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# GENERIC AND BRANDED PHARMACEUTICAL PRICING: COMPETITION UNDER SWITCHING COSTS*

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This article examines pricing in pharmaceutical markets where branded products face competition from generics. After providing evidence for brand premia and switching costs using prescription-level and matched socioeconomic data for the entire Swedish population, I estimate a dynamic oligopoly model and evaluate counterfactual policies that reduce the impact of frictions on pricing. Lengthening the procurement period reduces the impact of switching costs on prices. The policy increases prices on average, but more so for individuals with infrequent consumption, high education and income. In a counterfactual where brand choice decisions are moved from patients to medical experts, prices fall substantially.

Generic competition has an important role in reducing prescription drug prices. Following patent expiry, branded pharmaceuticals face competition from generic prescription drugs, and average prices decrease substantially (Conti and Berndt, 2018; Vondeling *et al.*, 2018). Yet, generic uptake is not universal, and stable low prices in the long run are not guaranteed. Even though generics provide medically equivalent alternatives[1] and medication does not carry any value beyond the treatment it provides, generics have a market penetration of less than 50% in most European countries (OECD, 2017). Additionally, branded originals often sustain higher prices (Conti and Berndt, 2018), and prices of prescription drugs in general can change frequently (Hauschultz and Munk-Nielsen, 2020b) or increase suddenly (Alpern *et al.*, 2014).

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The data and codes for this paper are available on the Journal repository. They were checked for their ability to reproduce the results presented in the paper. The authors were granted an exemption to publish parts of their data because access to these data is restricted. However, the authors provided a simulated or synthetic dataset that allowed the Journal to run their codes. The synthetic/simulated data and the codes for the parts subject to exemption are also available on the Journal repository. They were checked for their ability to generate all tables and figures in the paper; however, the synthetic/simulated data are not designed to reproduce the same results. The replication package for this paper is available at the following address: https://doi.org/10.5281/zenodo.7584309.

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[1] Counterfeit pharmaceuticals are a problem in large parts of the world. According to an OECD report (OECD, 2009), the incidence of counterfeit medicine is 1% across all medications, but is an increasing problem in some Asian and African countries. The problem of counterfeit medicine in the legal pharmaceutical industry in the European Union is less severe. In Sweden, counterfeit medicine has not received attention.

In this article, I seek to understand consumers' role in the high prices of originals, low uptake of generics and frequent price changes. In particular, I answer the research questions of how consumers' switching costs and brand premia affect firms' dynamic pricing incentives, and how those frictions should be factored into public policy decisions aiming to decrease the costs of prescription drugs for patients and government payers. This article proceeds in two steps. First, thanks to the regulatory structure of the Swedish prescription drug market, rich registry data and quasi-experimental settings, I show that consumers experience substantial brand premia and switching costs when choosing prescription drugs.[2] Second, I estimate a dynamic oligopoly model that incorporates the regulatory framework and offers firms the possibility to adjust prices in response to behavioural frictions. This behavioural pricing explains the persistence of high prices as well as the price dynamics of pharmaceuticals under generic competition. Using this model, I evaluate two policy counterfactuals that target the impact of switching costs and brand premia. In the first counterfactual, I evaluate a novel policy that increases the length of the procurement period and thereby reduces the impact of switching costs on pricing. The analysis reveals that switching costs are, on average, pro-competitive. However, the impact is heterogeneous as individuals with higher education and income and lower purchase, frequencies tend to benefit from more frequent price changes, which are due to pricing based on switching costs. In a second counterfactual, I show that a policy that aims to reduce brand premia by moving brand choice decisions from patients to medical experts results in lower prices.

Before estimating how prices would be impacted by switching costs and brand premia, I first explore the role of both of these behavioural frictions on consumer preferences for generic alternatives. I take advantage of the Swedish prescription market, in which patients are given monetary incentives to substitute to the cheapest available generic. Furthermore, pharmacists are required to explain and educate individuals about the medical equivalence of pharmaceuticals such that the Swedish system rules out inattention as a source of brand premia. Yet, we observe that up to 19% of individuals choose brands connected to additional costs. Showing behavioural frictions in a system where patients are not suffering from inattention is new to the behavioural economics literature. By comparing medical experts' consumption to general consumption as a measure of potential quality differences and by controlling for previous consumption, I show the key role of brand premia (experts are up to 26.4% or 2.5 percentage points less likely than non-experts to pay an additional price difference). Furthermore, switching costs play an important role (patients are up to 16% or 3.1 percentage points more likely to pay premia for a product if they consumed the identical product in the preceding month). Using a discontinuity surrounding patent expiration dates as a robustness check, I establish the causality of switching costs.

Having demonstrated patients' behavioural frictions, I use the sub-segment of high-dosage paracetamol pills to show the impact of the frictions on firms' pricing and how counterfactual pricing policies may affect patients. I estimate demand-side and supply-side models of branded and generic drugs, incorporating the regulatory framework and the behavioural frictions. The model estimates allow analyses of two counterfactuals. The first counterfactual evaluates effects

[2] The importance of switching costs in the retail market has been documented by Erdem and Sun (2001), Shy (2002), Viard (2007), Dubé *et al.* (2009), Shcherbakov (2016) and Rickert (2016). A substantial economic and marketing literature has addressed brand premia and the general concept of brand equity. Following Handel and Schwartzstein (2018), one may distinguish mental gaps from behavioural frictions that are in line with the neoclassical assumption of correct beliefs. For the latter, see Hortaçsu and Syverson (2004) for a discussion of risk aversion and possible information costs. Ackerberg (2001) discussed the importance of prestige effects. The other possibility is that consumers have mental gaps or psychological distortions (Handel and Schwartzstein, 2018). Also, the media has covered habit persistence and brand premia; see, for example, Mullainathan (2017) for *The New York Times*.

on prices and consumer welfare by changing the procurement procedure for prescription drugs. Under the hypothetical policy, firms are allowed to change the price of a product every 12 months instead of each month. Under this scenario, firms have a lower incentive to condition their prices on the switching costs of consumers. The results show that prices increase and patients' welfare decreases under the alternative regime with only annual procurement. As the counterfactual policy mimics the effects of lower switching costs, one can conclude that switching costs, on average, increase competitive pressure on prices.[3]

This article not only adds to the discussion about the competitive pressure of switching costs, but also analyses the heterogeneous welfare effects of the procurement counterfactual. Given the equilibrium prices of the benchmark with short procurement periods and the counterfactual prices with long procurement periods, I use individual-specific demand estimates that allow calculation of choice probabilities, and the consumer-specific price differences between the benchmark and the counterfactual. Under the counterfactual policy of extended procurement periods, most patients pay more for their painkillers. However, some patients profit from extended procurement periods. Using the individual-specific price differences based on the counterfactuals, I show descriptive correlation with patients' characteristics. In particular, patients who buy paracetamol infrequently and are highly educated, and have a high income pay more in the counterfactual scenario with longer procurement periods. The novel results indicate that a policy of longer procurement periods is anti-competitive on average, but could improve the welfare of patients who are caught in a firm's 'lock in and harvest' pricing strategy.

The second counterfactual investigates the situation in which all patients choose as if they were medical experts, limiting the role of brand premia in patients' choices. The hypothetical situation is closely related to directly targeting patients' perceptions of quality differences or a reform that makes substitution mandatory. In such a situation, substitution is mandatory if not opposed by a physician. Limiting brand premia is associated with price decreases and an increase in patients' welfare (costs for patients decrease by 4.1%). With less scope for brand premia, firms have less opportunity to take advantage of patients. A decrease in brand premia is profitable for the patients 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.

Finally, I conclude the article with a stylised counterfactual exercise that intends to shed light on the aggregate effects of brand premia, and switching costs on patients' and public health care expenditures. Using sub-segment-specific reduced-form estimates, I first show that, for most prescription drugs, patients experience brand premia and switching costs. Behavioural frictions are the largest for painkillers such as opioids or paracetamol products. I connect the reduced-form estimates to the structural model of the paracetamol market by imposing an assumption of a linear relationship between the size of the reduced-form estimates of switching costs and brand premia, and the counterfactual policy's impact on prices and, therefore, aggregate payment. This strong assumption allows me to evaluate the overall effectiveness of both counterfactual policies. From an aggregate expenditure perspective, a policy targeting a reduction in brand premia leads to larger aggregate changes in expenditures for patients and the public.

The estimation of behavioural frictions in the pharmaceutical market, as well as the study of the impact of a policy that targets behavioural pricing, contribute to the literature on behavioural economics as well as to the study of pharmaceutical market competition, and any setting where switching costs and brand premia are present. First, I add to the literature that documents

[3] The results are in line with theoretical (Rhodes, 2014; Cabral, 2016) and empirical (Dubé *et al.*, 2009) research that shows that moderate switching costs could lower prices.

behavioural frictions. Closest to this article, Bronnenberg *et al.* (2015) studied experts' choices of over-the-counter headache remedies, showing that experts are more likely to choose generic products. I use the same method of comparing choices of patients and medical experts to identify brand preferences. However, in contrast to Bronnenberg *et al.* (2015), I take advantage of the Swedish pharmaceutical system, in which patients do not search for a preferred brand on a shelf, but get educated about medical equivalence and actively have to oppose substitution. As inattention and search costs are not an explanation for brand choices, I add to the literature in documenting that brand preferences and switching costs persist even among regulated prescription drugs.[4] I also add to the literature by documenting switching costs among prescription drugs, in line with evidence presented by Feng (2022) and Hauschultz and Munk-Nielsen (2020a).

Second, the main contribution of this article is the investigation of behavioural pricing and policies that intend to reduce its impact. While brand premia are well known to be anti-competitive (e.g., Bronnenberg *et al.*, 2015), switching costs may increase or decrease competitive pressure,[5] and the empirical literature does not consider the heterogeneous effect of switching costs on consumers. This article shows that markets with switching costs may help to reduce average prices but potentially increase the range of prices paid by patients.

Finally, I add to a policy-relevant discussion on the regulation of markets where consumers experience frictions. I evaluate an increase in the length of procurement contracts, as it represents a realistic and easy-to-implement policy intervention.[6] To target pricing based on brand premia, I suggest a policy that moves the decision of choosing pharmaceuticals from non-experts to experts. While this change reduces consumers' freedom of choice, it has strong effects on pricing behaviour. The effects of switching costs are important for policymakers. First, switching costs are empirically important when evaluating firms' price incentives. Second, switching costs do not necessarily increase prices in equilibrium on average. Third, I show that switching costs have a heterogeneous impact across consumers. While a slight majority of patients benefit from paying lower prices when firms follow a 'lock in and harvest' pricing strategy, patients with lower income, less education and frequent prescriptions that likely relate to worse health conditions, pay more when firms condition their prices on switching costs. Firms take advantage of these consumers while others pay less. Policymakers must carefully evaluate the size and effect of switching costs in a pricing equilibrium. Furthermore, in some markets, such as the health care market, policymakers should consider potential heterogeneous effects that may be connected to negative welfare effects on vulnerable consumers.

## 1. Pharmaceuticals in the Swedish Health Care System

The pharmaceutical system is publicly funded. Prescription drugs are reimbursable.[7] Patients' co-payments depend on the yearly costs for pharmaceuticals. The higher the yearly costs, the

[4] Therefore, my approach differs from the existing literature on insurance choices (Handel, 2013; Marzilli Ericson, 2014; Handel and Kolstad, 2015; Ketcham *et al.*, 2015; Abaluck and Gruber, 2016; Bhargava *et al.*, 2017; Ho *et al.*, 2017; Miller, 2019), not only because I investigate consumer choices of physical consumption products, but also because inattention is not an option.

[5] 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).

[6] Granlund and Rudholm (2018) proposed a policy of a longer contract time and suggested that it decreases the possibility of collusion.

[7] 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, 2016c).

lower the fraction a patient has to pay out of pocket. Costs above a ceiling are entirely covered.[8] Almost half of the revenue from prescription pharmaceuticals is from coverage for patients who have reached the cost ceiling (Bergman *et al.*, 2012). Because of the low ceiling, a function of decreasing co-payments and generally lower drug prices, we do not observe non-linear price schedules as occur in the United States under Medicare Part D.[9]

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. Each product within a substitution group is medically equivalent. Only non-active ingredients such as colouring or sugar content may differ; however, medical equivalence is tested (Swedish Medical Product Agency, 2010). For specific drugs, such as for some anti-epileptics, an incremental variation of ingredients could have adverse health effects. In those cases, each product forms its own group, and substitution is not possible. In the case of pharmaceuticals with generic competition where substitution is medically appropriate, patients with a prescription for a product in a substitution group are incentivised to acquire the cheapest available generic in the substitution group. Substitution of the cheapest product happens at the pharmacy level (Sveriges Riksdag, 2002). A pharmacist is obliged to recommend the cheapest available generic to patients. Furthermore, pharmacists are required to explain the medical equivalence of the products. 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.[10] Third, the cheapest available product may not be in stock at the pharmacy. In such a case, the second cheapest product is dispensed.

The Swedish pharmaceutical market had a market turnover of $4.15 billion in 2015, with $3.08 billion due to prescription drugs; patients' co-payments accounted for $0.64 billion (TLV, 2016a). Since 2002, a tendering system based on a sealed-bid first-price auction determines prices of off-patent drugs in each substitution group. A pharmaceutical company that wishes to sell a product submits a price at the end of a month (month $t = 0$) for the month after the next (month $t = 2$). Companies have to bid a lower price than the specified ceiling.[11] The auctioneer publishes a preliminary list of prices in the middle of the next month (month $t = 1$). After the supplier of the cheapest product confirms the ability to service the entire Swedish market, prices are implemented.[12] Note that the pharmaceutical companies observe the list for month $t = 2$ before bidding for the month after that (TLV, 2016b).

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

[9] Drug purchases in Medicare Part D are characterised by the 'donut hole', a coverage gap for patients. Purchases of drugs are lower around this coverage gap as consumers decrease purchases as well as substitute drug expenses to the following year (Zhang *et al.*, 2009; Einav *et al.*, 2015; Dalton *et al.*, 2020).

[10] 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.

[11] The usual ceiling is 35% of the original brand product price before expiration of the patent. 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 authorisation was at least 15 years ago (TLV, 2016d).

[12] 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.

Pharmacy purchasing prices for reimbursable, patent-protected pharmaceuticals are also regulated. Manufacturers apply with a specific price for a patent-protected product. The Dental and Pharmaceutical Benefits Agency (TLV) determines whether the price requested by a manufacturer is reasonable. Assessment is based on a 'value-based pricing approach' that considers principles of equality, solidarity and cost-effectiveness (TLV, 2017).

Retail prices are regulated and dependent on the prices in the auction (or the value-based pricing for patent-protected products) as an almost linear function of pharmacy purchasing prices. The difference between the retail and pharmacy purchasing prices provides the pharmacy's trade margin.[13] Although some pharmacies were privatised in 2009, pharmacists are required to dispense the cheapest available product (Sveriges Riksdag, 2002). As noted, the pharmacy can dispense the second cheapest product if the cheapest product is not in stock.[14]

## 2. Data

I use data for painkillers (ATC code N02), antibiotics (ATC code J01) and anti-epileptics (ATC code N03) from January 2010 through June 2016 in Sweden.[15] The data are provided by Socialstyrlsen, the Swedish governmental agency for health and welfare (Socialstyrlsen, 2022). 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 (Swedish Dental and Pharmaceutical Benefits Agency, 2022). 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.

The patient-specific data are collected on the pharmacy level and reported to health authorities. After a transaction, a pharmacist records a personal identifier, the dispensed product and the time of the transaction. If an individual receives the cheapest available generic within a substitution group, the pharmacist solely records the dispensed product. In this case, the prescribed product is not recorded. However, by choosing not to oppose substitution, the physician has acknowledged the suitability of substitution to the cheapest available product. If a physician opposes substitution, the pharmacist records the dispensed product and the physician's decision to oppose substitution. If a patient opposes substitution, the pharmacist records the dispensed and prescribed products as well as the fact that the patient opposed substitution. Finally, also, the pharmacy can dispense a product that is not the product of the month if the cheapest product is out of stock. Also in this case, the pharmacist records why substitution to the cheapest product did not happen. Therefore, the data allow me to directly track if and why substitution is opposed.

By connecting the choices to Swedish registry data provided by Statistics Sweden (SCB) (Statistics Sweden, 2022), I observe the patient's place of residence (county and municipality) and some socioeconomic characteristics. The socioeconomic data consist of yearly income and details of the individual's education (length, degree and subject area). Finally, for non-prescription drugs,

[13] I describe the exact relationship between purchasing and retail prices in Online Appendix A.

[14] Additionally, a pharmacy can sell the remainder of the previous month's cheapest product in the first two weeks of a new month. Afterwards, pharmacies can sell the products at the pharmacy's purchasing price without profit. The pharmacy has no incentive to overstock the product.

[15] The selection of the three sub-markets is not intentional and based on data provision by Swedish authorities. 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.

Table 1. *Summary Statistics.*

| | Painkillers | Antibiotics | Anti-epileptics |
|---|---|---|---|
| *Panel A: product level* | | | |
| Number of substances | 10 | 24 | 4 |
| Number of substitution groups | 162 | 167 | 39 |
| Number of products | 629 | 513 | 96 |
| Average number of products in substitution groups | 3.22 | 2.44 | 1.97 |
| | (2.35) | (1.8) | (0.8) |
| Percent originals | 0.21 | 0.15 | 0 |
| | (0.41) | (0.35) | (0) |
| Percent generics | 0.76 | 0.72 | 0.82 |
| | (0.43) | (0.45) | (0.39) |
| Average price (in SEK) | 288.86 | 231.62 | 390.37 |
| | (342.62) | (291.11) | (383.73) |
| Average price of originals (in SEK) | 357.91 | 331.36 | – |
| | (425.91) | (312.03) | |
| Average price of generics (in SEK) | 266.45 | 195.46 | 377.77 |
| | (313.84) | (274.02) | (395.74) |
| *Panel B: consumer level* | | | |
| No. of purchase occasions (in millions) | 39.46 | 13.62 | 0.56 |
| No. of patients (in thousands) | 3,233 | 4,722 | 61 |
| Avg. purchase occasions per patient | 12.2 | 2.9 | 9.2 |
| | (26.14) | (3.48) | (14.08) |
| Avg. monthly total costs (in million SEK) | 47.67 | 23.04 | 2.78 |
| Avg. monthly co-payment (in million SEK) | 18.3 | 14.44 | 0.7 |
| *Panel C: substitution decisions* | | | |
| Fraction consuming the product of the month | 0.755 | 0.867 | 0.928 |
| | (0.43) | (0.339) | (0.258) |
| Fraction with substitution opposed by patient | 0.192 | 0.094 | 0.028 |
| | (0.394) | (0.292) | (0.166) |
| Fraction with substitution opposed by physician | 0.021 | 0.005 | 0.018 |
| | (0.145) | (0.07) | (0.133) |
| Fraction with substitution opposed by pharmacy | 0.031 | 0.034 | 0.025 |
| | (0.173) | (0.18) | (0.157) |

*Notes:* The table shows summary statistics for the three market segments of painkillers, antibiotics and anti-epileptics. Prices are in Swedish krona (10 SEK is approximately 1 USD). Panel A describes markets on the product level. Branded generics are included in the generics category. Panel B shows summary statistics considering patients' purchasing decisions. The number of purchase occasions is the sum of purchase occasions across consumers between January 2010 and June 2016. Average purchase occasions are the number of purchases by the average patient. The total costs include costs for insurance as well as for the patient (co-payment). Panel C describes substitution decisions. The fraction of consumption of the product of the month (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). SDs are given in parentheses.

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.

Panel A of Table 1 shows a basic market description. In the study period, the average number of products per substitution group was 3.22 for painkillers, 2.44 for antibiotics and 1.97 for anti-epileptics. For all three therapeutic groups, the majority of products are generics. Originals are on average more expensive than generics.

Panel B of Table 1 shows basic demand characteristics for all three markets. The number of purchase occasions is much higher for painkillers (approximately 39.5 million) and antibiotics (approximately 13.6 million) than for anti-epileptics (0.6 million). Also, the number of unique

patients who received an anti-epileptic is much lower than for painkillers or antibiotics (approximately 61,000 for anti-epileptics, compared with approximately 3.2 million for painkillers and 4.7 million for antibiotics).[16] Whereas painkillers and anti-epileptics are often repeatedly purchased by the same individual, antibiotics have a much lower average number of purchase occasions. Note also that a large variability exists among painkillers. The co-payment share is much lower for anti-epileptics than for antibiotics and painkillers. 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. Panel C of Table 1 shows the substitution behaviour of patients for the three therapeutic groups. In line with the regulatory intent, the majority of patients receive the cheapest product, the product of the month (PoM). However, heterogeneity between and within the therapeutic groups is observable: 75.5% of patients purchased the PoM when getting a prescription for painkillers, whereas 86.7% and 92.8% of patients purchased the PoM for antibiotics and anti-epileptics, 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.

## 3. Empirical Analysis

Before starting to analyse how behavioural frictions affect firms' pricing, I first turn to estimate switching costs and brand premia. Within the reduced-form analysis, I evaluate choices on the dispensing level, meaning that each dispensed prescription is one observation. In the demand estimation in Section 6.1, I use a discrete-choice model where I model choices in detail. The major advantage of the reduced-form framework is that it evaluates the importance of behavioural frictions without estimating a demand system. Consider the model

$$P(OpposeSubst_{ist} = 1) = \alpha + \beta_1 D_{ist-1} + \beta_2 Med_{it} + \beta_3 D_{ist-1} \times Med_{it} + \rho X_{it} + D_{is0} + \gamma_{st} + \varepsilon_{ist}, \quad (1)$$

where the outcome variable is a dummy that takes the value 1 if individual $i$ in period $t$ opposes substitution to the cheapest available product of substitution group $s$. In substitution group $s$ all products of the unique size × strength × 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. Here $D_{ist-1}$ is a dummy that takes the value 1 if individual $i$ chose the same product in the last purchase that occurred within a month of the current purchase and 0 if not;[17] $Med_{it}$ is the variable of interest, which examines the impact of whether a patient has had medical education as a physician; the $X_{it}$ are controls such as the logarithm of income, the geographical location and the general education level.[18]

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

[17] This model requires that the patient purchased the product in the previous month. If I also considered 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.

[18] I control for the geographical location on the county level to control for differences across counties. While prices are identical across regions of Sweden, some pharmacy retail brands differ across regions. Thus, the geographical fixed effects control to some degree for differences across pharmacy brands.

I use fixed effects of substitution groups in each time period ($\gamma_{st}$). 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 behaviour or perceived quality differences, for example, the price differences between products.

State dependence due to switching costs is measured by $\beta_1$ and perceived quality differences by $\beta_2$. 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 $D_{ist-1}$.[19] 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 $D_{is0}$, a dummy that takes the value 1 if patient $i$ consumed the same product as in $t$ 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).[20]

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. Having excluded that inattention plays a role, as patients get their information at the pharmacy level, I measure the perceived quality differences by $\beta_2$. 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 $\beta_3$ is not significantly different from zero.

I show results of the reduced-form evidence of model (1) in Table 2. For each therapeutic group (painkillers, antibiotics and anti-epileptics), I show results of the full model including all fixed effects and covariates. A purchase of a product within the last month increases the probability of opposing substitution for painkillers significantly by 3.1 percentage points (16%). The increase is an average across all painkiller substances.[21] For antibiotics, previous consumption is associated with a significant increase of 1.1 percentage points (11.5%). For anti-epileptics, 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 anti-epileptics, 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' learning plays a role. In detail, patients use anti-epileptics in the long term. Those patients that use anti-epileptics in the long term may have frequently switched in the past and therefore know about the equivalence within a substitution group. It is also possible that the patients are used to acting in response to the information of

[19] For example, patients may have brand preferences and choose the same product repeatedly. See further discussion in Dubé *et al.* (2010).

[20] 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) recommended a slight adjustment of using the within means of time-varying variables as well as including the initial periods. 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. The homogeneity of products and the clean choice environment reduce the problem of unobserved heterogeneity and the endogeneity of the initial condition.

[21] The share of patients that purchase repeatedly, independent of the probability of opposing substitution, could be higher for some products due to a higher addiction potential. Considering evidence from actual repeated purchases, I do not observe a direct increase of repeated purchases with addiction potential. For example, compared with opioids, paracetamol products are on average more often purchased repeatedly.

Table 2. *Regression Evidence, Probability of Opposed Substitution.*

| | Opposed substitution | | |
|---|---|---|---|
| | Painkillers | Antibiotics | Anti-epileptics |
| $D_{t-1}$ | 0.0309*** | 0.0108*** | −0.0060*** |
| | (0.0002) | (0.0005) | (0.0005) |
| $Med$ | −0.0547*** | −0.0249*** | −0.0112*** |
| | (0.0017) | (0.0007) | (0.0041) |
| $log(Income)$ | −0.0004*** | 0.0006*** | −0.0001 |
| | (0.0001) | (0.00003) | (0.0001) |
| $D_{t-1} \times Med$ | 0.0028 | 0.0018 | 0.0056 |
| | (0.0039) | (0.0036) | (0.0066) |
| Education | Yes | Yes | Yes |
| Control heterogeneity | Yes | Yes | Yes |
| Geographic fixed effects | Yes | Yes | Yes |
| Fixed effects | Subgroup×year-month | Subgroup×year-month | Subgroup×year-month |
| Mean opp. subst. | 0.192 (0.394) | 0.094 (0.292) | 0.028 (0.166) |
| Mean price SEK | 99.686 (138.94) | 122.691 (83.91) | 373.681 (211.07) |
| Mean overpayment SEK | 9.475 (25.102) | 10.766 (21.791) | 7.679 (26.639) |
| $D_{t-1}Increase$ | 16.04% | 11.52% | –21.04% |
| $Med$ increase | –28.46% | –26.42% | –39.49% |
| $N$ | 36,471,580 | 12,695,230 | 530,263 |
| $R^2$ | 0.2288 | 0.1215 | 0.0616 |

*Notes:* Linear least squares regression results for the segments of painkillers, antibiotics and anti-epileptics. One observation corresponds to one specific purchase occasion by a patient. The outcome variable is a dummy variable that takes the value 1 if a patient opposes substitution in order to receive a more expensive product. The patient bears the additional costs. Here $D_{t-1}$ 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 education categorised into six levels. Geographic fixed effects indicates if the model controls for county-level fixed effects. The lower part of the table shows the average fraction of opposed substitution as well as the price and average payment of those that oppose substitution (in Swedish krona; 10 SEK equals approximately 1 USD). Finally, I also state the percentage increase of opposed substitutions associated with past consumption (switching costs) and medical education (quality misconceptions). Standard errors are clustered on the individual level, adjusted for heterogeneity, and shown in parentheses. *** $p < 0.01$.

a pharmacist who recommends switching. Therefore, long-term usage lets patients learn that switching within a product group is possible.

Secondly, Table 2 shows that medical education is associated with a significantly lower probability of opposing substitution (painkillers, 5.5 percentage points or 28.5%; antibiotics, 2.5 percentage points or 26.4%; anti-epileptics, 1.1 percentage points or 39.5%). I interpret the difference as perceived quality differences. Note that the interaction between previous consumption and medical education is insignificant for all three therapeutic groups. In other words, medical education is not associated with higher or lower switching costs. The lack of effect supports the fact that perceived quality differences and switching costs induced by previous consumption are not correlated.[22]

To show robustness of the reduced-form estimation, I use a quasi-experimental setting to show causal evidence for state dependence due to switching costs for a small part of the substitution groups, those where a patent expired between 2010 and 2016. I show the results of the robustness check in Online Appendix B.2.

[22] In Online Appendix B.1, I show that patients with an education as a pharmacist are also less likely to oppose substitution. However, the effect is smaller than for medical experts. Furthermore, patients with a nursing degree show no differences from the general population.

## 4. 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. Most importantly, 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. Furthermore, modelling the supply side allows me 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 set-up of the demand side and then present the supply-side model.

### 4.1. *Demand*

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

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

Consumers are myopic and not forward looking.[23] Each product $j$ is part of a set of products that form a substitution group. As almost all prescriptions in Sweden are filled (Ekedahl and Månsson, 2004; Ax and Ekedahl, 2010), I assume that there is no outside good. Each coefficient of utility varies at least over the substitution group. First, there is a random brand-specific intercept $\gamma_{ijs}$. 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. Here $\rho_{is}$ captures the impact of switching costs and varies across each patient within a substitution group; $p^C_{jst}$ is the price of product $j$ at time $t$ corresponding to the patient-specific price based on the co-payment and eventual price differences between the cheapest and more expensive products. The price coefficient $\alpha_{is}$ also varies across consumers within a substitution group. Variable $h_{ijs}$ denotes the unobservable heterogeneity of patients and product characteristics, and $\varepsilon_{ijst}$ is an error term.

Estimation requires two adjustments to ensure identification of the price elasticity and switching cost estimates. It is possible that prices $p^C_{jst}$ are correlated with unobserved product characteristics, that is, $E[p^C_{jst} h_{ijs}] \neq 0$. 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 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, instruments $Z_{jst}$ are prices of other products from the same brand for the same therapeutic segment (painkillers). The instruments are comparable to the Hausman instruments (Hausman and Bresnahan, 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 form $p^C_{jst} = Z_{jst}\gamma + \rho_j + \mu_t + \kappa_{jst}$, where $\rho_j$ and $\mu_t$ are product and time fixed effects, respectively. The exclusion restriction requires that the idiosyncratic error term $\kappa_{jst}$ 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

[23] A prescription is connected to a fixed quantity. Patients do not have the possibility to stockpile.

should not violate the exclusion restriction.[24] As usual for the control function, the residuals $\kappa_{jst}$ enter the main estimation equation, and the error term of the main equation is adjusted accordingly.[25]

Second, I try to control for unobserved heterogeneity among consumers. As in Section 3, I control for the initial product choice of individuals that I observe in my sample. The final structural equation that incorporates the control function approach, as well as controls for unobserved heterogeneity, takes the form

$$u_{ijst} = \gamma_{ijs} + \rho_{is} y_{ijs,t-1} + \alpha_{is} p^{C}_{jst} + \mu_{is} y_{ijs,FIRST} + \lambda \kappa_{jst} + \epsilon_{ijst}, \tag{2}$$

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 in substitution group $s$.

### 4.2. *Supply*

In each period $t = 1, \ldots, \infty$, 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 $j = 1, \ldots, N_t$ sets a price $p_{jt}$ at $t$. The value of $p_{jt}$ has to be lower than a regulatory price ceiling $R$. 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. Second, the assumption allows for a tractable model solely investigating a specific substitution group. 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.[26] 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 $t$. 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, beside the marginal costs $c_{jt}$, which differ across time and brands, 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

[24] Advertisement may affect demands for brands in all substitution groups such that prices as well as unobserved demand characteristics are correlated. 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.

[25] In detail, let the old error be $\varepsilon_{ijst} = \lambda \kappa_{jst} + \epsilon_{ijst}$. As $p^{C}_{jst}$ is a function of $Z_{jst}$ and $u_{jst}$, it is uncorrelated with the new error $\epsilon_{ijst}$.

[26] The difference between the demand-side and supply-side prices is determined by the trade margins of the pharmacies; see Online Appendix A. For the substitution groups of interest (under consideration of the price ceiling), the relation between purchasing (supply side) and retail price (demand side) is linear. Given the retail price, consumers pay co-payments that depend on their yearly expenses and whether they choose the cheapest available product.

equilibria. Following previous literature (Maskin and Tirole, 1988; Ericson and Pakes, 1995) I reduce the equilibrium space to symmetric Markov perfect equilibria. One restricts sub-game perfect equilibria to only the payoff-relevant strategies of a sub-game. State variables are sufficient to determine a payoff. In detail, firms condition their strategy $\sigma_j$ on the cost shock $\varepsilon_{jt}$ and the state variables $\mathcal{S}_{jt}$, which include the lagged market shares ($m_{jt-1}$), the lagged number of firms ($|N|_{t-1}$), a dummy that 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 ($\sigma_j : (\mathcal{S}_{jt}, \varepsilon_{jt}) \rightarrow p_{jt}$). Given that firms discount future profits with $\delta \in (0, 1)$, the value function of firm $j$ is

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

The first term is the per-period profits. 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 and co-payments 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:

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

Here, $\phi_t$ of the consumers at $t + 1$ were already present in period $t$. 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 (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 period $t$. For $\tilde{m}^S_{jt+1}$, $\bar{y}_{jt-1}$ is given by the market shares in period $t$, $m_{jt}$. Here $(1 - \phi_t)$ 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.[27]

All in all, firms in $t$ estimate future profits by assuming that the average patient is the same as in period $t$. 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 $\sigma^*_j$ forms a Markov perfect equilibrium if and only if, for all $j \in N^s$, it holds that $V_j(\sigma^*_j, \sigma^*_{-j}, \mathcal{S}_{jt}, \varepsilon_{jt}) \geq V_j(\sigma_j, \sigma^*_{-j}, \mathcal{S}_{jt}, \varepsilon_{jt})$ for all $\mathcal{S}_{jt}$ and $\varepsilon_{jt}$.

[27] 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 $\phi_t$, as well as the average value of consumers having consumed a product in the previous period, $\bar{y}_{it-1}$. 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 the past period).

## 5. Estimation

### 5.1. *Demand*

At each point in time, an individual attaches a utility to a product (see (2)). First, I make an assumption about the choice set of consumers. 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 almost all of the actual purchases in the data are covered by the chosen choice sets. Next, I assume that patients are myopic and do not form expectations of future prices such that switching cost estimates would be dependent on beliefs about future prices.

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 (see (2)). Given each individual $i$ and time $t$, the choice set may change. I assume that $\epsilon_{ijst}$ 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 (see (2)). Technical details are provided in Online Appendix C.1.

### 5.2. *Supply*

On the supply side I use a two-step estimator. In the initial step I estimate the policy function that characterises 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 $\mathcal{S}_{jt}$ 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 period $t$. In practice, I estimate the pricing policy $\sigma^*$ in a reduced-form least squares regression:

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

Note that the number of competitors in the previous period is treated as a factor variable in order to increase flexibility. Therefore, $\eta$ corresponds to a vector of coefficients. Within the linear least square estimation of the pricing policy, I do not explicitly model that each price is subject to a price ceiling. Thus, the dynamic approach based on Bajari *et al.* (2007) comes with the costs of explicit consideration of price constraints that could be incorporated into a static setting such as in Dubois and Lasio (2018). In their approach, the authors considered multiple binding and non-binding pricing constraints when estimating price-cost margins in the French pharmaceutical market.

The second stage of the estimator uses the optimal policy function (see (4)), which is assumed to be generated by the play of a Markov perfect equilibrium to estimate unobservables that rationalise 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. Furthermore, I assume that the profit function is correctly specified and known up to the marginal costs. I assume that firms discount future monthly profit

with $\delta = 0.995$. Transition probabilities from the firms' points of view are estimated based on the assumptions presented in Section 4.2. The market share of the forthcoming period is a function of the demand characteristics within a period $t$ (see (3)). The value $\phi_t$, 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 period $t+1$ as in period $t$. Within the forward simulation at a given period $t$, the share $\phi_t$ 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 $\varepsilon_{jt}$ 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 $\sigma^*$ is a Markov perfect equilibrium, it has to hold that the expected valuation given a state vector ($\mathcal{S}_j^t$) is higher than any other pricing strategy $\sigma$. The time superscripts are dropped as the equation binds in each period. We observe a Markov perfect equilibrium if

$$V_j(\sigma_j^*, \sigma_{-j}, \mathcal{S}_j, c_j) \geq V_j(\sigma_j, \sigma_{-j}, \mathcal{S}_j, c_j).$$

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 50 initial parameters of the state vector $\mathcal{S}_j^0$. For each initial state vector, I forward simulate the valuation function over 100 periods using the optimal pricing policy $\sigma^*$, using the transition probabilities.

Furthermore, in each period a private $\varepsilon_j$ shock is drawn. Correspondingly, the simulation of the valuation function given a marginal cost factor $\hat{c}_j$ is given by $\hat{V}_j(\mathcal{S}_j, \sigma_j, \hat{c}_j)$.

I use 200 alternative policy functions $\sigma$ that are different to $\sigma^*$. Here I also simulate valuation functions by forward simulation. I denote one of the 50 initial draws of the state vector with $\mathcal{S}_j^R$ ($R = 50$) and the 200 non-optimal policy functions with $\sigma^k$ ($K = 200$). Given a marginal cost parameter $c^{tj}$, the difference between the optimal and non-optimal valuation functions is described by $g(\mathcal{S}_j^R, \sigma_j^k, \hat{c}_j) = \hat{V}_j(\mathcal{S}_j^R, \sigma_j^k, \hat{c}_j) - \hat{V}_j(\mathcal{S}_j^r, \sigma_j^*, \hat{c}_j)$.

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 minimise the function

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

The indicator function $\mathcal{I}$ takes the value 1 if $g(\cdot) > 0$. Thus, I minimise 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.

Overall, 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. Furthermore, 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.

## 6. Results

In the following, I describe the results for the demand and supply sides separately. I start by analysing the estimation of the model for paracetamol tablets in a high dosage of 1 g, with a package size of 30 tablets. Paracetamol is a common drug; however, it requires a prescription in high dosage. The substitution group of high-dosage paracetamol tablets is one of the largest in the substitution group system. On average more than 50,297 unique patients purchase paracetamol in a month. I choose paracetamol for the analysis of the structural model for multiple reasons. First, it is an essential drug for manufacturers as it is the most sold drug. A variety of patients are using paracetamol such that I consider more than just a small subset of patients. Second, paracetamol has been out of patent for decades, reducing the chances that patent runoffs drive switching costs. Finally, the supply side of the paracetamol substitution group suits well for the analysis. Competition is similar to the overall market's average, but offers a lot of variation, including the availability of generics and originals. Therefore, the model includes results from different market structures that we would also find in other substitution groups.

Nevertheless, the focus on paracetamol raises questions of external validity. In other pharmaceutical substitution groups, we likely observe different estimates of switching costs, brand premia and different price elasticities of demand. On the supply side, some substitution groups are characterised by the lack of original products or a different market structure. Dependent on all these factors, the impact of counterfactual policies may differ. The estimation of the model for paracetamol is a useful exercise to explore the mechanisms of behavioural frictions. However, each friction's impact on pricing may differ in other substitution groups.

Because paracetamol is no longer covered by a patent, the market for it has at least two competitors for the entire time period. Prices in the substitution group show some volatility, as shown in Figure 1. On average, a paracetamol package in the time period has a price of 72.13 SEK (approximately 7.2 USD). Over the study period I observe on average 3.72 competitors. Visual examination suggests that competition has lowered prices over the study period.[28] The figure shows that 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 could be rationalised as the actions of forward-looking firms that lock in customers with low prices, and then increase their prices and 'harvest' consumers who do not switch despite the higher costs.

### 6.1. *Demand*

I now turn to the presentation of the demand side. I estimate the demand side as well as the counterfactual on a randomised sample covering one-sixth of the population as well as on the sample of all individuals with a medical education. The reduction in sample size is needed to ensure a sufficiently flexible demand estimation.

Table 3 shows the results of the control function as well as the random coefficient model. Note that the random coefficients are assumed to follow a normal distribution. First, the linear regression of the first stage shows that prices of other painkillers from the same firm have a strong impact on prices. Next, I show results of the demand estimation.

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

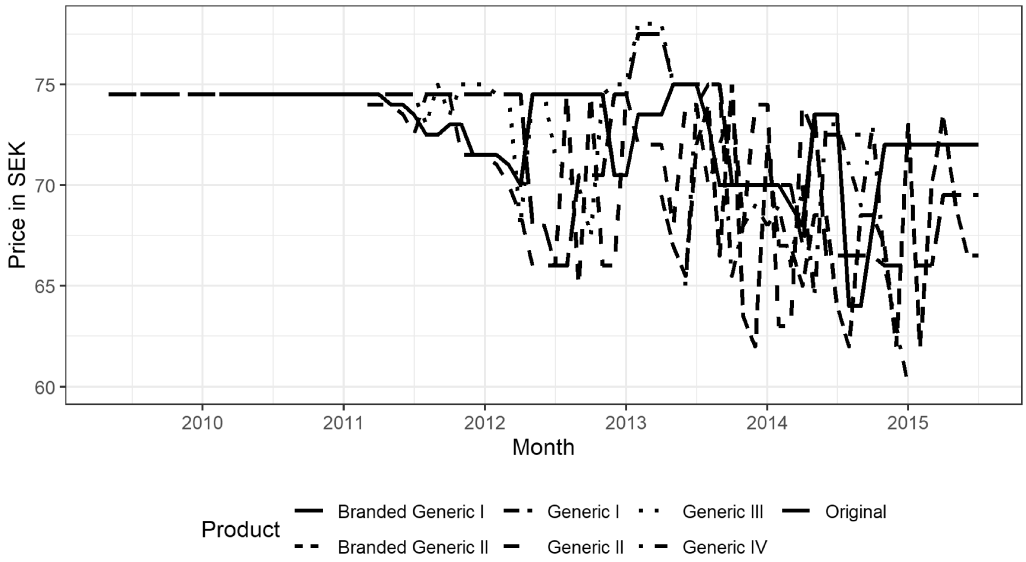


Fig. 1. *Monthly Prices in the Paracetamol Substitution Group.*
*Note:* Monthly prices in the substitution group for paracetamol, 1 g, 30 tablets, between 2010 and 2016. Paracetamol is off patent during the entire period. There is a price ceiling of 74.25 SEK (approximately 7.4 USD) that increased for two months to 78 SEK (approximately 7.8 USD).

Models 1 and 2 evaluate the demand of the random sample, whereas model 1-med and model 2-med consider only those patients with a medical education. First, the upper part of Table 3 presents the brand-specific intercepts. The middle part of Table 3 shows the mean and the SD of the random coefficients for prices and the previous consumption (corresponding to $\alpha_i$ and $\rho_i$ in the estimation in (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. Model 2 and model 2-med further control for unobserved heterogeneity by controlling for the first observation within the sample. I add the control function approach to control for potential price endogeneity in model 2 and model 2-med.[29]

The main results of Table 3 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 very reasonable in size. On average, patients are willing to pay approximately 0.175 USD more for a product when they have consumed it before (between 2% and 3% of the average price).[30] 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

[29] 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.

[30] Formally, the willingness to pay for consumer $i$ is defined as the state dependence coefficient ($\rho_i$) divided by the negative of the price coefficient ($\alpha_i$). Here, I take model 2, $WTP = 0.313/0.179 = 1.75$ SEK, which corresponds to 0.175 USD.

Table 3. *Regression Evidence, Demand Model.*

| | First stage | Model 1 | Model 2 | First-stage med. | Model 1-med | Model 2-med |
|---|---|---|---|---|---|---|
| Price of other painkillers | 0.103*** | | | 0.102*** | | |
| | (0.002) | | | (0.008) | | |
| Branded generic I | | 0.422*** | 0.687*** | | 0.112*** | 0.362*** |
| | | (0.005) | (0.008) | | (0.025) | (0.033) |
| Branded generic II | | –0.523*** | –1.501*** | | –1.049*** | –1.725*** |
| | | (0.013) | (0.028) | | (0.075) | (0.145) |
| Generic I | | –1.159*** | –0.556*** | | –0.98*** | –0.436*** |
| | | (0.01) | (0.014) | | (0.049) | (0.063) |
| Generic II | | –1.205*** | –0.812*** | | –1.042*** | –0.67*** |
| | | (0.008) | (0.01) | | (0.037) | (0.043) |
| Generic III | | –0.894*** | –0.499*** | | –0.866*** | –0.497*** |
| | | (0.014) | (0.016) | | (0.071) | (0.077) |
| Generic IV | | –1.54*** | –1.033*** | | –1.082*** | –0.766*** |
| | | (0.016) | (0.018) | | (0.07) | (0.107) |
| Random brand intercepts | | No | Yes | | No | Yes |
| Price mean | | –0.16*** | –0.179*** | | –0.444*** | –0.411*** |
| | | (0.002) | (0.002) | | (0.016) | (0.016) |
| $\sigma$ | | 0.384*** | 0.255*** | | 0.501*** | 0.427*** |
| | | (0.003) | (0.003) | | (0.02) | (0.02) |
| State dependence mean | | 0.536*** | 0.313*** | | 0.325*** | 0.176*** |
| | | (0.009) | (0.009) | | (0.059) | (0.064) |
| $\sigma$ | | 0.338*** | 0.124*** | | –0.294** | –0.251 |
| | | (0.019) | (0.037) | | (0.149) | (0.248) |
| Control function | | | –0.003*** | | | –0.012*** |
| | | | (0.001) | | | (0.003) |
| Including control function | | No | Yes | | No | Yes |
| Unobserved heterogeneity | | No | Yes | | No | Yes |
| Loglikelihood | | –308,422 | –269,276 | | –13,027.23 | –11,490.62 |
| Year-month FEs | Yes | | | Yes | | |
| Product FEs | Yes | | | Yes | | |
| $F$-statistics instruments | 3,601.74 | | | 150.66 | | |
| $N$ | 1,260,594 | 1,108,765 | 1,006,481 | 51,893 | 44,631 | 40,134 |
| $R^2$ | 0.06 | | | 0.057 | | |

*Notes:* Results from the mixed logit estimation and the control function. One observation is a patient choice in the substitution group of paracetamol, 1 g, 30 tablets. The first three columns consider a random sample (one-sixth of the full sample, random selection), whereas the remaining columns solely consider patients with a medical education. The first stage shows results of the control functions, while the models show results of the demand model where the outcome variable is a dummy that indicates if an individual has chosen a product. 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 SDs are excluded. Random coefficients are assumed to follow a normal distribution. The lower part of the table shows the random coefficients for price and the state dependence. Note that I also report the SD 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. The $F$-statistic shows the result of a weak instrument $F$-test. Standard errors are given in parentheses. $^{**}p < 0.05, ^{***}p < 0.01$.

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. On average, patients are willing to pay a 9.9% higher price for the most preferred branded generic compared with a non-branded generic.[31] These brand premia are similar to those of other

[31] I calculate the value by taking the coefficient of *Branded generic I* minus the average coefficient of *Generic I* to *Generic IV*. I calculate the willingness to pay for this difference.

consumer goods.[32] However, brand premia are higher for the entire sample than for the sample with medical education, who are only willing to pay 2.8% more for the branded generic. 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.

### 6.2. *Supply*

I now present supply-side results that include the estimation of the policy function and the marginal cost estimation. First, panel A of Table 4 presents the reduced-form estimate of the policy function as described by (4). It is the first step of the two-step estimation. The outcome variable of the 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 product of the month (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 ($|N_{t-1}|$) 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 panel A of Table 4 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. Furthermore, a higher number of competitors is correlated with lower prices, while the market size (higher demand) is correlated with higher prices. Given the policy function estimate in model 3 of Table 4, panel A and the transition function in (3), I estimate marginal costs.[33]

Given the two initial steps, panel B of Table 4 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.[34] 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. Estimates of marginal costs in each period for each firm are statistically different from zero. In panel B of Table 4 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 SDs for the estimates across time. The marginal costs vary only slightly over time. One observes some differences in the marginal costs across products; however, they are not large. In particular, the first branded generic, which also has the highest brand premia in the demand model, has lower market share. As it is part of a well-known generic brand that has a high market share in a lot of sub-markets, it is possible that a large product base 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 characterised by capturing all the variability or price changes such that markups do not change over time. Dynamic pricing would therefore be explained by marginal costs. However, I do not observe such a correlation as products with large

[32] For example, Goldfarb *et al.* (2009) showed brand premia for ready-to-eat cereal of 19% or lower; Wiggins and Raboy (1996) reported brand premia up to 5% for bananas and Ailawadi *et al.* (2003) found brand premia lower than approximately 20% for different consumer packaged goods.

[33] Note that the share of patients who stay in the market between $t$ and $t+1$ ($\phi_t$) is inferred from the descriptive statistics in the data. On average across the time periods, 22% (SD 0.032) of the patients stay in the market.

[34] Details of the estimates are presented in Online Appendix D.2.

Table 4. *Supply Side Results.*

*Panel A: policy estimation*

| | Price | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Share$(t-1)$ | 2.598*** | 2.568*** | 1.589* |
| | (0.925) | (0.871) | (0.889) |
| $I(NoComp.(t-1)=3)$ | | | 0.062 |
| | | | (0.851) |
| $I(NoComp.(t-1)=4)$ | | | −0.286 |
| | | | (0.856) |
| $I(NoComp.(t-1)=5)$ | | | −1.091 |
| | | | (0.942) |
| $PoM(t-1)$ | | 2.482*** | 1.752*** |
| | | (0.416) | (0.469) |
| $Quantity$ | | | 0.0001*** |
| | | | (0.00003) |
| Constant | 71.066*** | 70.080*** | 61.178*** |
| | (0.331) | (0.353) | (2.313) |
| $N$ | 272 | 272 | 272 |
| $R^2$ | 0.028 | 0.142 | 0.262 |

*Panel B: marginal cost estimation*

| Firm | Mean marginal costs |
|---|---|
| Original | 18.32 |
| | (4.30) |
| Branded generic I | 16.69 |
| | (1.87) |
| Branded generic II | 23.89 |
| | (1.02) |
| Generic I | 19.57 |
| | (1.09) |
| Generic II | 20.52 |
| | (1.19) |
| Generic III | 21.51 |
| | (0.78) |
| Generic IV | 19.27 |
| | (0.68) |

*Notes:* Panel A shows the 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 given in parentheses. $^{*}p<0.1$,$^{***}p<0.01$. Panel B presents a summary of marginal cost estimates (in Swedish krona; 10 SEK equals 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 was present. I present SDs of marginal cross across monthly pricing periods in parentheses.

market shares (such as the first branded generic) tend to have higher prices, but lower marginal costs.

## 7. Counterfactuals

In the counterfactual analysis, I first present the implementation procedure and then show that an extension of the contract length that mimics a reduction of switching costs increases prices

in equilibrium. In the second counterfactual scenario, all patients act as if they had a medical education, and prices decrease.

### 7.1. *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 6.2. 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 whether their 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. Furthermore, I show in Online Appendix E.1 a model selection method (LASSO) based on the policy function.[35] I show technical details of the algorithm and its implementation in Online Appendix E.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 before, I take advantage of the demand parameters. I take the average consumer and assume that firms know how many patients stay in the market. 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's product 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. Furthermore, equilibria may not be unique, and the employed algorithms may lead to a different equilibrium than those 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 5 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 those in the data. In the lower part of Table 5, I show a comparison of the market shares in data and in the simulated benchmark model. The relation between the different brands in the benchmark

[35] Performing a model selection, I show that PoM status in the previous period and the quantity are the most predictive regressors. I therefore choose the previous PoM as the new state space. The method of regularisation using machine learning methods is related to the solution concept offered by Thiel (2019).

Table 5. *Benchmark Model, Products.*

| | Mean data | SD | Mean benchmark model | SD |
|---|---|---|---|---|
| | *Prices* | | | |
| Mean price | 71.76 | 3.63 | 70.11 | 2.19 |
| Mean price original/mean price avg. generic | 1.01 | | 1.01 | |
| | *Market shares* | | | |
| Branded generic I | 0.25 | 0.1 | 0.27 | 0.07 |
| Branded generic II | 0.44 | 0.24 | 0.42 | 0.22 |
| Generic I | 0.06 | 0.06 | 0.05 | 0.03 |
| Generic II | 0.04 | 0.04 | 0.02 | 0.02 |
| Generic III | 0.01 | 0.03 | 0.01 | 0.01 |
| Generic IV | 0.03 | 0.04 | 0.02 | 0.02 |
| Original | 0.19 | 0.12 | 0.19 | 0.11 |

*Notes:* The table compares the data and the prediction from the benchmark model. The upper part of the table shows comparison of prices. Prices are reported in Swedish krona (10 SEK is approximately 1 USD). The second and third columns show the mean prices and SDs from observable prices in the substitution group of paracetamol, 1 g, 30 tablets. The fourth and fifth columns show the prediction from the model with one state variable. 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 conditional on being present in a market. Note that not all products are available in each month.

model fits the data reasonably well. Overall, the benchmark model's key characteristics are close to those of the actual data.

### 7.2. *Extension of the Procurement Contract Length*

In the first counterfactual I do not change the demand side, but change the institutional background. Firms in this 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, behavioural pricing that intends to lock in consumers and harvest them in the forthcoming period is more expensive for firms. 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.[36]

Technically, I use the same demand model as presented before. The frequency of price changes is reduced 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 that in the benchmark model. On the supply side, I assume that firms that are present in at least two months 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

[36] In Online Appendix E.3 I estimate a counterfactual in which I directly reduce switching costs on the consumer side. I show that the results are analogous.

Table 6. *Results of Counterfactuals.*

| | Benchmark model | Counterfactual procurement | Counterfactual brand premia |
|---|---|---|---|
| *Panel A: average prices* | | | |
| Mean price | 70.11 | 70.59 | 67.49 |
| | (2.19) | (1.84) | (2.45) |
| Branded generic I | 69.66 | 70.42 | 66.09 |
| Branded generic II | 74.35 | 74.53 | 72.01 |
| Generic I | 68.41 | 69.39 | 65.84 |
| Generic II | 69.5 | 70.59 | 67.88 |
| Generic III | 71.42 | 71.86 | 69.12 |
| Generic IV | 67.67 | 69 | 66.37 |
| Original | 70.78 | 70.25 | 67.81 |
| *Panel B: average expenditures and revenue* | | | |
| Avg. price for consumer | 70.49 | 70.77 | 67.63 |
| Compared to benchmark | | 0.4% | –4.05% |
| Avg. revenue per month (in million SEK) | 4.6 | 4.74 | 4.41 |
| Compared to benchmark | | 3.15% | –4.03% |

*Notes:* The table shows a comparison between the benchmark model and the two counterfactual scenarios. The first counterfactual is the different procurement process. The second counterfactual mimics the case of a decrease in brand premia when all patients act as though they have a medical education. Panel A reports prices in Swedish krona (10 SEK is approximately 1 USD). Panel B shows measures of consumer costs as well as total revenues. SDs are given in parentheses.

patients that stay in a market over two subsequent months ($\phi$) as well as the discount rate ($\delta^{NEW} = 0.95$). 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.[37]

Table 6 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' (70.59 instead of 70.11 SEK). In panel B of Table 6, I show results that incorporate the behaviour of consumers and corresponding market shares of products. 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 slightly higher in the scenario of a different procurement process compared with the benchmark model. Furthermore, the market cap for firms increases in the counterfactual scenario.

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. This result is in line with the research of Dubé *et al.* (2009), Arie and Grieco (2014), Rhodes (2014), Fabra and García (2015) and Cabral (2016). These authors showed theoretically as well as empirically that moderate switching costs may increase competitive pressure. Even though switching costs increase the market power of a firm with locked-in patients and therefore induce 'lock in and harvest' behaviour, prices on average are lower. Because firms have an incentive to decrease prices in order to lock in patients, and moderate switching costs (see the demand-side estimates) prevent prices from becoming too high in the harvest phase, prices may be lower when switching costs are present. Also, the lower SD of prices in the

[37] 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.

counterfactual with a different procurement contract length confirms the lower variability of prices.

#### 7.2.1. *Who profits from a longer procurement length?*

As longer procurement periods mimic a reduction in switching costs, I will use the procurement counterfactual to assess which consumers profit from pricing due to switching costs. Several factors need to be considered when evaluating the overall effect of switching costs. In the following, I analyse which consumers profit from longer procurement periods. As the longer procurement periods mimic a reduction of switching costs, one can generally assess which consumers profit from pricing due to switching costs. To analyse how different consumers are affected by the counterfactual, I compare individual choices under prices from the benchmark model and those of the counterfactual. For each set of prices, I use the individual-specific coefficients from the demand model and calculate choice probabilities. With the choice probabilities, I calculate the expected prices each individual will pay in each of the two scenarios. Thus, I obtain a distribution of price differences. Furthermore, I can then condition the average price differences for different types of patients and therefore access if price differences are correlated with patients characteristics.

Figure 2 describes the results. First, Figure 2(a) shows the distribution price differences between the counterfactual of longer procurement length and the benchmark (a positive difference means that a consumer pays more in the counterfactual when switching costs play a less important role). While most patients pay slightly more after the increase of procurement length, some pay less. Figures 2(b), 2(c) and 2(d) present some characteristics of consumers that pay more or less in the counterfactual. First, observe that patients who consume paracetamol more frequently are more likely to have lower costs in the counterfactual as repeated purchases are necessary to suffer from dynamic pricing. Second, lower income and lower education correlate with lower costs for patients in the counterfactual. Thus, individuals in the lower percentile of income and education profit the most from the counterfactual where procurement plays a less important role for firms' pricing motive.

In a market with switching costs, average prices may lead to the idea that policies reducing the impact of switching costs are non-optimal as they increase prices. However, the analysis of the counterfactual that mimics the reduction of switching costs as firms dynamic pricing in response to switching costs is less profitable shows that switching costs are pro-competitive on average and increase prices for a substantial subset of patients. In a market where firms engage in dynamic pricing, patients with high switching costs get exploited. A policymaker may have the objective to reduce such inequality, especially as patients with lower education, greater need for pharmaceuticals and lower income are more likely to have switching costs.

### 7.3. *Brand Premia*

In the second counterfactual, I show the impact of brand premia due to perceived quality differences on pricing and consumers' welfare. In practice, I use the demand estimates from the 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 sample of experts, but do not change the sample of patients that stay in a market over two subsequent months.

Table 6 shows descriptive statistics of the pricing equilibrium in the counterfactual with a decrease in brand premia. On average, prices in the counterfactual, with a decrease in perceived

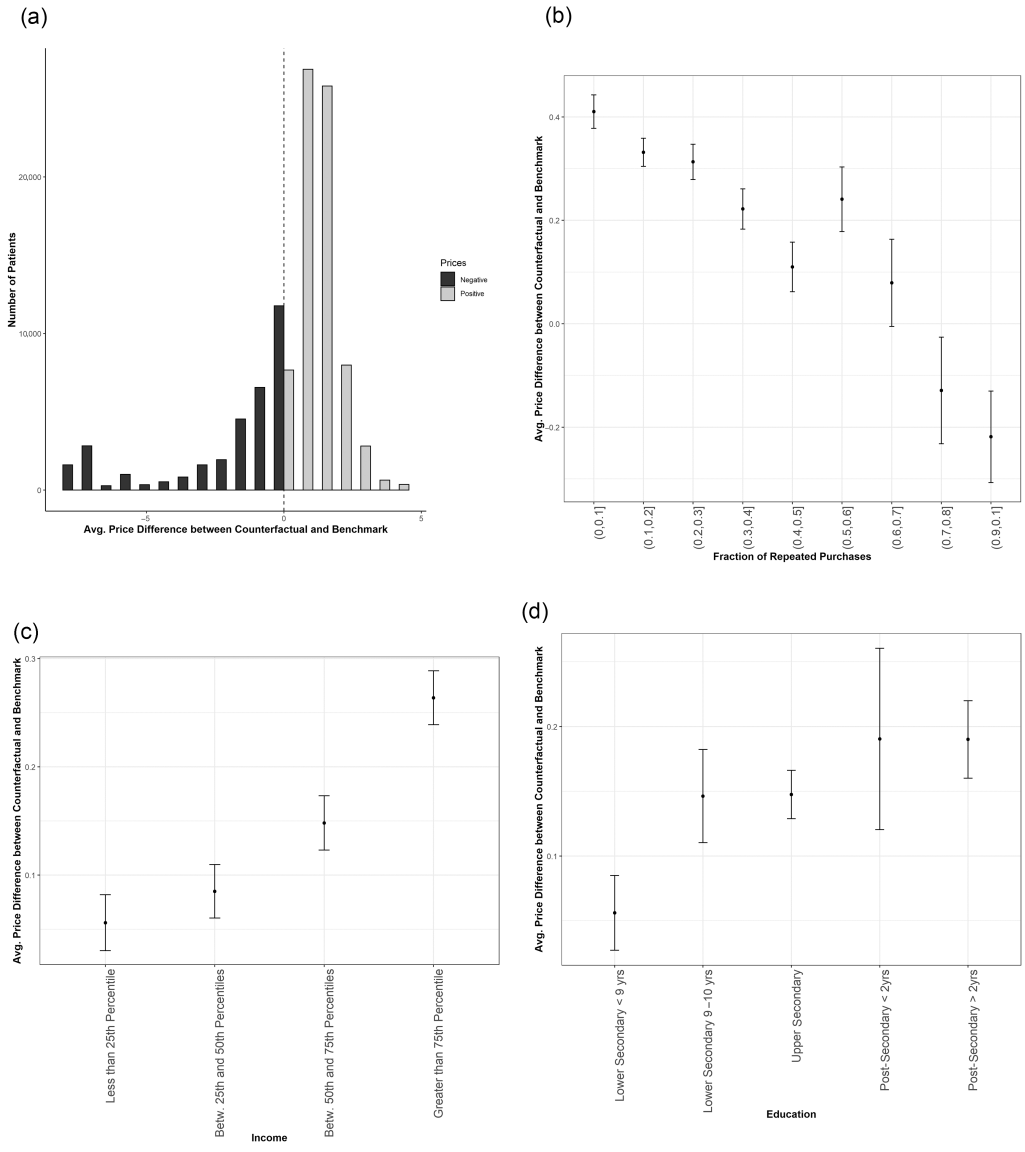


Fig. 2. *Profit and Loss from the Procurement Counterfactual.*

*Notes:* The four figures evaluate the heterogeneity of patients' payment in the procurement counterfactual compared with the benchmark scenario. Each observation considers a patient's individual purchase occasion given the prices in the counterfactual and the benchmark. Choice probabilities are estimated using results of the full demand model presented in (2). Panel (a) shows the distribution of purchase distributions according to the difference between the counterfactual and benchmark scenario. Panel (b) evaluates the mean price differences across the fraction of repeated purchases across consumers. Panel (c) presents the mean price differences across purchase occasions across income percentiles. Finally, panel (d) shows the price differences for different education levels. The error bars correspond to a 95% confidence interval.

quality differences, are lower than in the benchmark model (67.5 SEK versus 70.1 SEK). Thus, the results go in the opposite direction to 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.

Panel B of Table 6 shows the effects for the average consumer. With the decrease in perceived quality differences, the consumer pays on average 67.6 SEK for a product. Two effects play a role. First, prices are lower, as firms have less incentive to engage in behavioural 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 4.05% less for a product in the counterfactual scenario.

## 8. Discussion

This article provides evidence for switching costs and perceived quality differences in the Swedish pharmaceutical market. I estimate the impact of both behavioural phenomena on pricing through counterfactuals in the substitution group of paracetamol, 1 g. In the following, I provide a back-of-the-envelope calculation that quantifies aggregate effects of the counterfactuals across substitution groups on patients and public health care expenditure. Afterwards, I discuss policy implications.

### 8.1. *Aggregate Effects*

The effects of the increased length in procurement and the reduction in brand premia are based on the careful estimation that involves the estimation of demand, costs of firms and their maximisation procedure that involves competition. This is a time-consuming exercise, where the computer time alone required to run the simulations amounts to four days for one substitution group. Given that there are 400 substitution groups and it is not practicable to estimate the counterfactuals for each substitution group individually, I estimate the effects of the counterfactual using reduced-form estimates and connect them to the structural model of paracetamol. The procedure is the following. (1) For each substance group, I observe (different substances of painkillers, antibiotics and anti-epileptics), I estimate a model equivalent to (1) including year-month fixed effects. Estimates of $\beta_1$ give a raw estimate of the importance of switching costs, while $\beta_2$ shows the impact of brand premia. (2) I use the reduced-form and structural model estimates of the paracetamol substitution group to create a linear mapping between reduced-form estimates of behavioural frictions and the counterfactual impact on consumers and on public health care costs. This linear mapping assumes that each counterfactual has no effect on prices in case the respective behavioural friction is zero. The linear mapping is a reasonable assumption if a larger estimate of switching costs or brand premia can almost linearly map into the relative impact of a counterfactual. In Online Appendix F I show for the subgroup of paracetamol that changes in switching costs indeed lead to price changes close to that predicted from the linearisation. (3) Given the mapping, I calculate the counterfactual impact for each substitution group separately.

Consider the following example. Let paracetamol have a reduced-form switching cost estimate of 0.02, and we observe relative positive price changes in the counterfactual of longer procurement

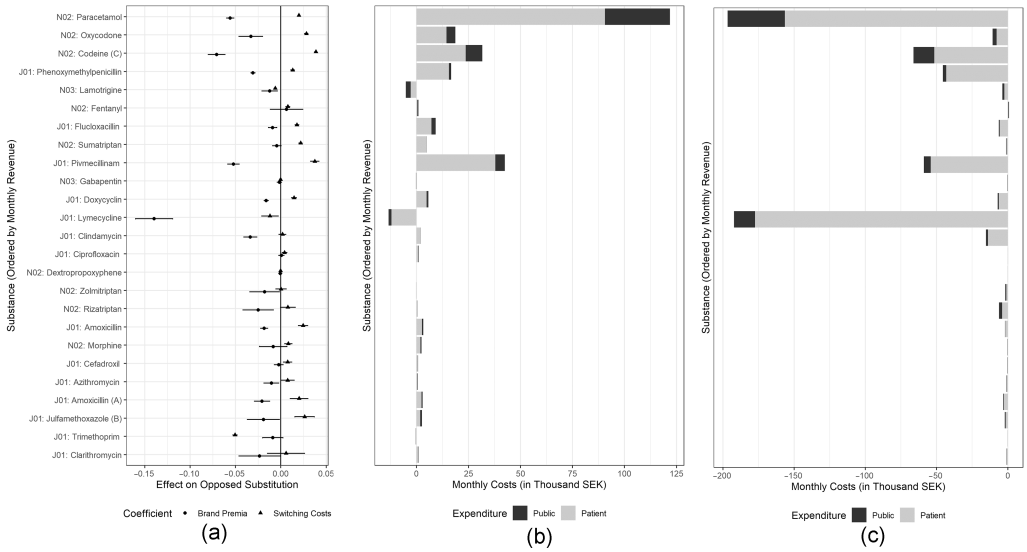


Fig. 3. *The Impact of State Dependence and Brand Premia across Drug Segments.*
*Notes:* The figures show the impact of an increased procurement length and a reduction of brand premia (in the case where all patients act as though they had medical education) on patients' costs and public expenditure. Panel (a) shows coefficients of the reduced-form model estimating brand premia and switching costs. The error bars correspond to a 95% confidence interval. I use a mapping of reduced-form estimates of brand premia and switching costs to estimate the impact of the counterfactuals on public and private expenditures in the segment of paracetamol, 1 g. Given this mapping, I calculate the effects of procurement (panel (b)) and reduced brand premia due to quality misconception (panel (c)) in the counterfactual for each individual segment. Both sub-figures show monthly costs where positive costs refer to higher costs for patients and the public health care system. Effects on public health care expenditures are shown in black while those on the patients' co-payments are shown in grey.

of 0.4% compared to the benchmark. If another product has a reduced-form estimate of 0.01, the corresponding impact on prices is estimated to be $0.01/0.02 \times 0.04\% = 0.02\%$. By multiplying the effect with the size of the market (size of public and patient expenditures), I calculate the aggregate effect of the procurement counterfactual.

The calculation allows me to estimate the aggregate effects of both counterfactuals in a simplified environment. The simplification comes with strong assumptions. First of all, I assume that the sizes of the behavioural friction in the reduced-form and discrete choice models are connected. Second, I assume that changes in behavioural frictions linearly translate into changes in the pricing when considering the counterfactual that reduces the impact of that friction on pricing. In a market without switching cost prices would not be affected by a longer procurement period. Finally, I assume that differences across drug segments do not alter this analysis. For example, the analysis does not consider differences in market structure.

Figure 3 shows the results of the back-of-the-envelope calculation. Figure 3(a) shows the reduced-form estimates for each substance. We see some heterogeneity in results. However, two observations are generally observable in most substitution groups. (1) Consumption in the last month increases the probability of a patient opposing substitution, which would mean positive switching costs. We see an especially high impact on painkillers such as opioids. (2) Having a medical education decreases the probability that a patient opposes substitution. Thus, we

observe brand premia due to perceived quality misconceptions. Figure 3(b) shows results of the procurement counterfactual on monthly expenditures in Swedish krona. Paracetamol has the highest effect on overall costs, meaning that costs for the public and patients increase. We see that the counterfactual especially has effects in the segments of painkillers and antibiotics, products with a large quantity and switching costs. Patients bear the majority of the additional costs. Figure 3(c) shows results of the counterfactual of reduced brand premia on monthly expenditures in Swedish krona. The counterfactual effects are large in the substitution groups of painkillers and antibiotics, where brand premia due to misconceptions are common. In comparison to switching costs, brand premia have a larger effect. The effects on patients' co-payments are large. Still, we observe savings for the public system as price differences between products decrease and the price of the cheapest available product decreases.

Across all products, the procurement counterfactual increases patients' cost by 0.2% and public costs by 0.06%. If all patients acted as though they had medical education, costs for patients across all groups would decrease by 0.7% and governmental costs would decrease by 0.1%. We observe differences between cost reduction for patients and the public spending in the counterfactual where everyone acts as though they had medical education. The intuition is as follows. If the price of the product of the month decreases, governmental and private costs decrease as the government only reimburses (to some degree) the cost of the lowest priced product. If a branded product decreases its price, but the price of the lowest-priced product remains constant, only patients' co-payments decrease. In the case of the reduction in brand premia, we see less expensive brands and more choices of the cheapest product. However, we observe fewer price changes of the cheapest available product.

### 8.2. *Policy*

The specific setting of the Swedish health care system shows that information provision and suggestion of substitution on the pharmacy level is not necessarily sufficient to ensure substitution to cheap generics. In numerous health care systems, the substitution decision is less strict as substitution is not suggested or presented as an option to the consumer. This analysis has shown that even in such a regulated market, where inattention is not an issue, we may see firms that build their pricing on behavioural phenomena. To quantify the impact of the brand premia and switching costs, I have presented two counterfactuals to evaluate the impact on consumers' decisions. Both counterfactuals may help policymakers that want to reduce health care costs for the public system or patients.

From an aggregate perspective, reducing perceived brand premia due to perceived quality differences has considerable effects. As medical experts tend to choose cheaper drugs, it would be one option to let physicians rather than patients decide about product choice. Another possibility would be to make substitution mandatory. However, this restricts freedom of choice substantially. Finally, there is also the possibility that information provision from a prescriber would help in changing brand premia. The current system in Sweden does not intend that prescribers explain differences between generic and branded pharmaceuticals. Information provisions of equivalence by the prescriber could indeed already reduce brand premia and reduce prices.

The counterfactual of an increased procurement length has shown that prices could increase if switching costs play a smaller role in a firm's pricing objective. Thus, markets with switching costs could have competitive effects and seem to be desirable. However, this paper documents an important inequality that comes with switching costs. In a market with switching costs, individuals

who consume products repeatedly and experience switching costs will overpay as they fall victim to firms' 'lock in and harvest' pricing. In comparison, individuals who do not experience switching costs can take advantage of low-price periods of the 'lock in and harvest' strategy. The problem for policy gets especially clear when observing that patients with lower education and lower income are likely to have worse health conditions and frequently need pharmaceuticals. Thus, switching costs may increase competitive pressure, but could increase inequality across buyers. Policymakers should carefully consider whether a portion of the consumers require protection. Increasing the procurement length is a realistic policy option that could help protect consumers who experience switching costs.

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Additional Supporting Information may be found in the online version of this article:

**Online Appendix**
**Replication Package**

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