used for long-lasting treatments, whereas antibiotics are mostly used for acute treatment of a bacterial infection. Average monthly purchase costs totaled 46.7 million SEK (approx. 4.67 million USD) for painkillers, 23.5 million SEK (approx. 2.35 million USD) for antibiotics and 2.8 million SEK (approx. 0.28 million USD) for antiepileptics. The co-payment share is much lower for antiepileptics (25% of the total payment) than for antibiotics (62% of total costs) and painkillers (38% of total costs). One reason for the difference in co-payments is the upper ceiling for medical expenses. Patients that have a longer treatment may reach the upper ceiling earlier and therefore have lower co-payments for pharmaceuticals. Another possibility is that patients oppose substitution to the cheapest pharmaceutical product more often when using painkillers and antibiotics than when using antiepileptics.

[Table III about here.]

The lower part of Table III shows the substitution behavior of patients for the three therapeutic groups.[36] In line with the regulatory intent, the majority of patients get dispensed the cheapest product, the product of the month

[35] The population of Sweden was approximately 9.85 million in 2016.

[36] Further summary statistics including differences between subgroups of the population are shown in the *Online Appendix B.*

(PoM). However, heterogeneity between and within the therapeutic groups is observable: 73.4% of patients purchased the PoM when getting a prescription for painkillers, whereas 89.9% and 92.9% of patients purchased the PoM for antibiotics and antiepileptics respectively. Patients who do not receive the PoM belong to one of the following three groups: They opposed substitution and pay the difference out of pocket, their physician opposed substitution, or the pharmacy opposed substitution because the PoM was out of stock. Patient opposition to substitution is the most common in all three therapeutic groups.

5 Empirical Analysis

Switching costs result in habit persistence.[37] Recent empirical literature estimates switching costs and examines the impact of switching costs.[38] This article on the Swedish pharmaceutical market differs from existing analyses in several dimensions. Patients in the Swedish market for prescription drugs under generic competition get a prescription from their primary health care provider and can choose between products within a pharmacy. The substitutability of products is determined by a medical governmental agency and further implicitly acknowledged by the prescribing physician, who can oppose substitution. When a patient chooses a product at a pharmacy, the cheapest available product is first presented and recommended to the patient as the default product. In comparison to other retail markets, where habit persistence may also be due to inattention, the pharmaceutical market is therefore characterized by a clean and structured environment.[39] Nevertheless, patients may have higher trust in a specific product after a successful treatment. Switching costs are therefore a psychological cost that a consumer bears after starting treatment with a specific product. Importantly, switching costs are induced by previous usage.

In addition to the estimation of switching costs, I add to the literature by identifying the effect of perceived quality differences on consumers' pharmaceutical choices. In the Swedish health care market, exchangeable pharmaceuticals are defined by a medical product agency, and a prescriber is able to prevent substitution. Labeling and advertising are regulated, and manufacturers have limited possibilities to differentiate themselves.[40] Therefore this study differs from most of the evidence from retail markets where products could potentially have a higher degree of differentiation.[41]

[37] I quantify switching costs by estimating a demand system in Section 7.1.

[38] Most of the evidence comes from choice data in the retail sector. Erdem and Sun (2001), Dubé et al. (2009), Shcherbakov (2016), Shy (2002), Viard (2007) and Rickert (2016) show recent evidence for switching costs in retail markets. Handel (2013) and Miller (2019) focus on health insurance markets, while Honka (2014) identifies switching costs in the auto insurance market. Thiel (2019) evaluates switching costs in the Dutch mortgage market, and MacKay and Remer (2019) examine switching costs in retail gasoline markets.

[39] Note also that the marketing of products is highly regulated. Firms have to label products in an informative manner. Advertisement of specific prescription drugs is forbidden.

[40] Advertisement of prescription drugs is not allowed in Sweden. In *Online Appendix F* I show that the advertisement expenditure of over-the-counter drug manufacturers is not correlated with preferences for prescription drugs from the same manufacturer.

[41] Just two examples from the large literature on brand preferences are Sullivan (1998) and Smith and Brynjolfsson (2001).

Nevertheless, specific pharmaceutical brands may carry a higher quality in physical or psychological terms.[42] It is possible that products have quality differences when using the approach of Bronnenberg et al. (2015).[43] My approach uses the same method, however, instead of evaluating drug choices dependent on the occupation, I use medical education as the proxy for an informational advantage. I control for true quality differences by comparing choices of experts (patients with a medical education) to others.[44] Figure II provides some preliminary graphical evidence for the effect of education on substitution decisions of painkillers.[45] Dependent on the subject of education, I show the likelihood of opposing substitution within the substitution group of painkillers. Patients with medical education have a lower likelihood of opposing substitution.

Figure II highlights three facts. First, compared with other subjects of education, medical education is connected to lower opposed substitution. Without controlling for additional covariates the difference is moderate. Second, patients with a medical education oppose substitution in 18% of purchases. This observation could be explained by several effects. One reason could be switching costs, which are the same for consumers with and without medical education. Therefore it is important to control for switching costs and show that switching costs are equivalent for experts and non-experts. Also there may be real quality differences between drugs, for example due to inactive ingredients. I capture this in the estimation by using the choice made by those with medical education as a proxy for real quality differences. Finally, educated physicians also could experience perceived quality differences. In this case, I underestimate the perceived quality differences. Third, patients with education for other occupations that are related to health care do oppose substitution with the same probability as the general population and more often than those patients with medical education as a physician.[46]

[Figure II about here.]

After controlling for the first explanation of brand premia, I note that it is still possible that consumers cannot evaluate all information or that consumers experience perceived quality differences. Bronnenberg et al. (2015) are not able to differentiate between these two explanations. It is possible that the consumers of the non-prescription

[42] A original branded pharmaceutical may have a higher quality or patients may view an original product as having a greater treatment effect than generic alternatives. Some placebo effects may be due to the branded product. (Branthwaite and Cooper, 1981; Kamenica et al., 2013).

[43] The authors estimate that if consumers in a health-care-related occupation, such as physicians, consume different headache remedies than others, they would find significant differences between the choice of consumers with and without a health-care-related occupation. For example, pharmacists buy national brands of headache remedies 9% of the time, whereas the average consumer purchases the more expensive version of a substance 26% of the time. Bronnenberg et al. (2015) argue that informational advantages such as the knowledge of ingredients of pharmaceutical products are important explanations. Bronnenberg et al. (2015) survey physicians, who knew on average 90% of the active ingredients of headache remedies while the average respondent knew 59%.

[44] The approach is further acknowledged by the literature, for example Handel and Schwartzstein (2018) argues that 'the ... strategy (comparing acknowledged experts to non-experts) is probably the most robust approach ..., assuming that expert can be appropriately differentiated'.

[45] Further graphical evidence is provided in *Online Appendix C.11*.

[46] Note that unlike in the United States, a medical degree as a physician does not build on another full degree. Further, the length of education of physician do not differ fundamentally from other professional degrees. In the main empirical specification of model 1 I control for the general education level.

headache remedies in the study by Bronnenberg et al. (2015) do not evaluate all available information, like reading the ingredients or comparing all prices in the retail shelf. On the other hand people may have perceived quality differences. Comparing experts with non-experts allows for both explanations, as experts may have lower information costs as well as fewer perceived quality differences (Handel and Schwartzstein, 2018). Because of the regulation in the Swedish prescription drug market, I am able to identify perceived quality differences and exclude information costs and inattention as explanations. In cases where patients have a prescription for a product that is not the cheapest product in a substitution group, they are informed at the pharmacy that a cheaper product with the same ingredients is available and that they may switch. The pharmacy explains that the two products are equivalent and may solely differ in their brand name. The patients therefore get all available information about ingredients and equivalence. Furthermore, a patient never has to search for cheaper products (Sveriges Riksdag, 2002).[47] Indeed, the patient has no information costs, so I am able to exclude the reasoning that patients have too high information costs and are therefore inattentive. Patients who oppose substitution and pay a brand premium are doing so because they either believe in the superiority of a product or, more likely, are uncertain about the real equivalence and decide to stick to a safe option. Given that I compare experts (patients with a medical education) to non-experts and thereby exclude real quality differences, the reason for the brand premia must be perceived quality differences.

Finally, simultaneous identification of switching costs and different sources of brand premia is of importance. It may be that the initial choice is due to perceived quality differences or other reasons for brand premia. Repeated choices may be due to perceived quality differences or due to switching costs. It is of importance to separately identify both frictions.[48]

In the following, I show reduced-form evidence.[49] The estimation strategy to identify switching costs and perceived quality differences is equivalent to the one in the demand estimation in Section 6.1 when using a discrete-choice model. The major advantage of the reduced-form framework is that it evaluates the importance of behavioral frictions without estimating a demand system including price elasticities. Consider the following model:

$$P(OpposeSubst_{ijt} = 1) = \alpha + \beta_1 D_{ijt-1} + \beta_2 Med_{it} + \beta_3 D_{ijt-1} \times Med_{it} + \rho X_{it} + D_{ij0} + \gamma_{st} + \varepsilon_{ijt}, \quad (1)$$

where the outcome variable is a dummy that takes the value 1 if individual i in period t opposes substitution of

[47] In *Online Appendix D* and *Online Appendix E* I show that the system is working as intended.

[48] The general approach of this paper follows existing approaches in the literature, such as that of Handel (2013). I disentangle brand preferences from switching costs but further try to estimate perceived quality differences.

[49] Further descriptive evidence of switching costs and perceived quality differences can be found in *Online Appendix B* and *Online Appendix C*.

product j, which belongs to substitution group s. In substitution group s all products of the unique size $\times$ strength $\times$ ingredient combinations are grouped. Opposing substitution corresponds to the case in which the patient pays the price difference to purchase another product instead of the PoM. D_{ijt-1} is a dummy that takes the value 1 if the last purchase of the product occurred within a month of the current purchase and 0 if not.[50] Med_{it} is the variable of interest, which examines the impact of whether a patient has had medical education as a physician. X_{it} are controls such as the logarithm of income, the geographical location and the general education level.

I use fixed effects of substitution groups in each time period (γ_{st}). Therefore I examine variation among individuals who purchase a product within a given month. Note that the fixed effects absorb important factors that may affect the individuals' switching behavior or perceived quality differences, for example, the price differences between products.[51]

State dependence due to switching costs is measured by β_1 and perceived quality differences by β_2. It is important to separately identify switching costs and perceived quality differences. To identify switching costs, it is important to consider unobserved individual heterogeneity that may be correlated with the lagged product choice dummy D_{ijt-1}.[52] I tackle this problem in two ways. First, I recover true state dependence due to switching costs by conditioning decisions to oppose substitution on the initial choice D_{ij0}, a dummy which takes the value 1 if patient i has consumed j in the first observed period. Intuitively, unobserved heterogeneity beyond state dependence would be captured by the initial choice of a product. However, the approach assumes that the initial choice is random and not correlated with unobserved heterogeneity (initial condition problem).[53] I show robustness in *Online Appendix C.4* by using sub-samples of patients without observed consumption in the first years of the 6.5-year panel. Secondly, I provide

[50] This model requires that the patient purchased the product in the previous month. If I would consider also the same calendar month the choice environment would be the same. Fixed effects would capture the corresponding differences in the outcome variable. Within this specification, I look at short-term induced state dependence with potential different choice environments, as the prices and PoM may have changed. In *Online Appendix C.2* I show robustness for a more lenient definition of previous consumption.

[51] The price difference between the prescribed product and the product of the month is identical for all patients. However, the absolute co-payment may vary across patients. For example, a patient who has reached the co-payment ceiling receives the PoM for free and would have to pay only the price difference when opposing substitution, whereas a patient who has not reached the ceiling pays for the PoM plus the difference when opposing substitution. In general, it would be possible that this reference dependence on the price of the PoM is (1) correlated with state dependence or medical education and (2) affects the probability of opposing substitution. In *Online Appendix C.3*, I show that higher co-payment levels are associated with a higher probability of opposed substitution, but the co-payment level does not influence estimates of switching costs or perceived quality differences. Further, I integrate patient-specific fixed effects in *Online Appendix C.5*.

[52] For example, specific individuals may have high brand preferences and choose the same product repeatedly independent of switching costs. See also further discussion in Dubé et al. (2010).

[53] As I do not observe the entire medical history, this is unlikely the case for all patients. Following Wooldridge (2005), it is possible to use a reduced-form approach of conditioning the unobserved household effects on the initial values and exogenous variables. Rabe-Hesketh and Skrondal (2013) recommend a slight adjustment of using the within means of time-varying variables as well as including the initial periods. Rabe-Hesketh and Skrondal (2013) argue that the inclusion of the initial condition of time-varying covariates as well as the within means may reduce the bias. In comparison to approaches in the literature, such as those of Erdem and Sun (2001), Skrondal and Rabe-Hesketh (2014) or Rickert (2016), I do not observe sufficient time-variant covariates of products, as they do not differ in any aspects besides their brand. I argue that the homogeneity of products and the clean choice environment reduces the problem of unobserved heterogeneity as well as the endogeneity of the initial condition. In *Online Appendix C.4* I follow a approach similar to that of Wooldridge (2005), using only time-variant individual characteristics when estimating a structural demand model.

quasi-experimental evidence for switching costs in Appendix A to show robustness.[54]

To estimate perceived quality differences, I evaluate whether patients with medical education have a higher or lower likelihood of opposing substitution towards a cheaper equivalent. Assuming that the real quality of a product is independent of the patient's education, I approximate the real quality differences of products by the choices of medical experts. Having excluded that inattention plays a role, as patients get their information at the pharmacy level, I measure the perceived quality differences by β_2.

Finally, simultaneous identification of state dependence and perceived quality differences depend on the time invariance of perceived quality differences. In the case that perceived quality differences (or the difference attributable to medical education) increase over time independent of consumption, I would underestimate the perceived quality differences and overestimate state dependence. However, I argue that the institutional setup of the Swedish pharmaceutical market excludes important reasons for time variance in perceived quality differences. The Swedish pharmaceutical market is highly regulated, forbids advertisement and therefore reduces the importance of goodwill and brand recognition. Further, I include the interaction of D_{ijt-1} and Med_{it}. As state dependence is induced through past consumption and not affected by perceived quality differences, I expect that β_3 is not significantly different from zero.

I show results of the reduced-form evidence of model 1 in Table IV. For each therapeutic group (painkillers, antibiotics, and antiepileptics) I show results of the full model including all fixed effects and covariates. In *Online Appendix C.1* I show results for the model without controlling for unobserved heterogeneity or control variables. I further explore the role of a more lenient definition of the lagged choice D_{ijt-1} in *Online Appendix C.2*.[55] Additionally, I show robustness using patient fixed effects in *Online Appendix C.5*.

A purchase of a product within the last month increases the probability of opposing substitution for painkillers significantly by 3.32 percentage points (17.75%). For antibiotics, previous consumption is associated with a significant increase of 1.16 percentage points (12.34%). For antiepileptics, the results are different: a previous purchase of the same product in the last month decreases the probability of opposing substitution. I interpret the positive coefficient of painkillers and antibiotics as real state dependence due to switching costs. For antiepileptics, previous consumption is negatively associated with opposed substitution, even though the size of the effect is small. One explanation for the lack of switching costs is that patients who are require antibiotics differ systematically from patients who require

[54] A discontinuity surrounding patent expirations and monthly price changes establishes that the effect is causal. In the first robustness check, I compare repeated purchases by patients who began treatment with an original product just before patent expiration with purchases by patients who started treatment just after patent expiration. The approach is related to the work of Feng (2017). In the latter robustness check, I use monthly price changes as a discontinuity by comparing repeated purchases by patients who began treatment before a price change with purchases by patients who started treatment after a price change. The results of discontinuities by price changes are shown in *Online Appendix C.10*.

[55] Specifically, in *Online Appendix C.2* I investigate the effect of defining the dummy D_{ijt-1} such that it takes the value 1 if patient i purchased the product in the previous purchase occasion overall rather than in the previous purchase occasion within the last month.

antiepileptics. Patients who require antiepileptics are typically on a longer course of treatment and are used to acting in response to the information of pharmacists.

Secondly, Table IV shows that a medical education is associated with a significantly lower probability of opposing substitution (painkillers: 4.88 percentage points, 26.1%; antibiotics: 2.45 percentage points, 26.06%, antiepileptics: 1.07 percentage points, 38.21%). I interpret the difference as perceived quality differences. Note that the interaction between previous consumption and medical education is insignificant for all three therapeutic. In other words, medical education is not associated with higher or lower switching costs. The lack of effect supports that perceived quality differences and switching costs induced by previous consumption are not correlated. Consumers who oppose substitution pay on average approximately 1.4 USD more than for the cheapest product.[56]

[Table IV about here.]

I provide a series of robustness checks in the appendices. In *Online Appendix D* I present a robustness check about the role of pharmacies. I show that there is no indication that pharmacies are responsible for patients opposing substitution. In *Online Appendix E* I investigate the role of prescribers. While the main model investigates opposition by patients, which is the most frequent observation (painkillers, 20.9%; antibiotics, 9.4%; antiepileptics, 2.8%), physicians may also oppose substitution when writing the prescription (painkillers, 2.4%; antibiotics, 0.5%; antiepileptics, 1.8%). I show that compared to patients without medical education, patients with medical educationn are less likely to pay for another painkiller. Roughly half of the effect is due to a lower likelihood of opposing substitution, as shown in Table IV; the other half of the effect is due to a higher possibility that the prescriber opposes substitution. *Appendix A*, *Online Appendix C.9* and *Online Appendix C.10* present quasi-experimental evidence for switching costs.

6 A Structural Model of Demand and Supply

This section introduces a model that allows me to structurally estimate the demand as well as the supply side of the Swedish pharmaceutical market. The reasons for the use of a model are manifold. First, an estimation of a demand function allows switching costs and perceived quality differences to be evaluated in monetary terms. Second, given the demand estimates, it is possible to relate the phenomenon of switching costs to general price levels, that is, one may address the open research question of whether switching costs make markets more or less competitive. Finally, modeling the supply side allows us to evaluate how firms' pricing strategies and consumers' costs would change under counterfactual scenarios. This section is divided into two parts. I first present the model setup of the demand side and then present the supply-side model.

[56] Note that the distribution of additional payments is right skewed, with the majority of patients paying only a small amount. I show details in *Online Appendix B.2*.

The modeling assumptions are similar to the Swedish institutional setting. The demand side uses standard approaches from demand estimation that incorporate state dependence from consumers. The approach builds on a standard discrete-choice setting in the fashion of Berry (1994). On the supply side, I assume that firms compete in an infinite horizon. In Sweden the substitution groups are independent markets, as patients receive prescriptions for specific substitution groups.[57] Firms can change their prices only monthly and simultaneously, as in a repeated price competition model. Manufacturers set prices, which are linearly translated to retail prices. Pharmacies have fixed retail margins, and prices are the same across all pharmacies in Sweden. Similar to Bajari et al. (2007), I use a two-step estimator to recover cost parameters.[58] The cost parameters are of importance when evaluating counterfactuals.

6.1 Demand

The utility of individual i purchasing product j in substitution group s at time t is defined as

$$u_{ijst} = \gamma_{ijs} + \rho_{is} y_{ijs,t-1} + \alpha_{is} p_{jst} + h_{ijs} + \varepsilon_{ijst}.$$

Consumers are myopic and not forward looking.[59] Each product j is part of a set of products that form a substitution group. Each coefficient of utility varies at least over the substitution group. First, there is a random brand-specific intercept γ_{ijs}. The variable $y_{ijs,t-1}$ is a dummy that takes the value 1 if a consumer i has already purchased product j during the last calendar month. ρ_{is} captures the impact of switching costs and varies across each patient within a substitution group. p_{jst} is the price of product j at time t.[60] The price coefficients α_{is} also varies across consumers within a substitution group. h_{ijs} denotes the unobservable heterogeneity of patients, and ε_{ijst} is an error term.

Estimation requires two adjustments to ensure identification of the price elasticity and switching cost estimates. Both variables are important structural parameters of the demand side. In detail, it is possible that prices p_{jst} are correlated with unobserved product characteristics, that is, $[p_{jst}\varepsilon_{ijst}] \neq 0$. The second bias is due to the correlation of the lagged product choice and the unobserved heterogeneity of individuals. Some patients may have characteristics that lead to a repeated choice of a specific product. The repeated choice would not be due to switching costs but due

[57] In *Online Appendix C.6* I show that substitution between substitution groups is uncommon.

[58] The applications of two-step estimators are growing. Some examples are found in the work of Misra and Nair (2011), Goettler and Gordon (2011), Sweeting (2013), Ryan (2012) and Collard-Wexler (2013).

[59] Note that a prescription is connected to a fixed quantity. Patients do not have the possibility to stockpile. Additionally, I show in *Online Appendix G.6* that lower prices are not correlated with higher purchases when a prescription is filled. Patients do not increase their purchases during sale periods as would be expected with forward-looking consumers (Hendel and Nevo, 2006), as the quantity is fixed by the prescription.

[60] Note that because of the co-payment function, the price varies across consumers. However, I use the absolute price of products (including co-payment and reimbursement costs) as a regressor. The price captures the decisions for all products, as price differences are out-of-pocket expenses. In the Appendix, I show a robustness check where individual-specific prices are used. A disadvantage of using patient-specific prices is the higher variance and weakness of instruments. However, results are robust to individual-specific price specification.

to personal characteristics.

I tackle the identification threats by two methods. First, I use a control function approach to deal with the endogeneity of prices. In the first stage of the control function, I regress instruments Z_{jst}. Z_{jst} are prices of other products from the same brand for the same therapeutic segment (painkillers, antiepileptics or antibiotics). The instruments are comparable to the Hausman instruments (Hausman, 1996). If a brand produces several painkillers in different strengths, forms or sizes, the prices of the products in other substitution groups are used as instruments. The intuition of the assumption is that all products of a brand have correlated prices due to shared cost factors (supply chain, procurement of substances); however, their demand is uncorrelated. The control function takes the following form: $p_{jst} = Z_{jst}\gamma + \kappa_{jst}$. The exclusion restriction requires that the idiosyncratic error term κ_{jst} be independent from Z_{jst}, $E[Z_{jst}\kappa_{jst}] = 0$. As an individual prescription is for a product in a specific substitution group, it is likely that there is no demand effect between substitution groups. Also, effects of advertisement should not violate the exclusion restriction.[61] As usual for the control function, the residuals κ_{jst} enter the main estimation equation, and the error term of the main equation is adjusted accordingly:[62]

$$u_{ijst} = \gamma_{ijs} + \rho_{is} y_{ijs,t-1} + \alpha_{is} p_{jst} + h_{ijs} + \lambda \kappa_{jst} + \varepsilon_{ijst}.$$

Second, I try to control for unobserved heterogeneity among consumers. As in Section 5, I control for the initial product choice of individuals that I observe in my sample.[63] The final structural equation that incorporates the control function approach, as well as controls for unobserved heterogeneity, takes the following form:

$$u_{ijst} = \gamma_{ijs} + \rho_{is} y_{ijs,t-1} + \alpha_{is} p_{jst} + \mu_{is} y_{ijs,FIRST} + \lambda \kappa_{jst} + \varepsilon_{ijst}, \tag{2}$$

where $y_{ijs,FIRST}$ is a dummy that takes the value 1 if the patient has taken product j in the first observable period in the sample when the consumer purchases a product of substitution group s.

[61] Advertisement may affect demands for brands in all substitution groups such that prices as well as unobserved demand characteristics are correlated. First, the strong regulation of the Swedish pharmaceutical market does not allow for advertisement of prescription drugs, i.e., the pharmaceutical products considered in this study. However, it could be possible that advertisements for OTC drugs have spillover effects on demand for prescription drugs. In *Online Appendix F* I show that the correlation between advertisement expenditure and perceived quality differences is low. Further, I show in *Online Appendix G.7* that (lagged) advertisement expenditures for OTC drugs are not correlated with prices of prescription drugs. I argue that OTC drug advertisement does not violate the exclusion restriction.

[62] In detail, let the old error be $\varepsilon_{ijst} = \lambda \kappa_{jst} + \varepsilon_{ijst}$. As p_{jst} is a function of Z_{jst} and u_{jst}, it is uncorrelated with the new error ε_{ijst}. Note that the control function approach is connected to strong functional assumptions. To show sensitivity I always report results without the control function.

[63] Similar to the analysis in Section 5, the identification of state dependence requires that a previous choice is not correlated with unobserved heterogeneity. In the main specification I solely control for the initial condition and assume that the initial condition is indeed unrelated to unobserved heterogeneity. In the *Online Appendix G.3* I extend the approach by following the approach of Rabe-Hesketh and Skrondal (2013) and Wooldridge (2005). Further, I show that the demand estimation is robust to a sub-sample analysis of patients that have not purchased any product within the first years of the sample.

6.2 Supply

In each period $t = 1, ..., \infty$, there are N_{ts} firms in substitution group s. Given that supply is separate for each substitution group I drop the subscript s. Each firm $j = 1, ..., N_t$ sets a price p_{jt} at t. The value of p_{jt} has to be lower than a regulatory price ceiling R. Note that each product is from a different firm within the substitution group. I assume that firms do not condition their prices on other substitution groups. I model the supply side with independent substitution groups for two reasons. First, it is reasonable that demand of substitution groups is independent, as prescriptions are for a specific substitution group. In *Online Appendix C.6* I further challenge the assumption of independent demand in substitution groups.[64] Second, the assumption allows for a tractable model solely investigating a specific substitution group. Prices p_{jt} are linearly connected to the wholesale prices. Because retailers (pharmacies) get a fixed markup for each dispensed product, I do not model pharmacies as separate agents. Within the estimation I calculate for each wholesale price p_{jt} a retail price that is a structural parameter of the demand; that is, I take care of the difference between demand and supply price.[65] However, for simplicity I do not denote the difference between the manufacturer price and the retail price.

The per-period profit of a firm at period t is defined as

$$\pi_{jt} = [p_{jt} - c_{jt}] m_{jt} Q_t,$$

where c_{jt} represents the marginal costs of firm j in t, and m is the market share of j at time t. Note that the market share is a function of several variables associated with the demand side. Finally, the exogenous quantity (measure of market size) of the substitution group s is given by Q_t.

Before turning to the continuation profits of a firm, I make two assumptions. First, costs are defined as the sum of a constant and a random privately observed shock within each period. So besides the marginal costs c_{jt} that differ across time and brand, a random shock $\varepsilon_{jt} \sim N(0,1)$ enters the marginal costs. The assumptions about the marginal costs are rather weak. I allow for changes of marginal costs over time as well as differences between periods.

The second assumption considers firms' beliefs about future demand. The beliefs affect the continuation payoffs as firms form expectations about future payoffs. In each time period, firm j makes a decision about setting its own price. Such a dynamic game has a continuum of Nash equilibria. Following previous literature (Maskin and Tirole, 1988; Ericson and Pakes, 1995) I reduce the equilibrium space to symmetric Markov perfect equilibria. One restricts subgame perfect equilibria to only the payoff-relevant strategies of a subgame. State variables are sufficient to de-

[64] In detail, I test whether the share of a substitution group is associated with the relative price of the cheapest product compared with other substitution groups. As I do not find an effect, I conclude that substitution between substitution groups seldom occurs.

[65] The difference between the demand and supply side prices is determined by the trade margins of the pharmacies; see *Online Appendix A*. For the substitution group of interests (under consideration of the price ceiling), the relation between purchasing (supply side) and retail price (demand side) is linear.

termine a payoff. In detail, firms condition their strategy σ_j on the cost shock ε_{jt} and the state variables $\mathscr{S}_{jt}$, which include the lagged market shares (m_{jt-1}), the lagged number of firms ($|N|_{t-1}$), a dummy which indicates whether firm j had the cheapest product in the previous period (PoM_{jt}) and the total market size of the segment (Q_t). Formally, the strategies are defined as the mapping of the state variables and the cost shock to the prices ($\sigma_j : (\mathscr{S}_{jt}, \varepsilon_{jt}) \rightarrow p_{jt}$). Given that firms discount future profits with $\delta \in (0,1)$, the value function of firm j is

$$V_{jt}(\mathscr{S}_{jt}, \varepsilon_{jt}) = (p_{jt} - c_{jt}) m_{jt} Q_t + \delta E[V_{jt+1}(\mathscr{S}_{jt+1}, \varepsilon_{jt+1} | \mathscr{S}_{jt})].$$

The first term is the per-period profits. The market share of a product is dependent on the state variables. The marginal costs c_{jt} are private information to the firm and equal to the cost shock ε_{jt}, and the market size Q_t is fixed because patients with a prescription do not have an outside option. The second term describes the expectation from the valuation at period $t+1$. It incorporates the expectation of how the state vector evolves. I make distinct assumptions about firms' beliefs regarding the development of the market share to reduce the computational burden and the state space. I assume that firms are not able to predict future patients and their random coefficients perfectly. However, firms have knowledge about important key factors of the dynamic demand. I assume that firms (1) know the share of consumers that stay in a market at t, (2) have knowledge about the average coefficients of the demand side described in the previous section and (3) know about the average product choice of consumers who have started a treatment in their first period. Correspondingly, the expectation about future market shares is a discrete function, dependent on the transition probability of consumers between periods as well as the demand estimates:

$$E[m_{jt+1}, \mathscr{S}_{jt+1} | \mathscr{S}_{jt}] = \phi_t E[\tilde{m}^S_{jt+1}] + (1 - \phi_t) E[\tilde{m}^{NS}_{jt+1}]. \tag{3}$$

Here, ϕ_t of the consumers at $t+1$ have been already present in t. Those consumers who were present in the last period consume product j $\tilde{m}^S_{jt+1}$ times in period $t+1$. The market share is evaluated from firm j's point of view at time period t. Firm j does not know the customer base in the forthcoming period and approximates it by the average customer of the current period. The demand model presented in Model 2 with average coefficients among customers is used for calculating the market shares. For parameters of the patient-specific first consumption $y_{ij,FIRST}$, I use the average of consumers in t. For $\tilde{m}^S_{jt+1}$, $\bar{y}_{jt-1}$ is given by the market shares in t, m_{jt}. $(1 - \phi_t)$ presents the patients who purchase a product in the forthcoming period but are new. Here I again use the average parameter values of all parameters and coefficients except for $\bar{y}_{jt-1}$, which is set to zero as the consumers are new.[66]

[66] In detail, the average coefficients are the same in each period. However, I keep track of the average first choices $\bar{y}_{jFIRST}$ and average number of patients remaining in the market ϕ_t, as well as the average value of consumers having consumed a product in the previous period,

All in all, firms in t estimate future profits by assuming that the average patient is the same as in t. However, they incorporate the dynamic effects of state dependence and newly entering patients. The assumptions decrease the computations described in the forthcoming section while incorporating the most important demand features.

A strategy forms a Markov perfect equilibrium if and only if for all $j \in N^s$ the strategy σ_j^*, $V_j(\sigma_j^*, \sigma_{-j}^*, \mathscr{S}_{jt}, \varepsilon_{jt}) \geq V_j(\sigma_j, \sigma_{-j}^*, \mathscr{S}_{jt}, \varepsilon_{jt})$, for all $\mathscr{S}_{jt}$ and ε_{jt}. A Markov perfect equilibrium is also subgame perfect. Note that uniqueness is not guaranteed. The estimator presented in the preceding section does not assume that there is a unique equilibrium. However, it builds on the assumption that firms play and stick to one equilibrium.

7 Estimation

The demand and the demand-side estimations are based on some distinct assumptions. In the following I present the assumptions as well as the econometric details of the estimation for the demand and supply sides respectively. The availability of extensive individual choice data allows the estimation of the demand and supply sides separately.

7.1 Demand

At each point in time, an individual attaches a utility to a product (Equation 2). The institutional background of the prescription process plays an essential role that determines the choice sets, the products a patient actively compares before making a decision. Initially, a patient receives a prescription for a specific product from the physician. At the pharmacy level, the prescription allows the pharmacist to dispense one product in the substitution group. If the prescribed product is the cheapest available product that month and the patient does not request another product, the pharmacist dispenses the prescribed product. If the product is not equal to the cheapest available product, the pharmacist presents the option of a medically equivalent substitution, which reduces the cost for the patient. In general, the patient could request any product in the substitution group and pay additional costs, but in practice patients typically choose either the PoM or the prescribed product. I assume that the patient's choice set consists of three components: the prescribed product, the PoM (which is always presented by the pharmacist) and previously consumed products (products a patient actively knows). The reduction of the choice set improves the approximation of reality as consumers do not compare all products at the pharmacy level. Note that 98.89% of the actual purchases in the data are covered by the chosen choice sets. A second assumption concerns the behavior of patients. I assume that patients are myopic and do not form expectations of future prices such that switching cost estimates would be

$\bar{y}_{it-1}$. When estimating the market share of a product using the averages, I keep track of key aspects determining the demand side. First, new customers do not necessary have each product in their choice set. I follow the assumption of the demand side such that the PoM is always part of the choice set while products that are not in the choice set get weighted by their fraction of choice set considerations in the actual data (i.e., the fraction of choices in past period). Second, for consumers that stay in the market $\bar{y}_{jt-1}$ and $\bar{y}_{jFIRST}$ are potentially correlated. Therefore, I keep track of the correlation in the data and weight choice probabilities accordingly.

dependent on beliefs about future prices. Note that in comparison to most retail markets, patients get prescriptions for a specific amount of medication, such that stockpiling is not possible.[67]

Given the choice set, a patient compares the products and decides among those with the higher utility. Utility is estimated by the demand-side equation 2. Given each individual i and time j, the choice set may change. I assume that ε_{ijst} is independent and identically distributed extreme value type 1, such that choice probabilities follow a logit distribution. A patient chooses a product j over k at t if $U_{ijst} \geq U_{ikst}$. I follow standard discrete-choice literature in estimating coefficients of the structural equation 2. Technical details are provided in *Online Appendix G.1*.

7.2 Supply

On the supply side I use a two-step estimator. In the initial step I estimate the policy function that characterizes the pricing of firms. In the second step I use forward simulations and the assumption that the firms play a Markov perfect equilibrium to estimate marginal costs.

The approach is based on methods proposed by Hotz and Miller (1993) and Bajari et al. (2007). The main idea is to initially recover the conditional choice probabilities from observed prices within the data. The parameters of the policy function are the state variables. (For firm j, the state variables $\mathscr{S}_{jt}$ are the lagged market shares m_{jt-1}, the lagged number of firms ($|N|_{t-1}$), the market size (Q_t) and a dummy that indicates whether j was the PoM in the previous month (PoM_{jt-1}).) Conditional on the state variables, firms set their prices in t. In practice, I estimate the pricing policy σ^* in a reduced-form least squares regression:

$$p_{jt} = \alpha + \beta m_{jt-1} + \eta |N_{t-1}| + \rho Q_t + \gamma PoM_{jt-1}. \tag{4}$$

Note that the number of competitors in the previous period is treated as a factor variable in order to increase flexibility. Therefore, η corresponds to a vector of coefficients.

The second stage of the estimator uses the optimal policy function (Equation 4), which is assumed to be generated by the play of a Markov perfect equilibrium to estimate unobservables that rationalize the optimal policy. I estimate the marginal costs for each competitor within each period. I can recover the marginal costs because of several key assumptions. First, I assume that firms play a single Markov perfect equilibrium. Further, I assume that the profit function is correctly specified and known up to the marginal costs. I assume that firms discount future profit with $\delta = .995$.[68] Transition probabilities from the firms' points of view are estimated as described in Section 6. The

[67] In *Online Appendix G.6* I present an additional empirical test in the fashion of Hendel and Nevo (2006) and show that lower prices are not correlated with a higher purchased quantity of medication.

[68] The discount rate corresponds to the monthly periods.

market share of the forthcoming period is a function of the demand characteristics within a period t (Equation 3). The demand estimates are from the random utility model of the consumer sample at t. Given average random coefficients (i.e., $\bar{\alpha}$ for the price coefficient) from the sample at t, $\tilde{m}^S_{jt+1}$ is the choice probability, and $\hat{m}_{jt}$ approximates the previous consumption, and therefore equals yjt within the choice model. The same method is used to approximate $\tilde{m}^{NS}_{jt+1}$, but y_{jt} is 0 as all patients are new. The value ϕ_t, estimated from the data, describes the share of customers that stay in a market at period t, that is, the share of patients who are the same in $t+1$ as in t. Within the forward simulation at a given period t, the share ϕ_t is constant. All in all, the transition probability estimates incorporate the dynamic factors of prices on market shares in the future but decrease the complexity of the demand system as firms take period-specific demand as an approximation of the future. Finally, I assume that the distribution of the private shocks ε_{jt} is known and given by $N(0,1)$. The assumptions are in line with those of Bajari et al. (2007).

With the assumption that the optimal pricing strategy σ^* is a Markov perfect equilibrium, it has to hold that the expected valuation given a state vector ($\mathscr{S}^t_j$) is higher than any other pricing strategy σ. The time superscripts are dropped as the equation binds in each period.

$$V_j(\sigma^*_j, \sigma_{-j}, \mathscr{S}_{\mathbf{j}}, c_j) \geq V_j(\sigma_j, \sigma_{-j}, \mathscr{S}_{\mathbf{j}}, c_j)$$

The valuation function at each period is dependent on the marginal costs. It is therefore possible to use the theoretical assumption of this inequality of a Markov perfect equilibrium when estimating marginal costs. Before making use of the objective function, I simulate the continuation function by forward simulation. I start with 500 initial parameters of the state vector $\mathscr{S}^{\mathbf{0}}_{\mathbf{j}}$. For each initial state vector I forward simulate the valuation function over 100 periods using the optimal pricing policy σ^*. I impose the assumption of transition probabilities described in Section 6. Specifically, at each point in time, I simulate the path for 100 forthcoming periods under the assumption that firms are forward looking but do not know the exact customer base. Nevertheless, firms do incorporate the effects of dynamic demand into their pricing. Furthermore, in each period a private ε_j shock is drawn. Correspondingly, the simulation of the valuation function given a marginal cost factor $\hat{c}_j$ is given by $\hat{V}_j(\mathscr{S}_j, \sigma_j, \hat{c}_j)$.

I use 200 alternative policy functions σ that are different to σ^*. Also here I simulate valuation functions by forward simulation. I denote one of the 500 initial draws of the state vector with $\mathscr{S}^{\mathbf{R}}_{\mathbf{j}}$ ($R = 500$) and the 200 non-optimal policy functions with σ^k (K=200). Given a marginal cost parameter c^{tj}, the difference between the optimal and non-optimal valuation function is described by

$$g(\mathscr{S}^{\mathbf{R}}_{\mathbf{j}}, \sigma^k_j, \hat{c}_j) = \hat{V}_j(\mathscr{S}^R_j, \sigma^k_j, \hat{c}_j) - \hat{V}_j(\mathscr{S}^r_j, \sigma^*_j, \hat{c}_j).$$

Given that the optimal strategy represents the equilibrium, I can construct the objective function in order to estimate the marginal costs. I search for the marginal costs that minimize the following function:

$$\min_{\hat{c}_j} Q(\hat{c}_j) = \frac{1}{K}\frac{1}{R}\sum_{k=1}^{K}\sum_{r=1}^{R} \mathscr{I}\{g(\mathscr{S}_{\mathbf{j}}^{\mathbf{R}}, \sigma_j^k, \hat{c}_j) > 0\} g(\mathscr{S}_{\mathbf{j}}^{\mathbf{R}}, \sigma_j^k, \hat{c}_j)^2.$$

The indicator function $\mathscr{I}$ takes the value 1 if $g(\cdot) > 0$. Thus, I minimize the squared difference between the estimated valuation functions for those cases when the alternative policy function is greater than the valuation function for the optimal policy function that represents the equilibrium.[69]

Note that I estimate marginal costs for every period and every company. The path is calculated given the demand within the period. The approach allows for different marginal costs within time as well as across companies. Further, the companies have knowledge about the general key factors of demand. Nevertheless, I do not require knowledge of the entire demand system, that is, individual patients and random coefficients of future patients.

8 Results

In the following I describe the results for the demand and supply sides separately. Furthermore, I separately execute the estimation for each substitution group. Having an immense amount of data, I describe the detailed results for specific subgroups where random samples of consumers are considered. I start by analyzing the estimation of the model for paracetamol tablets in a high dosage of 1 gram. Paracetamol is a common drug; however, it requires a prescription in high dosage. The random sample of consumers that is used covers the entire time. The randomized sample covers one-sixth of the population.[70]

Because paracetamol is no longer covered by a patent, the market for it has at least two competitors for the entire time period. I provide basic summary statistics for the substitution group in Table V. The average number of competitors is 3.72, and the average price is 72.13 SEK (approx. 7.2 USD). During the 6.5 years studied, three products entered and two products exited the market. On average, 69,000 purchases were made by 52,000 customers with a prescription each month. There are three different kinds of products in the market: an original product, branded generics and other generics. Branded generics may differ from other generics as consumers know about the specific brands even though the products are not originals.

Prices in the substitution group show some volatility, as shown in Figure III. Visual examination suggests that

[69] Note that I take advantage of the linearity of the profit function in the unobservables, the marginal costs. This approach reduces the computational burden of the estimation as I do not have to simulate the paths for each marginal cost estimate separately.

[70] In *Online Appendix G.3*, I provide a robustness check for the demand side using data for all consumers of high-dosage paracetamol. I consider a less flexible model and show that estimates of switching costs, perceived quality differences and price coefficients confirm the results of the flexible model using a random sample.

competition has lowered prices over the study period.[71] However, the substitution group shows specific price patterns that are described in Janssen (2018). That is, the cheapest products one month often drastically increase in price in the subsequent period, compared with the overall variation in prices in the substitution group. Theoretically, the price patterns are rationalized within Markov perfect equilibria given the institutional environment and switching costs. Firms are forward looking and lock in customers with low prices; then, they increase their prices and 'harvest' consumers who do not switch even though there are higher costs.

[Table V about here.]

[Figure III about here.]

8.1 Demand

I described demand in Section 6.1 and its estimation in 7.2. I start by presenting the control function, the results of a least squares regression of prices of i in t on the instruments (the average of other prices of products from the same manufacturer in other substitution groups in a specific month). For the substitution group of high-dose paracetamol, I present the first-stage regression in Table VI. Results show that the first stage is strong.[72]

[Table VI about here.]

Table VII shows the results of the random coefficient model for the random sample.[73] Models 1 and 2 evaluate the demand of the entire sample, whereas Model 1-Med and Model 2-Med consider only those patients who have a medical education. First, the upper part of Table VII presents the brand-specific intercepts (for Model 2 and Model 2-Med the mean of the random brand intercepts). The middle part of Table VII shows the mean and the standard deviation of the random coefficients for prices and the previous consumption (corresponding to α_i and ρ_i in the estimation in Equation 2, respectively). In the lower part, I describe the specification of the different models. Model 1 and Model 1-Med use the random coefficients of previous choice and prices, as well as non-random brand intercepts.[74] Model 2 and Model

[71] Note that there were only two competitors before 2012. Both firms do undercut the price ceiling, which was 74.25 SEK (approx. 7.4 USD) for most of the study period. For two months, the price ceiling was increased to 78 SEK (approx. 7.8 USD). I do not model the increase for those two months separately.

[72] Given the single regressor, it has a t-statistic of 626.81.

[73] In *Online Appendix G.3* I use the full sample and show robustness in a less flexible model.

[74] Note that I use the total costs and do not differentiate between patients according to their co-payment. Whereas prices are the same for all patients, the absolute payment may differ because of their varying co-payments, as noted previously. In the reduced-form analysis I show that the level of co-payment is not a threat for identification (see *Online Appendix C.3*). Further, in *Online Appendix G.5* I show that the demand estimation of the structural equation 2 is robust to an alternative measure of prices that incorporates the level of co-payment.

2-Med further control for unobserved heterogeneity by controlling for the first observation within the sample.[75] I add the control function approach to control for potential price endogeneity in Model 2 and Model 2-Med.[76] Given that I cannot interpret the coefficient for state dependence directly, I report the mean of the willingness-to-pay for the state-dependent coefficient. Formally, the willingness-to-pay for a consumer i is defined as the state dependence coefficient (ρ_i) divided by the price coefficient (α_i). Table VII reports the corresponding mean across patients. Finally, I also report the willingness-to-pay for a branded generic compared with a a non-branded generic. In detail, I calculate the willingness to pay from the brand intercepts of comparing Branded Generic I to the average values of the intercepts of Generic I to Generic IV.

The main results of Table VII are the following: First, the mean of the price coefficient for each specification is negative and significant. Note that individuals with a medical education are more price sensitive than the general sample. Second, consumers who purchased a specific drug in the preceding period are significantly more likely to purchase a product in the current period. This effect is significant in all specifications, for the full sample as well as the sample with a medical education. Note that the willingness-to-pay estimates are reasonable in size. Consumers are willing to pay approximately 0.875 USD (12% of an average price of 7.2 USD) more for a product when they have consumed it before. For the difference between the entire sample and the sample with a medical education, it is important to investigate the differences in terms of the brand intercepts, which translate to perceived quality differences. The default value is the only original product in the market. The intercepts show that branded generics have a generally higher demand within all model specifications. However, the difference to the original is higher for the entire sample than for the sample with medical education. Nevertheless, the difference between patients with and without a medical education is not very high within this substitution group. Finally, generics are less likely to be bought, everything else being equal.[77] The results are in line with the general result that brand premia, as a result of perceived quality differences, are observable. Patients with a medical education are less prone to perceived quality differences, even if those differences are not high in this substitution group.

[Table VII about here.]

[75] By controlling for the initial choice I try to measure true state dependence by the lagged choice. However, I assume that the initial condition is unrelated to the unobserved heterogeneity. As I do not observe the entire medical history but only the first observation in the sample, the estimate may be biased (initial condition problem). I provide two robustness checks: I show reduced-form evidence in section 5; specifically, I show that results are robust when considering those patients without any consumption within the first years of the sample. Secondly, I estimate demand in a less flexible model and use the approach recommended by Wooldridge (2005) in *Online Appendix G.3*.

[76] Note that a small brand does not have other products within the group of painkillers during the entire panel period such that I run out of instruments for part of the sample. Accordingly, the sample gets smaller. In *Online Appendix G.4*, I estimate another demand specification in which I substitute missing instruments with own prices. The results are similar to the ones of the main specification.

[77] To provide additional interpretation I show cross-price elasticity as well as elasticity of demand implied by the demand estimation in *Online Appendix G.2*. The elasticities confirm two observations: (1) Consumers with medical education are more price sensitive, which translates to higher own-price elasticities for all products. (2) Consumers with medical education have especially higher cross-price elasticities with respect to price changes of originals and branded generics.

8.2 Supply

The results for the supply side are ordered in several stages. First, I show and discuss results of the policy estimation. Second, I show some details about the transition estimation, which reduces the complexity of the supply side. Third, I present the final estimates of the marginal costs.

First, Table VIII presents the reduced-form estimate of the policy function as described by Equation 4. Therefore, the outcome variable of a least squares regression is firm j's price in period t (p_{jt}). I explore three different models. Model 1 solely includes the previous market shares (m_{jt-1}) and a constant. Model 2 further includes the PoM dummy of the previous month (PoM_{t-1}), and Model 3 also considers the dummies for the number of competitors in the previous period ($|N_{-1}|$) as well as the market size (Q_t). The policy function is an estimate of the equilibrium strategy of firms. Each firm plays a symmetric Markov perfect equilibrium. Therefore, the results in Table VIII do not carry any causal interpretation. However, the three models show that the previous market share and the previous PoM are correlated with a higher price in the next period. The results are stable and significant. Furthermore, a higher number of competitors is correlated with lower prices, while the market size (higher demand) is correlated with higher prices.

[Table VIII about here.]

Second, the expectation of a firm's future market share is described in Equation 3. In detail, the market share in $t+1$ is dependent on (1) the strategy of firms, (2) the demand estimate and base of consumers in t and (3) the share of patients who stay in the market between t and $t+1$ (ϕ_t). The latter is inferred from the descriptive statistics in the data. On average across the time periods, 19.2% (standard deviation, 0.025) of the patients stay in the market.[78]

Given the two initial steps, Table IX shows the estimates from the marginal costs for each firm across time on average. The marginal cost estimates are heterogeneous across firms and vary over time.[79] In Table IX I show the average marginal costs for each firm over the periods in which the firm was present in the market. I also present the standard for the estimates across time. The marginal costs vary only slightly over time. The two branded generics in the market seem to have slightly lower marginal costs. The estimate would suit the assumption that branded generics have a high market share in a lot of markets, which decreases marginal costs due to distribution. The estimates of the marginal costs are lower for the branded generics than for generics with lower market shares because of economies of scale. In addition to the variability of marginal costs, one may assess the suitability of the marginal cost estimates by comparing variability of prices, marginal costs and markups. Biased estimates of marginal costs may be characterized

[78] In *Online Appendix H.1* I show ϕ_t for each time period. Note that ϕ_t is always between 0.1 and 0.25. No clear time trend is visible.

[79] Details of the estimates are presented in *Online Appendix H.2*. I present the point estimates as well as standard errors for the marginal costs of each brand within each period. I obtain the standard error by bootstrapping over different market histories. Estimates of marginal costs in each period for each firm are statistically different from zero. Even though the marginal cost estimates show sporadic decreases in some periods, the estimates vary within reasonable bounds. The standard deviation estimates in Table IX confirm the behavior.

by capturing all the variability or price changes such that markups do not change over time. Dynamic pricing would be therefore explained by marginal costs. In *Online Appendix H.3* I show the markups as well as the correlation between prices and marginal costs. I show that there is not a strong correlation between prices and marginal costs; that is, the variation in prices is not explained by the estimates of marginal costs.

[Table IX about here.]

9 Counterfactuals

In the counterfactual analysis, I first present the implementation procedure and then show that an extension of the contract length which mimics a reduction of switching costs increases prices in equilibrium. In the second counterfactual scenario, all patients act as if they were physicians, and prices decrease. In *Online Appendix I.3* I show the results for a direct reduction of switching costs on the patient side. The results are in line with the increased contract length, i.e. prices change in a lower frequency: lower switching costs increase prices.

9.1 Implementation

Technically the implementation of counterfactuals requires me to estimate the policy that represents a Markov perfect equilibrium. Consistent with the Markov perfect strategies in the previous section, firms condition their strategy on all state variables. Because the environment or demand parameters change within the counterfactual scenario, I cannot use the policy function presented in Section 8. Instead, I need to compute Markov perfect equilibria by value (or policy) iterations and solve for a pricing equilibrium during each iteration. Because the computational burden increases exponentially with the number of state variables, I simplify the environment as follows.

I reduce the state space $\mathbf{S}_t$ to only one variable, the PoM status. Thus, firms condition their prices on the knowledge of which product was the cheapest in the preceding month. The reduction of the state space is strong. The reduction is motivated by the need for a simplified environment. Further, I show in *Online Appendix I.1* a model selection method (LASSO) based on the policy function.[80] I show technical details of the algorithm and its implementation in *Online Appendix I.2*. In general, the algorithm works as follows: I perform a value iteration that incorporates the equilibrium conditions due to the assumption that firms play a Markov perfect equilibrium. The following steps are done in each period: As in Section 8, I take advantage of the demand parameters. I take the average consumer and assume that

[80] Performing a model selection, I show that PoM status in the previous period and the quantity are the most predictive regressors. I assume that firms do not know about future quantity development, such that the PoM status plays the most important role in intertemporal relationships between pricing decisions. I therefore choose the previous PoM as the new state space. Note that the benchmark model shows that the reduction in state space provides a good match for the actual data. The method of regularization using machine learning methods presented in *Online Appendix I.1* is related to the solution concept offered by Thiel (2019).

firms know how many patients stay in the market.[81] Firms assume that the average consumer is constant. I further use the marginal cost estimates from the previous sections. The marginal cost estimates are different across firms. For each possible state (each firm could have been the PoM in the previous month), I start with an initial guess of the value function for each firm (V^0). In each iteration k for each state I search for an equilibrium in prices. Note that the search for the mutual best reply (equilibrium) incorporates the static prices, the transition to the state of the next period ($\pi(\mathbf{S}^{t+1}|\mathbf{S}^t, p_j, p_{-j})$) and the value function that is dependent on the state ($V^k(\mathbf{S}^t)$). Given continuation values I update the best replies for each player in each state. I update the Bellmann equation and get a new estimate for the value function V^k. During each iteration I update the value function until convergence.

Note that the simplification and estimation come with two major concerns. The first concern is a computational one. The grid of used prices may lead to different equilibria and therefore prices. Further, equilibria may not be unique, and the employed algorithms may lead to a different equilibrium than the ones chosen by firms. The second concern is the simplification of the state space. To tackle both concerns, I explore the results of the simplified model and compare it with the observable prices before turning to the counterfactuals. Within the benchmark model I do not change the environment, and I use the demand estimates as well as the marginal cost estimates.

Table X shows some basic statistical measures of the prices and market shares in the data as well as the benchmark model. The simulated prices in the benchmark model are slightly lower than the ones in the data.[82] The divergence is due to fiercer competition between two competitors in the benchmark model. In the lower part of Table X I show a comparison of the market shares in data and in the simulated benchmark model. Except for the second branded generic, which is available in only a few time periods, the relation between the different brands in the benchmark model fits the data reasonably well. Overall, the benchmark model's key characteristics are close to those of the actual data. Finally, *Online Appendix I.2* describes several approaches to reduce concerns of multiple equilibria.

[Table X about here.]

9.2 Procurement: An Extension of the Contract Length

In the first counterfactual I do not change the demand side but change the institutional background. Firms in the first counterfactual are allowed to change their prices only once each year. Note that consumers' switching costs are still relevant, as some consumers may start a treatment within one year and continue into the next. However, behavioral pricing that intends to lock in consumers and harvest them in the forthcoming period is more expensive for firms.

[81] In comparison to the procedure used in Section 8, I do not adjust the choice sets and initial purchases (and correlation to previous choices) when estimating demand. The adjustment reduces the computational burden.

[82] Note that the mean price in the data diverges between Table X and Table V as I compute the average over all months in Table V, whereas Table X presents the mean across all months *and* all firms because it is used for comparison of the benchmark and the data.

Firms would need to have lower prices over a longer term and therefore forgo profits. Overall, this counterfactual is motivated by two aspects. First, it incorporates a realistic policy change, as it solely changes the timing of the current pricing policy. Second, the counterfactual directly reduces switching costs as (1) the number of consumers whose use of the product continues over several years gets smaller and (2) consumers tend to oppose substitution less often when the time since the last purchase of a more expensive product increases. In *Online Appendix I.3* I estimate a counterfactual in which I directly reduce switching costs on the consumer side. I show that the results are analogous.

Technically, I use the same demand model as presented before. The frequency of price changes reduces from 72 to 6. Within each new period, consumers are treated equally. The state variable still shows whether a firm had the cheapest product in the preceding period. The effect on the next period's demand, however, is reduced. The market share is equivalent to the one in the benchmark model. On the supply side, I assume that firms that are present in at least two month of the year are present for the entire year. This assumption increases competition over the studied time periods. However, the possible policy change would come with increased competition, because firms would be able to enter and exit only once a year and it is reasonable that firms would stay in a market longer. As the length of the periods changes, I adjust the share of patients that stay in a market over two subsequent months (ϕ) as well as the discount rate ($\delta^{NEW} = .95$). Finally, the estimation of the prices in equilibrium is equivalent to that in the benchmark model, as I change only the sample of a single period and reduce the number of periods.[83]

Table XI compares market outcomes of the different counterfactuals and the benchmark model. The average price is higher in the scenario with a 'product of the year' rather than a 'product of the month' (70.49 instead of 69.56 SEK). This result is not necessarily surprising and is in line with the research of Arie and Grieco (2014), Cabral (2016), Dubé et al. (2009), Fabra and García (2015) and Rhodes (2014). These authors show theoretically as well as empirically that moderate switching costs may increase the competitive pressure. The longer procurement periods in this counterfactual scenario lead to a lower possibility for firms to take advantage of switching costs. I therefore simulate a policy change comparable to a case of lower switching costs, which is possible to implement. In *Online Appendix I.3* I show analogous results in the case of direct reduction of switching costs. Even though switching costs increase the market power of a firm with locked-in patients and therefore induce 'lock in and harvest' behavior, prices on average are lower. Because firms have an incentive to decrease prices in order to lock in patients, and moderate switching costs (see demand-side estimates) prevent prices from becoming too high in the harvest phase, prices may be lower when switching costs are present. This argument is strengthened by the standard deviation of market shares across all products and companies, which is twice as large in the benchmark model as in the counterfactual. Also, this result is in line with the argument presented for dynamic pricing with higher variability of market shares in the

[83] Note that I do not model entries and exits. I assume existence of a product within a year if the product is available in at least two months of the respective year. Therefore I implicitly increase competition, which could in principle reduce prices in equilibrium.

benchmark model.

In the lower part of Table XI I show results that incorporate the behavior of consumers and corresponding market shares of products. First, I show the price of purchases by an average consumer over the entire time period. The results of the price for the average consumer are comparable to the general price statistics. In detail, the average purchase price for a consumer is 2.08% higher (70.69 SEK) in the scenario of a different procurement process compared with the benchmark model (69.25 SEK). Further, the market cap for firms increases (by 4.11%) in the counterfactual scenario.

Overall, the counterfactual leads to the conclusion that lowering the possibility of reacting to switching costs by reducing the frequency of price changes is, on average and overall, not welfare-enhancing for the consumer. The results are in line with the firms' behavioral pricing (i.e., lock in and harvest) in the benchmark model with moderate switching costs. Preventing the behavior leads to higher prices on average because then the firms do not reduce prices with the intent to lock consumers in. Note that the results are not uniform for all consumers. Indeed, consumers with high switching costs and frequent purchases profit from the new procurement process as there is no 'harvesting' by firms that charge high prices, whereas new consumers or those with no switching costs suffer from higher prices because there is no 'lock in' with low prices.

9.3 Brand Premia

In the second counterfactual, I show the impact of brand premia due to perceived quality differences on pricing (behavioral pricing) and consumers' welfare. In practice, I use the demand estimates from the reduced sample of patients with medical education and estimate the supply side, holding the original quantity and cost factors fixed. I use the state dependence coefficients from the reduced sample of experts but do not change the sample estimate of the share of patients that stay in a market over two subsequent months (ϕ).

Table XI shows descriptive statistics of the pricing equilibrium in the counterfactual with a decrease in perceived quality differences. On average, prices in the counterfactual, with a decrease in perceived quality differences, are lower than in the benchmark model (67.66 SEK vs. 69.56 SEK). Especially the prices of the original and the branded generics decrease. Therefore the results go in the opposite direction than in the counterfactual with a different procurement process. The reasons are that experts have lower brand preferences and have a higher price elasticity. The new demand leads to stronger competition between existing firms and therefore lower prices. However, the effects are not strong, as the differences of the demand estimates are not particularly strong in this specific substitution group.

The lower part of Table XI shows the effects for the average consumer. With the decrease in perceived quality differences, the consumer pays on average 67.15 SEK for a product. Two effects play a role. First, prices are lower, as firms have less incentive to engage in behavioral pricing and to take advantage of brand preferences due to perceived

quality differences. Second, consumers themselves are less willing to pay brand premia, as perceived quality differences have decreased. Thus, they tend to consume cheaper products. Overall, the average consumer spends 3.03% less for a product in the counterfactual scenario. When considering the entire revenue of the market within the 6.5 years, consumers overall spend 3.86% less.

[Table XI about here.]

10 Conclusion

In this article I provide causal evidence for switching costs and perceived quality differences in the Swedish pharmaceutical markets for painkillers and antibiotics, whereas the phenomena do not exist in the market for antiepileptics. I estimate switching costs through several identification strategies (panel data methods, quasi-experiments of patent expiration and time discontinuities) and show that, because of switching costs, patients are up to 15% more likely to pay an additional amount for prescription painkillers and antibiotics. Because of the unique institutional background of the data, in which patients are always informed about the equivalence of drugs and the price differences, and by differentiating between consumers with and without medical knowledge, this paper makes a novel contribution to the field by identifying brand premia due to perceived quality differences. I compare drug choices between patients who have a medical education to those who do not. By ruling out the possibility that inattention is the reason for brand premia (because drugs are not advertised and pharmacists explain to patients that the drugs are equivalent), I show that perceived quality differences lead to significant overpayment by non-experts.

The results of the reduced form as well as the structural analysis are of high relevance for policymakers. Switching costs and perceived quality differences not only are important behavioral phenomena but also shape the pricing behavior of firms. Concentrating on a specific subgroup, I estimate that both switching costs and perceived quality differences are important for the pricing of pharmaceuticals. While perceived quality differences result in a reduction of competitive pressure and therefore increased prices, the effect of switching costs on prices may be ambiguous. While switching costs may be anti-competitive, I have shown in a realistic policy-simulating experiment that switching costs may decrease prices. The main intuition is that having sufficient incoming patients leads to investment and harvesting behavior of firms. Although some patients with switching costs may oppose substitution for their pharmaceuticals, patients without switching costs can actually profit from lower prices as firms try to lock in those patients that experience switching costs. On average, patients may profit from switching costs. From a public perspective, a realistic change in the procurement of pharmaceuticals does not increase consumers' overall welfare, as less dynamic pricing and 'lock in and harvest' behavior increases the price for the average consumer. Before intervening in a market with

switching costs, a policymaker should understand the details of the market structure to evaluate whether switching costs are pro- or anti-competitive.

This article also sheds light on the relevance of consumers' perceived quality differences when it comes to prescription drugs. The specific setting of the Swedish health care system shows that information provision on the pharmacy level is not necessarily sufficient to ensure substitution to cheap generics. Possibly, prescription of the cheapest generic on the physician level would help to decrease perceived quality differences.

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Figure I: Timeline of Auction

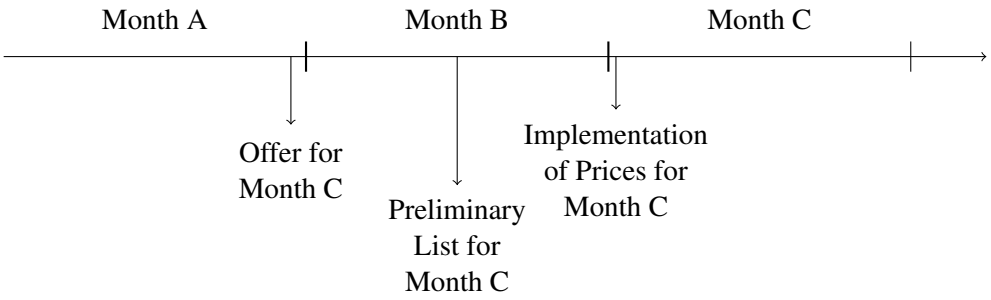
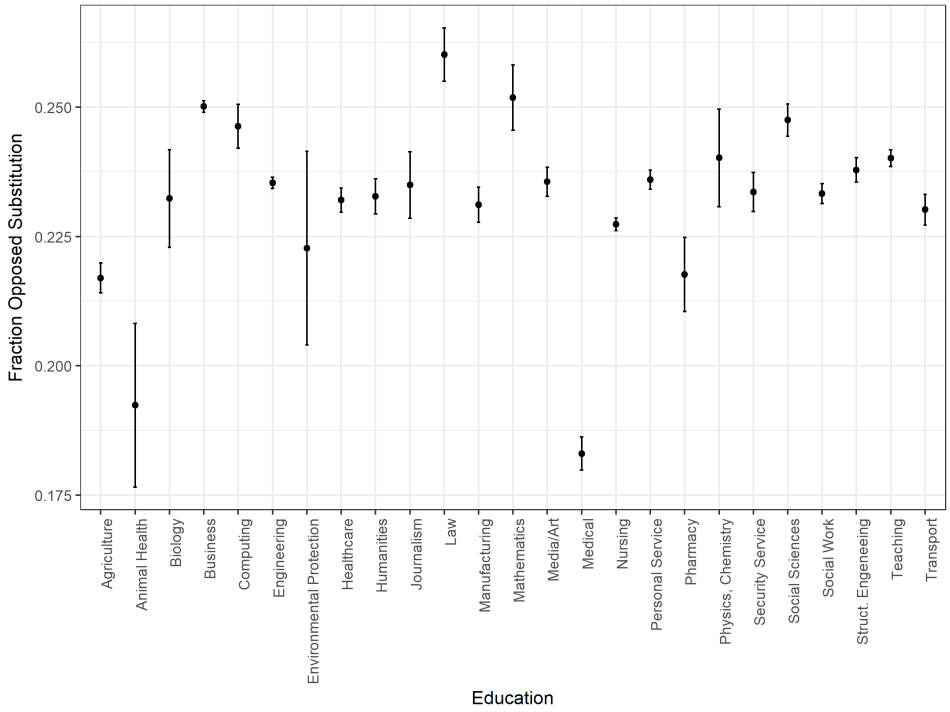
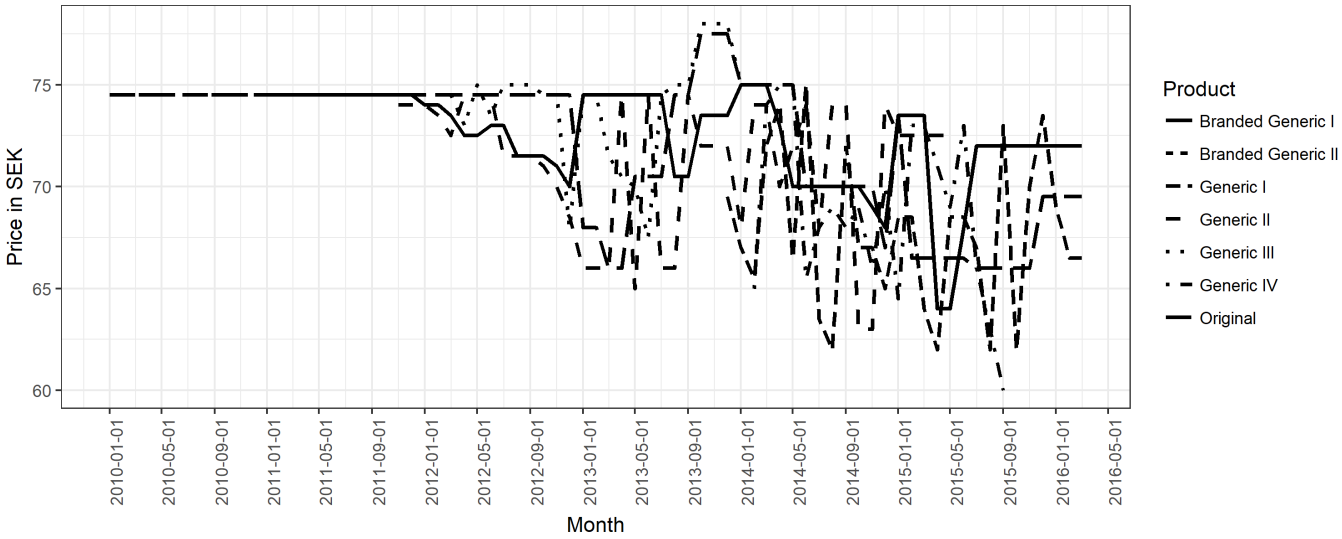


Figure II: Subject of Education and Substitution Decision



Notes: Fraction of patients that oppose substitution when consuming painkillers dependent on the subject of education. The education is divided into 25 different subjects, ordered alphabetically. The error bars correspond to a 95% confidence interval. 'Medical' refers specifically to the education needed to become a physician.

Figure III: Monthly Prices in the Paracetamol Substitution Group



Note: Monthly prices in the substitution group for paracetamol, 1 g, 30 tablets, between 2010 and 2016. There is a price ceiling of 74.25 SEK (approx. 7.4 USD, for two months it was increased to 78 SEK, approx. 7.8 USD) in place.

Table I: Co-Payment Structure

Price	Reimbursement	Max. Total Out-of-Pocket Payment
$p \geq 4300$	100%	
$3500 \leq p < 4300$	90%	1800 SEK
$1700 \leq p < 3500$	75%	1700 SEK
$900 \leq p < 1700$	50%	1300 SEK
$p < 900$	0	900 SEK

Price	Reimbursement	Max. Total Out-of-Pocket Payment
$p \geq 5400$	100%	
$3900 \leq p < 5400$	90%	2200 SEK
$2100 \leq p < 3900$	75%	2050 SEK
$1100 \leq p < 2100$	50%	1600 SEK
$p < 1100$	0	1100 SEK

Notes: Co-payment structure for cumulative health care expenditure (including prescription drugs) before (upper panel) and after (lower panel) 2012. Reimbursement is calculated for expenses during an entire year, beginning with the first expenditure. Prices are in SEK. 10 SEK are approximately 1 USD.

Table II: Summary Statistics

	Painkillers	Antibiotics	Antiepileptics
Number of Substances	10	24	4
Number of Substitution Groups	158	147	36
Number of Products	566	438	72
Average Number of Products in Substitution Group	1.95	1.61	1.38
	(1.13)	(0.83)	(0.39)
Percent Original	0.3	0.19	0
	(0.35)	(0.32)	
Percent Generics	0.7	0.75	0.76
	(0.35)	(0.35)	(0.33)
Average Price (in SEK)	333.2	255.7	393.3
	(390.2)	(344.4)	(275.7)
Average Price Original (in SEK)	395.6	334.6	
	(487.4)	(355.4)	
Average Price Generics (in SEK)	299.7	221.7	352.1
	(355.5)	(344.7)	(265)

Notes: Summary statistics for the three market segments of painkillers, antibiotics and antiepileptics. Prices are in SEK (10 SEK are approx. 1 USD). Branded generics are included in the generics category. Standard deviations are in parentheses.

Table III: Summary Statistics of Purchases

	Painkillers	Antibiotics	Antiepileptics
No. of Purchase Occasions (in millions)	38.54	13.79	0.57
No. of Patients (in thousands)	3,196	4,731	60
Avg. Purchase Occasions per Patient	12.1	2.9	9.4
	(26.3)	(3.5)	(14.1)
Avg. Monthly Total Costs (in million SEK)	46.73	23.46	2.87
Avg. Monthly Co-payment (in million SEK)	17.88	14.66	0.73
Fraction Consuming PoM	0.734	0.866	0.929
	(0.44)	(0.34)	(0.26)
Fraction with Substitution Opposed by Patient	0.209	0.094	0.028
	(0.41)	(0.29)	(0.16)
Fraction with Substitution Opposed by Physician	0.024	0.005	0.018
	(0.15)	(0.07)	(0.13)
Fraction with Substitution Opposed by Pharmacy	0.034	0.03	0.026
	(0.18)	(0.18)	(0.16)

Notes: Summary statistics for the three market segments of painkillers, antibiotics and antiepileptics. The number of purchase occasions is the sum of purchase occasions across consumers between January 2010 and June 2016. Average purchase occasions shows the number of purchases of the average patient. The total costs include costs for insurance as well as for the patient (co-payment). The total costs as well as co-payment measures are in USD per month on average. Prices are in SEK (10 SEK are approx. 1 USD). The lower part of the table describes substitution decisions. The fraction of consumption of the PoM describes the fraction of purchase occasions in which a patient consumed the PoM. If a patient does not consume the PoM, it is because of one of the three displayed reasons (substitution opposed by the patient, substitution opposed by the physician or substitution opposed by the pharmacy). Standard deviations are in parentheses.

Table IV: Regression Evidence, Probability of Opposed Substitution

	Painkillers 'Opp.'	Antibiotics 'Opp.'	Antiepileptics 'Opp.'
D_{t-1}	0.0332***	0.0116***	-0.00401***
	(0.000262)	(0.000570)	(0.000516)
Med	-0.0488***	-0.0245***	-0.0107**
	(0.00173)	(0.000676)	(0.00391)
$D_{t-1} \times Med$	-0.00304	0.00101	0.00650
	(0.00390)	(0.00354)	(0.00659)
$log(Inc)$	-0.0000237	0.000680***	0.0000675
	(0.0000909)	(0.0000369)	(0.000128)
$Constant$	0.108***	0.0799***	-0.00888***
	(0.00121)	(0.000610)	(0.00244)
Education	Yes	Yes	Yes
Control Heterogeneity	Yes	Yes	Yes
Geographic Fixed Effects	Yes	Yes	Yes
Observations	32923856	12326138	500363
R^2	0.264	0.121	0.063
Fixed Effects	'SubGroup*Time'	'SubGroup*Time'	'SubGroup*Time'
Mean Opp. Subst.	0.187 (0.39)	0.094 (0.291)	0.028 (0.164)
Mean Price SEK	94.6 (152)	133 (125)	393 (391)
Mean Overpayment SEK	11.2 (26.6)	14 (24.4)	14.4 (29.9)
D_{t-1} Incr.	17.75%	12.34%	-14.32%
Med Incr.	-26.1%	-26.06%	-38.21%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Linear least squares regression results for the segment of painkillers, antibiotics and antiepileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value a if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. D_{t-1} is a dummy that takes the value 1 if a patient has consumed the product in the previous purchase occasion in the last month. Med is a dummy that takes the value 1 if an individual has medical education. Log(Income) is the logarithm of income. Education indicates if the model controls for the level of education according to the grades in a six-step grid. Geographical indicates if the model controls for county-level fixed effects. Fixed Effects indicates if the model controls for substitution group × month fixed effects. In the lower part of the table I show the average fraction of opposed substitution as well as the price and average payment of those that oppose substitution (in SEK, 10 SEK equal approximately 1 USD). Finally, I also state the percentage increase of opposed substitutions that are associated with past consumption (switching costs) and medical education (quality misconceptions). Standard errors are clustered on the individual level and adjusted for heterogeneity. Standard errors are in parentheses.

Table V: Summary Statistics, Paracetamol, 1 g

	Paracetamol, 1 g
Avg. Number of Competitors	3.72
	(0.99)
Avg. Price (in SEK)	72.13
	(0.259)
Entries	3
Exists	2
Avg Purchase Occasions per Month	509,843
	(38,945)
Unique Customers per Month	315,864
	(15,847)

Notes: Summary statistics for substitution group of paracetamol, 1 g, 30 tablets. 10 SEK corresponds to approximately 1 USD. The average values show the average over months. Standard deviations are in parentheses.

Table VI: First Stage of Control Function

	Price
Price of Other Painkillers	0.2361***
	(0.00037)
Constant	53.877***
	(0.0735)
N	623,017

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Results of the first-stage estimation. One observation is the price of a product in the substitution group of paracetamol, 1 g, 30 tablets. The regressor is the average price of other products from the same manufacturer in the Swedish market for painkillers. Standard errors are in parentheses.

Table VII: Regression Evidence, Demand Model

	Mod.1	Mod.1-Med	Mod.2	Mod.2-Med
Branded Generic I	.609***	.280**	.815***	.606***
	(.007)	(.086)	(.015)	(.165)
Branded Generic II	.245***	.122	-.671***	-.834**
	(.009)	(.110)	(.024)	(.261)
Generic I	-.792**	-.632***	.024	-.155
	(.015)	(.164)	(.021)	(.265)
Generic II	-1.164***	-.631***	-.487***	-.604**
	(.013)	(.139)	(.016)	(.182)
Generic III	-1.894***	-1.731***	-.796***	-.609
	(.020)	(.213)	(.045)	(.711)
Generic IV	-1.180***	-.856**	-.599***	-.508
	(.024)	(.271)	(.031)	(.358)
Random Brand Intercepts	No	No	Yes	Yes
Price Mean	-.097***	-.167***	-.109***	-.135***
	(.003)	(.028)	(.002)	(.024)
σ	.396***	.285***	.169***	.216***
	(.004)	(.041)	(.003)	(.032)
State Dependence Mean	2.02***	1.70***	.955***	1.093*
	(.022)	(.353)	(.020)	(.467)
σ	.756***	.038	.103***	.269
	(.034)	(.764)	(.032)	(.682)
Control Function	no	no	yes	yes
Unobserved Heterogeneity	no	no	yes	yes
WTP State Dependence (SEK)	20.8	10.2	8.75	8.1
WTP Branded Generic to Avg. Generic (SEK)	19.2	7.4	11.7	8.0
Log-Likelihood	-170,687	-1,197	-110,005.36	-849.08
N	655,228	3,873	555,685	3,267

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Results from the mixed logit estimation. One observation is a patient choice in the substitution group of paracetamol, 1 g, 30 tablets. The outcome variable is a dummy that indicates if an individual has chosen a product. Mod.1 and Mod.2 consider the random sample (1/6th of the full sample, random selection), whereas Mod.1-Med and Mod.2-Med solely consider patients with a medical education within the random sample. The upper part of the table shows product-specific intercepts, dependent on branded generics and generics; the default value is the original. Note that the coefficients are partly random and estimates of standard deviations are excluded. The lower part of the table shows the random coefficients for price and the state dependence. Note that I also report the standard deviation of the random coefficients. Control Function indicates if the control function approach for endogenous prices has been used. Unobserved Heterogeneity indicates if the model controls for problems due to unobserved heterogeneity. WTP State Dependence shows the point estimates of the average willingness to pay for state dependence in SEK (10 SEK are approx. 1 USD), i.e., how much an average patient is willing to pay in order to receive the same product as in the last period. WTP BrandedGeneric to Avg. Generic describes the willingness to pay to receive a branded generic compared to the mean of all other generics. Standard errors are in parentheses.

Table VIII: Policy Estimation

	Price		
	(1)	(2)	(3)
Share $(t-1)$	2.598^{**}	2.568^{***}	1.589^{*}
	(0.817)	(0.727)	(0.797)
$I(NoComp.(t-1)=3)$			0.062
			(0.350)
$I(NoComp.(t-1)=4)$			-0.286
			(0.478)
$I(NoComp.(t-1)=5)$			-1.092
			(0.683)
PoM$(t-1)$		2.481^{***}	1.752^{***}
		(0.386)	(0.474)
Quantity			0.0001^{***}
			(0.00003)
Constant	71.066^{***}	70.080^{***}	61.182^{***}
	(0.370)	(0.411)	(2.203)
N	272	272	272
R^2	0.028	0.142	0.262
Notes:	$^{*}\ p<0.05$, $^{**}\ p<0.01$, $^{***}\ p<0.001$		

Notes: Linear least squares regression results for the estimation of the policy function. One observation corresponds to the monthly price of a product in the substitution group of paracetamol, 1 g, 30 tablets. The outcome variable is the price of a product in period t. All regressors are state variables of the supply side: Share$(t-1)$ is the market share in the preceding period. $I(NoComp.(t-1)=3)$, $I(NoComp.(t-1)=4)$, and $I(NoComp.(t-1)=5)$ are dummies that take the value 1 if in the preceding period the number of firms was equal to 3, 4 or 5. PoM$(t-1)$ is a dummy that takes the value 1 if the firm was the cheapest product in the previous month. Standard errors are in parentheses.

Table IX: Marginal Cost Estimates

Firm	**Mean Marginal Cost**	**Standard Deviation**
Original	14.82	5.50
Branded Generic I	13.75	2.11
Branded Generic II	11.68	2.86
Generic I	16.89	3.23
Generic II	14.52	1.25
Generic III	14.01	2.18
Generic IV	14.41	1.84

Notes: Summary of marginal cost estimates (in SEK; 10 SEK approximately 1 USD) for different firms in the market of paracetamol, 1 g, 30 tablets. Note that the marginal costs are the means of the marginal costs estimated for each period in which a product has been present.

Table X: Benchmark Model, Products

	Mean Data	SD	Mean Benchmark Model	SD
Prices				
Mean Price	71.80	3.65	69.56	2.49
Original/Avg Generic	1.013		1.024	
Market Shares				
Mean Share	0.27	0.1	0.26	0.1
Original	0.32	0.16	0.25	0.17
Branded Generic I	0.53	0.17	0.53	0.08
Branded Generic II	0.49	0.29	0.31	0.10
Generic I	0.15	0.13	0.17	0.04
Generic II	0.08	0.09	0.14	0.04
Generic III	0.03	0.07	0.12	0.03
Generic IV	0.07	0.11	0.11	0.02

Notes: Comparison between data and prediction from the reduced model (benchmark model). The upper part of the table shows comparison of prices. Prices are reported in SEK (10 SEK are approx. 1 USD). The second and third columns show the results from observable prices in the substitution group of paracetamol, 1 g, 30 tablets. The fourth and fifth columns show the prediction from the reduced model with one state variable, the benchmark model. The mean prices correspond to the mean across all periods and all available products. The lower part of the table shows statistics for market shares. Note that not all products are available in each month.

Table XI: Results of Counterfactuals

	Benchmark Model	Counterfactual Procurement	Counterfactual Brand Premia
Average Prices			
Mean Price	69.56	70.49	67.66
	(2.49)	(3.13)	(2.72)
Original	70.71	71.15	68.83
Branded Generic I	69.67	73.10	67.48
Branded Generic II	68.80	66.40	66.28
Generic I	70.48	72.70	69.01
Generic II	68.93	68.68	67.01
Generic III	68.20	68.30	65.92
Generic IV	68.14	69.25	67.13
Shares			
Mean Share	0.26	0.22	0.28
	(0.1)	(0.05)	(0.09)
Average Expenditures and Revenue			
Price for Avg. Consumer	69.25	70.69	67.15
Compared to Benchmark		2.08%	−3.03%
Total Revenue (in m)	265	276	255
Compared to Benchmark		4.11%	−3.86%

Notes: Comparison between the benchmark model and the two counterfactual scenarios. The upper part of the table reports prices in SEK (10 SEK are approx. 1 USD). The first counterfactual is the different procurement process. The second conterfactual mimics the case of a decrease in brand premia. The middle part of the table shows the average shares of all products across all periods. The lower part of the table shows measures of consumer costs and total revenue. $Price\ for\ Avg.\ Consumer$ is the price an average consumer would pay. The following row shows the percentage change from the benchmark model. $Total\ Revenue$ is the total market revenue (price and fixed quantity) during the 6.5-year period. Standard deviations are in parentheses.

Appendix

Patent Expiries: Switching Costs

I use a quasi-experimental setting to show causal evidence for state dependence due to switching costs. The results serve as a robustness check for the general evidence of the general regressions. Similar to Feng (2017), I take advantage of the introduction of generic products after patent expiries. Correspondingly, I compare the repeated purchasing behavior of consumers who start their treatment with a drug for the first time shortly before expiration of a patent to those patients who start treatment shortly after the patent expired.

I begin by describing a specific but representative example of a substance for which a patent has expired. Figure A.1 describes the monthly market shares of different brands within a substitution group of the substance oxycodone. Oxycodone is an opioid and is used as a strong painkiller. OxyContin, the branded version of oxycodone, had patent protection until October 2012. Figure A.1 shows a steady reduction of the original's market share after the patent expired. After the patent expired, the original lost market share to the new competitors. The main reason for this development is that consumers began to be reimbursed for the cheapest product, which was the newly authorized generic product.

[Figure A.1 about here.]

I reduce the sample to patients who started taking a product in this substitution group for the first time in the sample three months before and three months after the patent expired. The former is the control; the latter, the treatment group. I consider the repeated purchases of the two different groups after the initial purchase. Figure A.2 shows the difference in market shares of products between the group who started three months before the patent expiry and the patients who started three months after the patent ran out. It is observable that the original branded product has a higher market share among those that started treatment with the original for more than one year after the generics entered the market.

[Figure A.2 about here.]

I continue by presenting the general framework of estimating the impact of state dependence due to switching costs. First of all, I identify those substitution groups where a patent has expired. I use eleven substitution groups of oxycodone, six substitution groups of rizatriptan (a painkiller used against migraines) and three substitution groups of

clindamycin (an antibiotic).[84] I reduce each sample to the purchase of those patients who started purchasing a product three months before or after patent expiry. The treatment group is the group who started with one of the entering generics three months after the patent ended. Correspondingly, the group of patients starting treatment three months before the end of the patent is the control group. The basic intuition is that the groups are randomized, as patients cannot influence their medication starting date.

$$Y_{it} = \alpha + \beta_t Y_{i0} + \varepsilon_{it}$$

The variable Y takes the value 1 if a patient i consumes one of the newly entered products (generics). Given that I use the sample of patients whose initial consumption lies between three months before and after a patent expiry, t is the number of months after the initial consumption, which is designated as $t = 0$. I instrument Y_{i0} by Z_i, which shows whether a consumer is in the treatment group. Note that the sample only includes repeated purchases by consumers. The exclusion restriction of the approach relies on the assumption that patients are randomly selected into the treatment and the control groups. Given that patients need prescriptions from a primary health care provider for all three substances and given that patients of the studied substances need immediate treatment when prescribed, it is unlikely that patients self-select into one of the two groups.

Table A.1 and Figure A.3 show coefficients for β for the first three months (β_3) and the fourth to sixth months (β_6) after the initial purchase for each substitution group containing the substance Oxycodone.[85] Within Table A.1 each row corresponds to an individual substitution group. The first two columns describe the regression results where the outcome variable Y_{it} takes the value 1 if a patient takes a newly entering product during the first three months after initial consumption. The first column shows the coefficient of the first stage in the instrumental approach, whereas the second column is the coefficient of the second stage.[86] The third and fourth columns present the first and second stages, where the outcome is the fourth to sixth months. Figure A.3 shows the second-stage coefficients (β_3 and β_6) for each substitution group containing the substance oxycodone.

The first stage is strong for all specifications. The results of the second stage suggest that there is a strong state dependence during the first three months in the substitution groups of oxycodone.[87] For the longer time horizon, the

[84] Rizatriptan has the ATC code N02CC04. The original brand name is Maxalt. Clindamycin's ATC code is J01FF01. It is used against a number of bacterial infections. The brand name is Dalacin.

[85] Note that I include detailed tables for the substitution groups of Maxalt (the original brand of rizatriptan) and Dalacin (the original brand of clindamycin) in *Online Appendix C.9*. Results are similar.

[86] Note that I document display intercepts for simplicity.

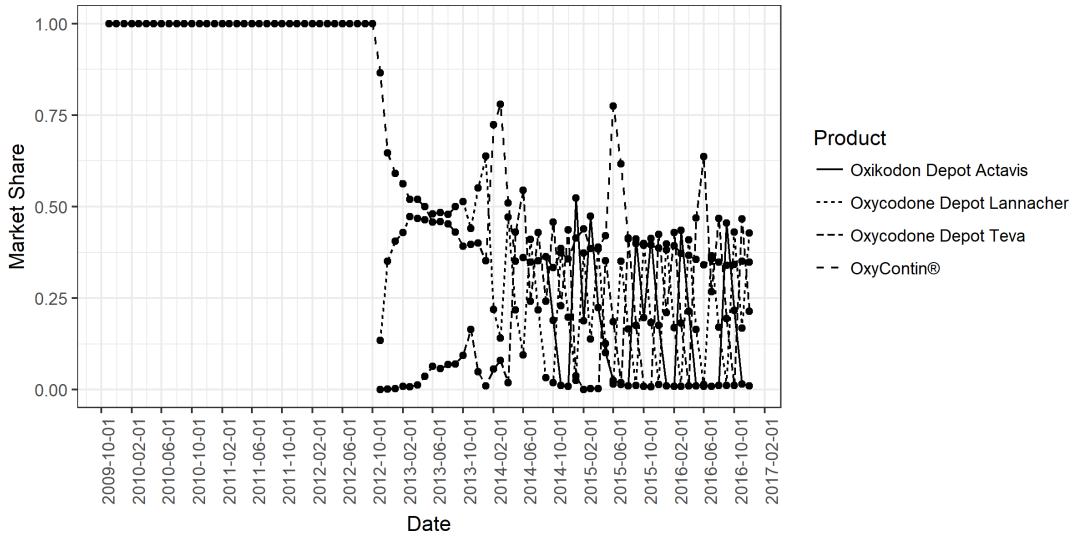
[87] Rizatriptan and clindamycin show similar results, as shown in *Online Appendix C.9*.

state dependence diminishes. In general, patients who start with a generic are more likely to consume a generic three months later than those who started with an original product. The analysis for the different group of substances is in line with the general regression evidence. Patients experience habit persistence or have switching costs.

[Table A.1 about here.]

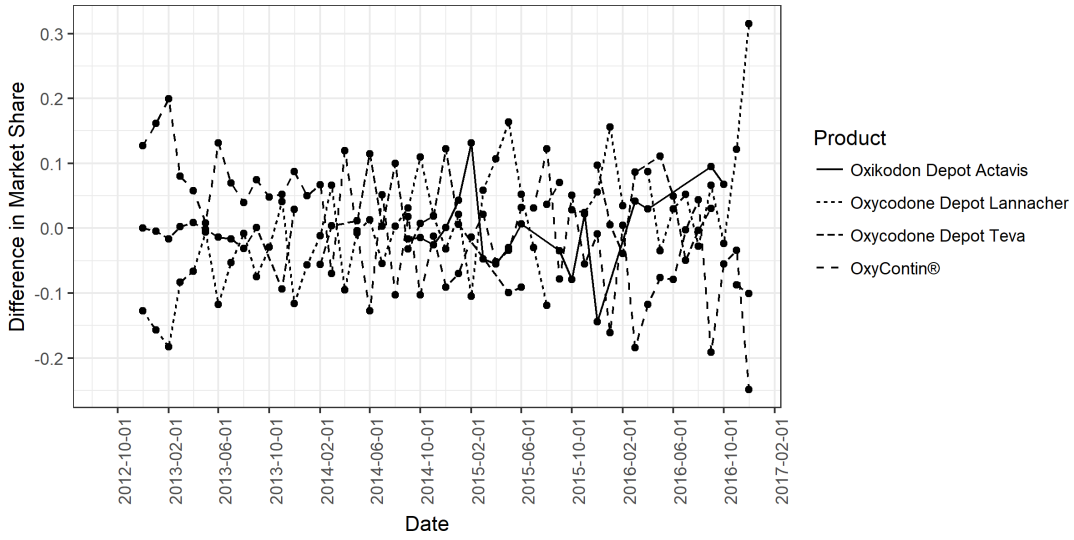
[Figure A.3 about here.]

Figure A.1: Market Shares, Oxycodone



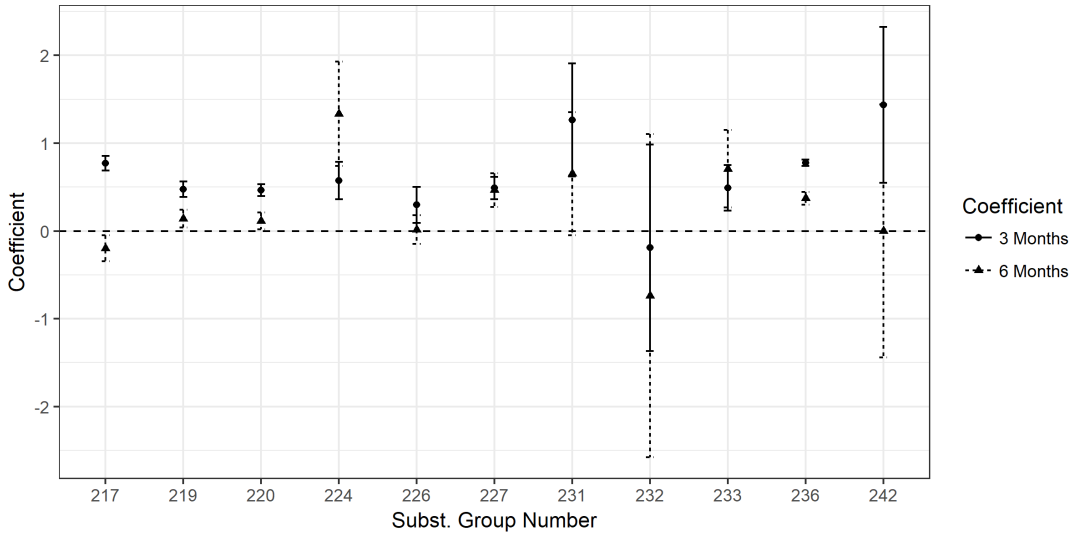
Notes: Monthly market shares in the substitution group of oxycodone before and after patent expiry of the original product, OxyContin. Each observation stands for the monthly market share of a brand.

Figure A.2: Difference in Market Shares, Oxycodone



Notes: Considering only repeated purchases of consumers who started purchasing an oxycodone substance for the first time three months before or after patent expiry, the graph shows the differences between market shares of the repeated purchases by patients who started three months before and three months after the patent expired. The group that started in the three months before the patent expiry initially consumed OxyContin, while the patients who started after the patent expiry consumed either OxyContin or a generic (including branded generic). A share over 0 implies that a product was purchased relatively more often by patients who started before the patent expiry compared with patients who started after the patent expiry.

Figure A.3: Instrumental Variable Regression Results, Oxycodone



Notes: The graph shows second-stage coefficients for different substitution groups of cxycodone. Coefficients for each substitution group are divided into coefficients for the initial three months and for months four to six. A coefficient for the first three months equal to $\beta_3 = .5$ indicates that the initial consumption of a generic increases the possibility of purchasing a generic again during the following three months by 50%. Error bars show 95% confidence intervals.

Table A.1: Instrumental Variable Regression Results, Oxycodone

Substitution Group	First Stage, Months 1-3	β_3	First Stage, Months 4-6	β_6
242	0.185***	1.4385***	0.125***	-0.002
	(0.045)	(0.45)	(0.045)	(0.729)
231	0.269***	1.2645***	0.2775***	0.6525*
	(0.05)	(0.326)	(0.067)	(0.354)
227	0.341***	0.4895***	0.3215***	0.4655***
	(0.016)	(0.065)	(0.02)	(0.097)
224	0.304***	0.5735***	0.2115***	1.3325***
	(0.023)	(0.108)	(0.031)	(0.302)
220	0.416***	0.4655***	0.4125***	0.1165**
	(0.011)	(0.035)	(0.015)	(0.049)
217	0.437***	0.7725***	0.4395***	-0.1975**
	(0.013)	(0.042)	(0.024)	(0.076)
233	0.288***	0.4915***	0.2495***	0.7075***
	(0.028)	(0.133)	(0.035)	(0.224)
232	0.021***	-0.191	0.0125***	-0.736
	(0.008)	(0.599)	(0.007)	(0.937)
226	0.068***	0.2985***	0.0955***	0.015
	(0.006)	(0.105)	(0.01)	(0.083)
219	0.108***	0.4765***	0.1135***	0.1415***
	(0.005)	(0.045)	(0.006)	(0.051)
236	0.32***	0.7755***	0.4165***	0.3715***
	(0.005)	(0.019)	(0.01)	(0.037)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Results of the instrumental variable regression for different substitution groups of oxycodone. The first stage of the instrumental variable regression is shown, first for the initial three months and then for months four to six. The coefficients for the second stage are in columns β_3 and β_6. Standard errors are in parentheses.