Markups on Drop-Downs: Prominence in Pharmaceutical Markets

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Abstract

We study the effect of product prominence in consumer search on demand and equilibrium prices using data from Danish pharmaceutical markets. Variation in prominence comes from alphabetical ordering in physician IT-systems. We find that both prescriptions, prices, market shares and revenue decrease in alphabetical rank. We estimate a structural ordered search model which confirms that physicians actively search. They react to patient expenditures, albeit less than patients, and increase search effort for low-income and female patients. Sorting products by price would reduce equilibrium expenditures by 5%, which is more than a removal of search frictions would achieve.

Keywords: Ordered search, pharmaceuticals, market power, prominence.

JEL Classification: D83, L13, D12.

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1 Introduction

In the supermarket or on internet search engines, some products are easier to find than others. This can be a source of market power for prominent firms, because it reduces the cost of considering their products relative to competing ones. Since at least Stigler (1961) and Nelson (1970), economists have acknowledged the role of consumer information frictions for market power, firm conduct, and price dispersion (Varian, 1980). Theoretically, prominence has been shown to be an advantage which ran result in either higher prices (Arbatskaya, 2007) or lower prices (Armstrong et al., 2009) depending on preferences and search costs.

We study the effect of product prominence on equilibrium prices and market shares using a dataset covering all transactions and prices in Danish pharmacies between 2005 and 2016. Prominence arises because prescribing physicians in Denmark use a search engine to find drugs which presents results in *alphabetical order*. This generates arbitrary variation in brand prominence for physicians across products, which we use to estimate its effect on prescription shares, market shares, and prices.

Our setting allows us to overcome two concerns that typically complicate the study of prominence in market settings: first, positioning is often either a choice or a product itself and thus an endogenous outcome (as in e.g. Jerath et al., 2011; McDevitt, 2014). Second, in experiments where prominence is randomized among consumers, one can study the causal effect of prominence on demand (Agarwal et al., 2011; Blake et al., 2015; Ursu, 2018), but not the effect on prices because firms set the same prices for the treatment and control groups. In our setting alphabetical rank varies both across markets and over time so we can assume that the measured effects take into account adjustment of equilibrium prices and beliefs.

We find that alphabetical rank is important in determining which drug physicians put on the prescription. In our preferred regression specification with product-level fixed effects, the prescription share decreases 4.9%-points per alphabetical rank in duopoly markets. This passes through to consumer purchase so that market share decreases 2.4%-points in alphabetical rank, and prices decrease 4.7% per rank in duopoly markets. In more competitive markets, the effects are numerically smaller but still negative. Note that by including product fixed effects, our results are robust to any time-constant firm-level unobservables that might be correlated with name choice.[1] While the reduced form results tell us the causal effect of prominence on prices under the given information structure, we use a model to quantify the relative importance of preferences and information frictions for physicians and patients, and consider counterfactual search architectures.

We build a structural econometric model of physician prescription and consumer purchase. The physician exerts costly effort to browse through the list of available brands, trading off search costs against expected savings to the consumer. The consumer takes the prescription to the pharmacy and conducts ordered search under the guidance of the pharmacist who is mandated to recommend the cheapest available product (a process called *generic substitution*) and influenced by the brand on the prescription. This makes the prescribed and the cheapest products particularly cheap to inspect and thus prominent to the consumer.

Estimation is made tractable due to recent methodological breakthroughs in estimation of ordered search models. Armstrong (2017) and Choi et al. (2018a) have independently shown how to recast "Pandora's Rule" for optimal search (due to Weitzman, 1979) as a static discrete choice problem. However, the discrete choice utilities are latent variables that require integration. Moraga-Gonzalez et al. (2018) overcome this with an equivalent specification whereby choice probabilities are available in closed form and integration can be done in a single step after estimation is completed. This significantly reduces the computational cost of estimating the model.

The estimated model shows that the physician is not ignorant about the induced effect on the consumer, but neither is she a perfect search agent. We find that physicians search more for females and for poor consumers. We interpret the latter as evidence that physicians have social preferences across consumers consistent with redistribution. On the other hand,

[1] Institutionally, firms are moreover greatly limited in their ability to change name, which we discuss in Section 2.1.

the physician responds less to variation in consumer expenditures than the consumer does, with a physician coefficient on log expenditure of -0.67 compared to the patient's own coefficient of -1.32.

We use the model to investigate the counterfactual effects of either removing search frictions for the physician or implementing an alternative search architecture. We conduct these experiments both for frozen prices and solving numerically for the counterfactual mixed strategy price equilibrium. Reassuringly, we find that the equilibrium in the baseline produces decreasing prices in rank, consistent with what we observe in the data.

For frozen prices, a removal of physician search frictions only reduces expenditures by 0.1% in duopoly markets. Allowing firms to adjust their prices and solving for the counterfactual equilibrium, we find that expenditures fall by 1.7%. This is mostly driven by prominent firms lowering their prices in response to their lost market power, but partly by a slight price increase by the firms furthest down the list.

Conversely, when we rank products in the physician IT system based on price we find a uniform decrease in prices across all rank positions and a 5.2% reduction in expenditures. In duopolies, the first firm's price drops by 6.1% and the second firm's by 3.5%. In contrast, prices dropped by 2.6% and 0.9% for free search. This is because the inelastic demand segment caused by prescriptions is now directed towards the cheapest product. This removes the previous incentive for prominent firms to raise prices to exploit their inelastic customers and instead focus on participating in the competition to be cheapest. In this way, we have shown that the information frictions can be harnessed in the design of the search architecture to improve competition and market outcomes.

We conduct two further counterfactuals to provide a frame of reference for the magnitudes. We show that simply prohibiting physicians from writing prescriptions to original manufacturers would reduce costs by 3.2%. This demonstrates the important role of prescriptions in explaining the demand for the typically high-priced branded drugs post patent expiration which was highlighted e.g. by Feng (2019). Second, we conduct a counterfactual experiment in which the physician is forced to always prescribe the cheapest product, thus fully removing the physician margin of choice. In duopoly markets, this reduces costs of 10.3%. This represents an upper bound to what can be achieved by affecting prescriptions but is not itself a realistic policy as the physician may have medical reasons for preferring one generic to another for a specific consumer.

We contribute to a growing recent literature on the importance of brands and prescriptions in pharmaceutical markets. Previous work has shown that information frictions are an important determinant of patient choice: for instance, expert and novice consumers differ in their propensity to buy generics (Bronnenberg et al., 2015; Janssen, 2019) and the effect of prescriptions on demand has been documented in a randomized experiment where the physician by default would prescribe the cheapest (with the possibility of an opt-out), finding a 5.4% increase in generic consumption, Patel et al. (2014). Our contribution to this literature is to document the effect of this prescription decision on equilibrium prices.

Our paper also contributes to a literature studying how search frictions affect prices empirically. We study a centralized market, whereas the previous literature has largely focused on decentralized markets with studies of such as mutual fund fees (Hortaçsu and Syverson, 2004), credit card interest rates (Galenianos and Gavazza, 2018), mortgage prices (Allen et al., 2019), and used book prices (Ellison and Ellison, 2018). In decentralized markets, search frictions keep buyers from meeting individual sellers, which affords a form of local monopoly power. In our case, consumers are unaware of the full choiceset but all consumers pay the same price on the same date for a given product.

We also contribute to an empirical literature investigating the importance of choice architecture for consumer choices. For retirement-savings decisions, status quo bias (Samuelson and Zeckhauser, 1988) has been used to explain sub-optimal decisions (Madrian and Shea, 2001; Beshears et al., 2009; Choi et al., 2011). For health insurance plan choice, Abaluck and Gruber (2011) documented choice inconsistencies among the elderly. Abaluck and Gruber (2016) argue that consumers make worse decisions in when presented with a larger choiceset. Our model has a similar implication for fixed prices, but we present evidence that firms exploit these information frictions by charging higher prices, and we argue that this competitive channel is first-order.

The rest of the paper is organized as follows. Section 2 describes the data and the institutional setting. Section 3 presents descriptive evidence and Section 4 empirical results. In Section 5 and Section 6 we present the structural model and counterfactual simulations and the final section concludes.

2 Data and Institutional Setting

2.1 Institutional Setting

Denmark has a universal single-payer healthcare system which also subsidizes prescription drugs. To contain costs, the government therefore regulates both the supply and demand side which we will describe in turn.

Prices are set in a centralized platform in a mechanism akin to a first price position auction. Every 14 days, firms simultaneously submit prices to the Danish Medicines Agency (DMA) for all their products. Each drug competes with other drugs that belong to the same "substitution group" (which will also be our definition of a market) which is a group of drugs having the same substance, strength, dose and similar[2] pack size as measured in number of Defined Daily Dosages (DDDs). All products that have a submitted price in the system are available for the consumer to purchase at that price, but the cheapest product (the winner) receives a prominent position in the market because pharmacists are mandated to recommend that consumers switch to this product. It is technically legal to buy and sell prescription drugs outside this system, but since the government subsidy will not apply in that case, no pharmacies do this.

The demand side is influenced by both final consumers, who purchase and pay for the medicine, physicians that write prescriptions, and pharmacists who recommend the cheapest product. Consumers contact their physician to obtain a prescription which gives them

[2] The definition of a substitution group allows for a variation of $\pm 10\%$ in the quantity (measured by DDD) within the group.

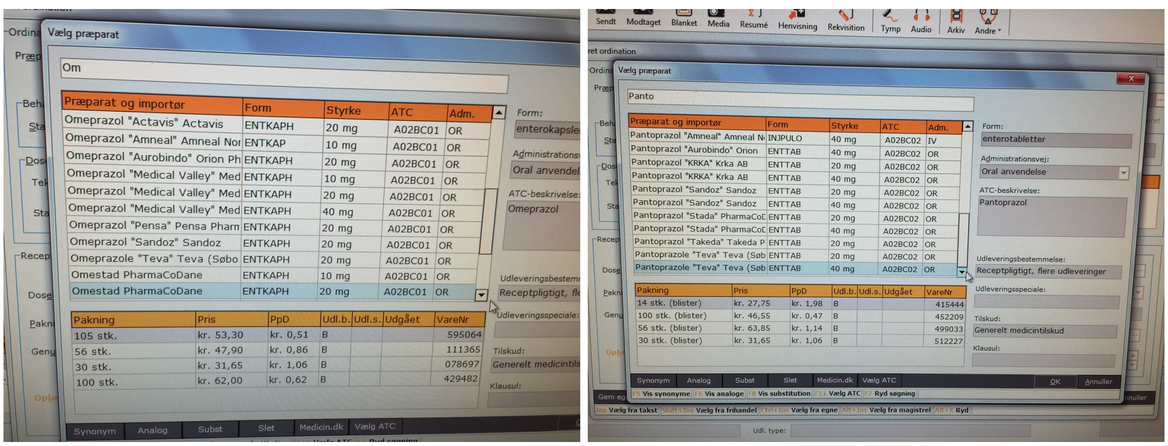
right to purchase pharmaceuticals from a specific substitution group. When consulting the patient, the physician must choose one of the available products in the substitution group; it is not possible for the physician to specify that she has no preference for one firm's generic over another in the substitution group. Physicians make this choice in an IT system, which transfers the prescription electronically to the pharmacy. There is no monetary incentive involved when physicians write prescriptions.

The alphabetical ranking of brands is important because of the design of the search tool in the physicians' IT system. When physicians types in a query, e.g. "Omeprazole", packages with a name matching the search term are presented in alphabetical order by the name of the package, as illustrated in Figure 2.1. To get the price information, the physicians click on the product, and the information is presented in a box below.

Figure 2.1: Search engine illustration

(a) Example 1: Omeprazole

(b) Example 2: Pantroprazole



The ability of firms to change name for their products is limited by regulation. Under Danish law, pharmaceutical product names can take one of two forms: 1) A *special name* which is to be approved by the government, and must comply with a number of rules (It must be different from all other international non-proprietary names for instance, must be pronounceable etc.). 2) a Danish or international non-proprietary drug name (e.g. penicillin) followed by the company name, i.e. `Molecule ("Firm A")`. Typically, the original manufacturer will fall into category 1, while most generics fall into category 2. We restrict attention to generics of this naming form and will focus on markets where a maximum of two products have names of a different form. This ensures that in the markets we study, the order of the generic firms in the search rank is determined by the company name, and the branded product will appear either before or after the block of generic products depending on the alphabetical ranking of the proprietary and non-proprietary names of the molecule.[3]

The pharmacist's role in the mechanism is to guide demand towards the cheapest product in the market, which they are legally mandated to. This is referred to as *generic substitution* and appears in most countries in some variation.[4] Pharmacist margins on prescriptions are dictated by the government and do not depend on consumer choice. The logistics of transporting products to pharmacies is carried out by a fully regulated state-mandated duopoly that is independent of the pharmacies. Pharmacies are required to stock the winning product, and can typically obtain any product within a few days. The pharmacy industry as a whole is heavily regulated with respect to entry and ownership structure (they must be owned by a pharmacologist, which for instance bars supermarket chains from entering the market).[5]

In the end, the consumer makes the final choice and pays for the product. The consumer receives a fraction of the cheapest price in subsidy. This fraction increases in annual expenditure, starting at 0% and eventually reaching 100% for consumers with very high accumulated expenditures (see Appendix Figure A.1). However, a consumer must pay the full price difference between the cheapest product and the chosen product out of own pocket. This structure of insurance implies that the consumer receives a fixed subsidy regardless of which product gets chosen and then pays the prices. This allows us to simplify

[3]For example, ATC N03AX09 has proprietary name Lamictal and non-proprietary name Lamotrigin, whereas ATC C10AA01 has names Zocor and Simvastatin. For those two markets, the branded firm thus comes before (N03AX09) and after (C10AA01) generics, respectively.

[4]If multiple firms bid the lowest price, the pharmacist may choose which to recommend.

[5]From a political economy perspective, the current pharmacies have an incentive to comply with government regulation by for instance handing out the cheapest products in order to avoid a negative political focus on the pharmacy industry. In this way, pharmacies reduce the incentive for politicians to reform and liberalize the sector.

the structural model and abstract from insurance.

2.2 Data

Our dataset is merged from a number of sources. Most importantly, we rely on the universe of all transactions of prescription drugs in Danish pharmacies in the period 2005–2016. Each row in that dataset contains an identifier for the purchasing consumer, the prescribing physician, and product identifiers for the purchased and prescribed product (which may be different). In addition, each row contains product and consumer information such as the price, pack size, form and the subsidy received. We augment this dataset with all prices from an online source maintained by the Danish Medicines Agency (DMA) who runs pharmaceutical auctions. This gives us information on available products that didn't sell in a two-week period and thus did not appear as a transaction. We construct patent expiration dates by combining data on special European patent extension dates (SPCs) from the Danish Patent and Trademark Office with data on molecule marketing approval dates from the DMA. We merge this data with consumer demographics (age, income, gender and education) from Danish population registers. We do not observe whether a product is generic or branded directly. Instead, we define a product as generic if it has quotation marks in its name, which indicates that a product belongs to naming category 2 as described above. We also run robustness checks with a broader definition, where we define a generic as a product that was not present before patent expiration in a market where we observed at least one such.

2.2.1 Sample selection

We will now briefly cover our sample selection criteria and refer to Appendix Table A.1 for further details. We focus on all price-periods after April 1st 2005, where a reform drastically changed the pricing system (see Kaiser et al., 2014), and our last period of data is the final two weeks of 2016.

We only keep product-periods that satisfy the following criteria: minimum one year after patent expiration; at least one generic product present; product name (in the IT system) must be observed; and between two and eight firms active. The last constraint removes monopoly markets and a small number of markets with a large number of firms. This results in a dataset with 348,494 product-period observations, covering 99,4 million transactions, which we will use to study of the effect of prominence on prescription shares, prices, market shares, and revenue.

From this set of potential product-periods, we choose a further subsample to be used in our structural model of physician and consumer choice. There, we restrict to the period before 2014 where we have data on consumer demographics. Finally, we drop a small number of transactions (0.1%) where a the purchasing consumer could not be matched to the demographic registers. This leads to 60.0 million transaction conducted from 172,502 product-periods. We base our choice estimation on a random 1% subsample of this.

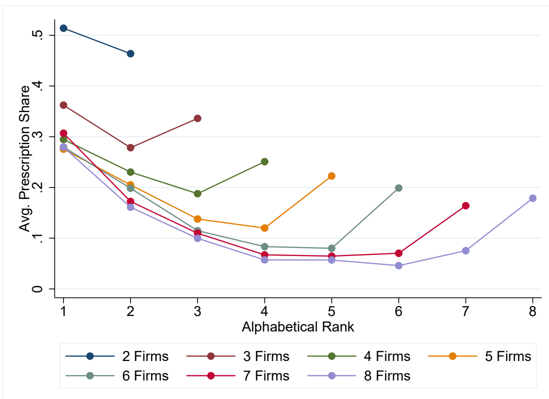
3 Descriptive evidence

Figure 3.1 shows the relationship between the alphabetical rank of a product on the x-axis and the average or median of four different outcome variables on the y-axis, and as such display the raw associations in the data to provide an overview.

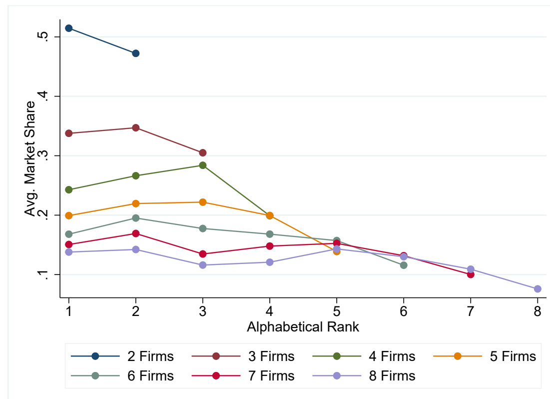
The reason why the alphabetical rank of a product matters to market outcomes is that it affects physician prescriptions. We illustrate the relation between prescriptions and alphabetic rank in Figure 3.1a. The graph shows that the earlier in the alphabet a firm is, the more prescriptions it obtains. Furthermore, the effect flattens out from rank 4 and onwards, indicating that the effect of rank is most important for the first couple of clicks down the list in the IT system. One thing stands out: the last product has a markedly higher average prescription share than the second to last. This is because the original manufacturer either comes first or last in a substitution group due to the naming conventions described in Section 2. Appendix Figure A.3 shows the frequency with which a given product is a generic depending on rank.

Figure 3.1: Alphabetical Rank and Market Outcomes

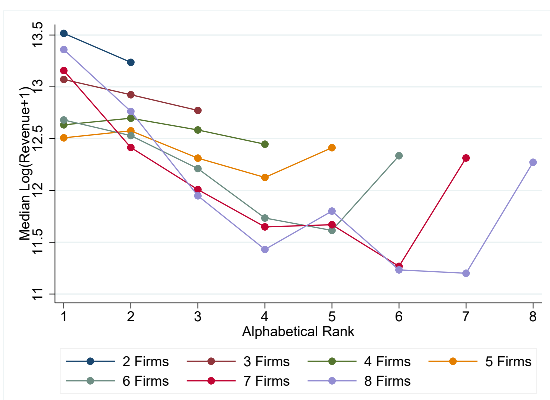
(a) Prescription share



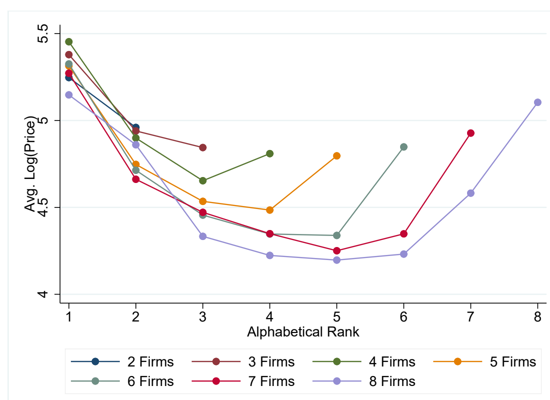
(b) Market share



(c) Revenue



(d) Price



Note: All figures are constructed using our product-level dataset (i.e. an observation is a product-period) including all products both branded and generic. Since 5 % of observations have zero revenue we add 1 to revenue before taking logs and plot the median value by rank.

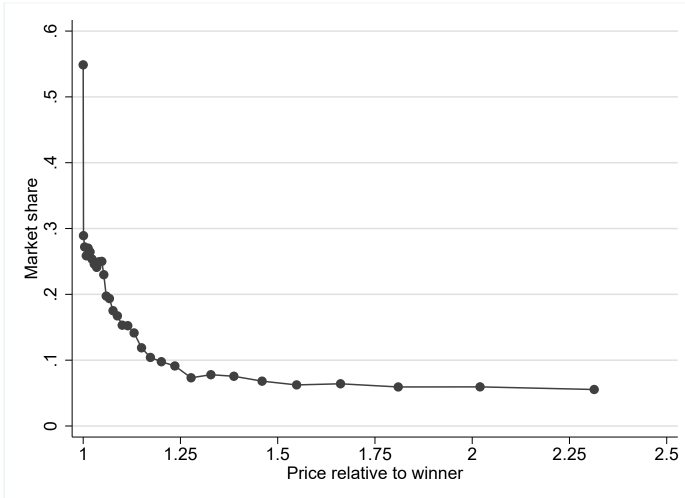
Figures 3.1b and 3.1c show that both market share and revenue are declining in alphabetical rank, although as one might expect, the relationship is less stark. This shows that being prominent appears to be an advantage to firms.

Figure 3.1d shows the average log unit price by the alphabetical rank of the firm. The relation between price and alphabetical rank appears to depend on market structure. For markets with two, three, and four firms the slope is negative, but in less concentrated markets the price-rank gradient flattens.

Next, we turn to the shape of the demand curve, describing how patient purchase depends on price. Figure 3.2 shows on the x axis the price relative to the winning price in the market, and on the y axis the average market share within bins. When the relative price is 1, it means that the product had the cheapest price in the market during that period, and on average such products received about 55% market share. For the product-periods with a price just a tiny bit above the minimum price, the market share was instead just under 30%. This sharp discontinuity at the minimum price is due to *generic substitution*, whereby the pharmacist is mandated to recommend that the consumer buy the cheapest available product. This discontinuity in demand eliminates pure strategy equilibria, since firms have a strong incentive to undercut. However, Figure 3.2 also shows that a non-negligible market share accrues to products with very high prices: products with prices more than 100% over the minimum price managed to still attract a 10% market share on average. These two features together – a discontinuity at the bottom, but a non-zero market share at high prices – make the demand side reminiscent of the "shoppers and loyals" model of Varian (1980).

It is important to note that the figures above are comparisons of raw means and thus, at this point, merely reflect associations. We address endogeneity issues in Section 4 using fixed effects regressions.

Figure 3.2: Demand discontinuity at the minimum price



Note: The figure shows binned averages of the market share of products plotted against the price relative to the cheapest product on the x-axis. For example, an x-value of 1.0 indicates that the product was the cheapest, whereas a value of 2.0 indicates a price 100% higher than the minimum price. An observation is a product-period. Note that because the plot includes products across markets with different numbers of firms, and because firms sometimes tie at the cheapest, we should not expect the plot to integrate to one.

4 Regression Results

In this section, we estimate the effect of alphabetical rank on prescription share, price, market share and revenue share using fixed effects regressions. The unit of observation is a product, j, in a two-week period, t. As described in Section 2, our sample is restricted to observations after 2005 for off-patent markets where at least 2 firms but no more than 8 firms were present. Our primary sample has 697,630 observations of product-periods. In all specifications we cluster standard errors at the market level (substitution group). In our preferred specification, this results in 1552 clusters. We present summary statistics for our main regressions sample in Table 4.1.

Table 4.1: Summary Statistics

	mean	sd	p10	p50	p90
No. firms	4.19	1.77	2.00	4.00	7.00
No. generic def 1	2.23	2.07	0.00	2.00	5.00
No. generic def 2	3.22	1.84	1.00	3.00	6.00
log(revenue)	5.97	1.34	4.66	5.59	7.84
log(price)	1.19	1.54	-0.46	0.92	3.12
Years since patent exclusivity	10.83	8.93	2.31	8.17	23.21
N	697,636				

4.1 Econometric Specification and Identification

We will present results for four different outcomes, collectively labelled y_{jt}: the logarithm of the unit price, the prescription share, the market share, and the revenue share.[6] We consider variations of the following regression model:

$$y_{jt} = \rho_1 R_{jt} + \rho_2 R_{jt} \times J_{m_j t} + \sum_{k=3}^{8} \delta_k \mathbf{1}(J_{mt} = k) + \mathbf{x}_{jt}\beta + \eta_{jt} + \varepsilon_{jt}, \tag{4.1}$$

where m_j is the market to which product j belongs, $J_{m_j t}$ is the number of products available in the market in period t (so δ_k are dummies for the number of active firms), $R_{jt} \in \{1, ..., J_{m_j t}\}$ is the alphabetical rank , $\mathbf{x}_{jt}$ is a vector of controls, which includes dummies for the number of years since patent expiration. Lastly η_{jt} is short-hand for time and/or product fixed effects. We use different specifications for η_{jt} to use different sources of identifying variation. We allow the effect of rank R_{jt} to depend on the level of competition by including the interaction between rank and number of firms in the market, so the effect of rank is composed of the linear effects, ρ_1,ρ_2. In the following, we discuss identification under various specifications of η_{jt}.

We use fixed effects to address the possibility that firms early in the alphabet are fundamentally different from firms late in the alphabet, something that would bias pooled estimates. Our main concerns are 1) that some firms may game the system by strategically

[6] The revenue share is defined as the revenue (price times quantity) for product j out of total revenue earned by all firms in the same market and period.

choosing a name that is early in the alphabet and 2) that entry may be endogenous to alphabetic rank and demand factors. We address the first concern by including firm fixed effects f_j (of which there are 72), in all specifications. This means that if one firm always ranks first whenever it is active, its outcomes will not provide variation the contributes in identifying ρ_1, ρ_2. It will, however, affect the rank of other firms, since it may push competitors further down the list when it enters. In some specifications, we also include market fixed effects, which for example absorbs time constant market-specific demand factors, such as the therapeutic area of the drug or the cost of production.

To address potential differences between products early and late in the alphabet we further estimate a specification where we use product fixed effects, η_j. The product fixed effect is identical to a fixed effect for each firm-market pair, since products do not change owning firms in our setting.[7] Therefore, the product fixed effect would in particular absorb any firm or market fixed effects. Moreover, it captures any differences in product characteristics that might exist between (bioequivalent) drugs in a market: color of the coating, shape of the pills or brand perception. In this specification, the variation in alphabetical rank comes from entry or exit of competitors with names positioned earlier in the alphabet. In one market, a competitor may enter that does not affect the rank of firm j (if the entrant is later in the alphabet), whereas another firm may enter that overtakes firm j, reducing its rank. In this way we get separate identification of the alphabetical rank and the number of firms conditional on η_j. Finally, this specification is robust to entry on time-constant unobservables since this is essentially an effect where specific firms (e.g. last in the alphabetical list) only tend to enter specific markets (e.g. ones that have particularly inelastic consumers).

Lastly, we implement a specification that addresses entry on time-varying market unobservables by onsidering a specification with market-by-date fixed effects, complemented by firm (f_j) fixed effects, by setting $\eta_{jt} = \eta_{m_j t} + \eta_{f_j}$. Here, there is only variation in alphabetical rank within a market across the different products, so the identifying variation for ρ_1, ρ_2

[7] If one generic firm acquire's the legal right to sell a product from another firm, it would result in a new product ID and the name of the package would have the new owner's firm name.

is instead based on a direct comparison between products of different ranks. Most importantly, this specification controls for time-varying market-specific unobservables. Imagine for example that high-ranking firms are only active when demand is extremely high, and that this high demand causes prices to increase in general (creating endogeneity). That effect would be captured by $\eta_{m_j t}$.

4.2 Results

We present results for the four outcome variables of interest. In all specifications, the marginal effect of rank under a given market structure is computed as the sum of the direct effect (ρ_1) and interaction effect with number of products, $\rho_1 + \rho_2 \times J$. To avoid evaluating this expression, Table 4.2 summarizes all the following tables, showing the results from our preferred specification with product-level fixed effects for all four outcomes. We see that all four outcomes are decreasing in alphabetical rank, but that the slope becomes numerically smaller when more firms are present in the market. In the following, we will go through each outcome separately and compare results across specifications of η_{jt} and discuss statistical significance.

Table 4.2: Marginal Rank Effects and Market Structure

	$\log(p_t)$	Prescription Share	Market Share	Revenue Share
$J = 0$	-.063	-.061	-.027	-.023
$J = 2$	-.047	-.049	-.024	-.020
$J = 3$	-.040	-.043	-.023	-.018
$J = 4$	-.032	-.037	-.021	-.017
$J = 5$	-.024	-.031	-.020	-.015
$J = 6$	-.017	-.026	-.019	-.014
$J = 7$	-.0089	-.020	-.017	-.012
$J = 8$	-.0011	-.014	-.015	-.010

Note: The table shows the effect of alphabetical rank on each respective outcome variable for different levels of competition measured as the number of available products (J). The effects are computed as $\hat{\rho}_1 + \hat{\rho}_2 J_{m_j t}$. The marginal effects are computed using our preferred regression specification with fixed effects at the product and period level, $\eta_{jt} = \eta_j + \eta_t$.

Table 4.3 shows results for the effect of alphabetical rank on the share of prescriptions in a market accruing to a specific product. Across specifications we find a strong significant negative effect ranging between -0.061%-points with product fixed effects and -0.059%-points with market-by-date fixed effects. Since it is the prescribing physician that browses through products in alphabetical order on the computer screen, there would be no reason to expect an effect on consumer choice or pricing, were the physician's choice not affected by the product rank.

Table 4.3: Prescription share

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.0319**	-0.0538***	-0.0564***	-0.0607***	-0.0587***
	(0.00995)	(0.00731)	(0.00797)	(0.00669)	(0.00843)
Rank×No. Firms	0.00111	0.00516***	0.00558***	0.00591***	0.00605***
	(0.00151)	(0.00106)	(0.00114)	(0.000790)	(0.00122)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	1552	1552	1547	1540	1475
Observations	697636	697635	697630	697511	685368

Note: Standard errors clustered at the market level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As shown in Table 4.2, the marginal effect of rank on prescriptions is significantly negative for all levels of competition, starting at -.049 with 2 firms to -.014 with 8 firms.

The next set of results investigates to what extent a prescription gets converted into purchase in the Danish system. Table 4.4 presents results for regressions of market share on alphabetical rank. Again we find a significant and negative main effect ranging between -0.027%-points with product-level fixed effects and -0.022%-points in the specification with only company and period fixed effects. These results document that the physician's choice of product from the drop-down list passes through to the consumer's purchase decision. A patient is more likely to buy a product simply because it is on the prescription. In Table 4.2, we see that the marginal effect of rank on market share is always negative, ranging from -.024 with 2 firms to -0.16 with 8 firms.

It is important to note that because firms can adjust their prices in response to increased demand, the estimated effect that we present of prominence on both physician and patient choice are after equilibrium adjustment. If prominent firms increase their prices, as we shall shortly see that they do in most markets, the price response will to some extent offset the effect of prominence on market share. Therefore, we should expect to estimate a numerically smaller effect of prominence, than what we would see if we could hold prices fixed. For policy purposes, an effect after equilibrium adjustment is most relevant, since it is rarely the case that firms are unable to adjust their prices in response to a policy.

Table 4.4: Market share

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.0223***	-0.0379***	-0.0245***	-0.0274***	-0.0223***
	(0.00641)	(0.00581)	(0.00633)	(0.00553)	(0.00675)
Rank×No. Firms	0.00222*	0.00387***	0.00240**	0.00149*	0.00209*
	(0.000982)	(0.000865)	(0.000922)	(0.000717)	(0.000985)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	1552	1552	1547	1540	1475
Observations	697636	697635	697630	697511	685368

Note: Standard errors clustered at the market level.

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

Table 4.5 shows how prices are affected by prominence. Qualitatively, all specifications robustly show the same result: prices are generally downward sloping in rank, but the slope flattens with more firms. In the specification with product-level fixed effects, the price-rank gradient is zero when more than 8 firms are present. This is consistent with what we saw in the raw averages in Figure 3.1d. The quantitative magnitudes of the pooled OLS results are very large, consistent with the raw averages, but as soon as we add company and market fixed effects, the magnitudes fall to much more plausible levels in the range of 4.5%–6.3% per rank, diminishing by 0.5-0.7%-point per extra firm active. As Table 4.2 showed, the marginal effect of rank starts at 4.7% for duopoly markets, and is 0.1% with 8 firms.

Table 4.5: Log price regressions

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.592***	-0.359***	-0.0444**	-0.0629***	-0.0506**
	(0.0609)	(0.0498)	(0.0159)	(0.0168)	(0.0166)
Rank×No. Firms	0.0723***	0.0425***	0.00556	0.00772***	0.00772*
	(0.00969)	(0.00796)	(0.00288)	(0.00202)	(0.00305)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	1552	1552	1547	1540	1475
Observations	697636	697635	697630	697511	685368

Note: Standard errors clustered at the market level.

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

Since market shares are decreasing in alphabetical rank and prices are either decreasing or mostly flat, it is perhaps not surprising that the firm's revenue as a fraction of total market revenue is also decreasing in alphabetical rank, as shown in Table 4.6. The pattern similar to the one in Table 4.4 where market share is the outcome. Revenue share decreases between 2.2%-point in alphabetical position in the specification with product-level fixed effects and 4.4%-point in the specification with company fixed effects only. Hence, in equilibrium it is a profitable advantage for firms to be ranked early in the alphabet. The reason why we prefer to use revenue share and not log revenue is the high prevalence of zero sales in our data. As a robustness, Table A.2 in the appendix presents regressions using log revenue as outcome, and they show a similar pattern.

Table 4.6: Revenue share

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.0206***	-0.0339***	-0.0270***	-0.0229***	-0.0263***
	(0.00623)	(0.00577)	(0.00640)	(0.00531)	(0.00683)
Rank×No. Firms	0.00188	0.00346***	0.00272**	0.00156*	0.00261*
	(0.000982)	(0.000884)	(0.000958)	(0.000740)	(0.00102)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	1552	1552	1547	1540	1475
Observations	697636	697635	697630	697511	685368

Note: Standard errors clustered at the market level.

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

Note: Here, we use all products regardless of whether they are generic og branded.

In general, all the results presented above have been on the full sample of products. In spite of the fact that we use product fixed effects, one might still wonder if branded and generic products are too dissimilar to compare. Therefore, as a robustness we also run the same regressions on the sample consisting exclusively of generics according to either a wide or a narrow definition of generics. The wide definition results in 348,491 product-period observations over 711 markets, and the results are presented in Appendix Sections A.2 and A.3 respectively. The qualitative picture is the same and all estimates are statistically significantly different from zero at the 5% level.

5 Model

In this section we outline a structural model of physician and consumer brand choice and generic substitution in the Danish market for pharmaceuticals. We consider choices by two decision makers: Physicians search in their IT system for a product to prescribe and consumers search in the pharmacy for a product to purchase. Our exposition is an adaptation of the empirical approach developed by Moraga-Gonzalez et al. (2018).

5.1 The Physician's Choice

5.1.1 Physician objective function

Physicians choose which product, indexed by j, to prescribe to consumer i by maximizing utility

$$u_{ij} = \omega_{ij}(p) + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim F^{\varepsilon}(\cdot),$$

where ε_{ij} represents an unobserved utility component, and $\omega_{ij}(p)$ is a deterministic utility function, measuring how physicians think prices affect consumer welfare, which we will detail below. Both ε_{ij} and p – and therefore $\omega_{ij}(p)$ – are unknown to physicians but can be learned by searching product j at the random search cost $c_{ij} \sim F^c(x; \mu_{ij})$, with μ_{ij} being a location parameter. A market consist of J products that can be bought with the same prescription, meaning that all J products contain identical active substance in the same quantity (they are bioequivalent) but may have different brands. We will assume that the search is ordered, so physicians decide which object to inspect next (i.e. the order of search is not random). Most importantly, our model should reflect that it is easier to search some products than others. For example, products that are further down the list (i.e. which have higher alphabetical rank) may be harder to find, and branded products may be easier to find than generic due to brand recognition. We therefore let the search cost location parameter depend on a vector of consumer and product characteristics $\mu_{ij} = \mu(x_{ij})$ where in x_{ij} we include product characteristics like rank and a dummy for the product being generic as well as consumer characteristics such a gender, age and income. Prior to searching, physicians hold (degenerate) price expectations p^E on which their search decisions are based. The distribution of the unobserved utility component ε_{ij}, F_{ε}, is known before search. We use $F^u_{ij}(\cdot|p)$ to represent the cdf of u_{ij} for a given set of prices, $p \in \mathbb{R}^J_+$, and $f^u_{ij}(\cdot|p)$ the corresponding pdf.

5.1.2 Solution of dynamic search problem

The ordered search problem of the physician has the same structure as in Weitzman (1979) and can therefore be solved using "Pandora's rule," which provides an index rule for optimal search in the dynamic problem. Following Moraga-Gonzalez et al. (2018), we now explain how the solution implies that our structural model can be estimated with a simple logit procedure. To introduce the algorithm, suppose that the best product that a physician has already searched has value $\overline{u}$. The marginal gain from searching product j then writes

$$\begin{aligned} \mathbb{E}\left(\max\{u_{ij},\overline{u}\}\right) - \overline{u} - c_{ij} &= \mathbb{E}_{\varepsilon}\left(\max\{\omega_{ij}(p^E) + \varepsilon - \overline{u}, 0\}\right) - c_{ij} \\ &\equiv H_{ij}(\overline{u}) - c_{ij}. \end{aligned} \tag{5.1}$$

For each product and individual, we can then define the reservation value, r_{ij}, as the solution to the equation

$$H_{ij}(r_{ij}) = c_{ij}.$$

Note that if the distribution of physician utility, $f(\varepsilon_{ij})$, has positive support everywhere on $[0;\infty)$, and is continuous, then $H(\overline{u})$ is strictly decreasing. Hence, there is a one-to-one mapping between c_{ij} and r_{ij}, so that the inverse

$$r_{ij} = H_{ij}^{-1}(c_{ij}). \tag{5.2}$$

is well-defined. Pandora's rule for optimal search is to first open the product with highest reservation value, then the product with second highest and so on. When no product has a reservation value higher than the highest observed utility, the search stops and the physician picks the product with highest utility among the searched products. The reservation price is decreasing in c_{ij}, so if physicians for instance expect all firms to charge identical prices, then they will open first the product with lowest search cost, which in our model on average means the first-ranked firm. So in our model, alphabetically ordered search arises endogenously when the search cost is lowest for the first-ranked products: so long as the physician does not expect value to be greatly declining in rank, she will conserve search effort and start by inspecting the first few products and stop once she expects too small rewards for continued search.

"Pandora's Rule" is attractive because it avoids solving a potentially high dimensional dynamic programming problem with backwards induction. However, as shown in Choi et al. (2018b); Armstrong (2017) the problem can be simplified even further, because it can be cast as a discrete choice problem. To do this, one "opens all the boxes" and computes for each product the index

$$w_{ij} = \min\left\{r_{ij}, u_{ij}\right\} \tag{5.3}$$

A physician that chooses $\arg\max_j w_{ij}$ will choose the same product as a physician who searches according to Pandora's Rule. The prescription share of product j, s_j^{presc}, therefore equals the share of transactions for which w_{ij} were larger than the corresponding index for all alternative products,

$$\Pr(j \text{ prescribed}) = \Pr\left(w_{ij} > \max_{k \neq j} w_{ik}\right)$$

Equation (5.3) shows that a search model implies a discrete choice model. Using the fact that the reservation value distribution is directly linked to the search cost in the following way

$$\begin{aligned} F_{ij}^{r}(r) &= \Pr\left[H_{ij}^{-1}(c_{ij}) \leq r\right] = \Pr\left[c_{ij} \geq H_{ij}(r)\right] \\ &= 1 - \Pr\left[c_{ij} \leq H_{ij}(r)\right] = 1 - F_{ij}^{c}\left[H_{ij}(r)\right] \end{aligned}$$

The distribution of w, F_{ij}^{w}, can then be written in terms of the search cost distribution and the match value distribution

$$\begin{aligned} F_{ij}^{w}(x) &= 1 - \left[1 - F_{ij}^{r}(x)\right]\left[1 - F_{ij}^{u}(x)\right] \\ &= 1 - F_{ij}^{c}\left[H(x)\right]\left[1 - F_{ij}^{u}(x)\right] \end{aligned} \tag{5.4}$$

Computing prescription probabilities involves solving a $J-1$ dimensional integral, but using the relationship in (5.4), this may be done straightforwardly using e.g. simulation techniques.

However, the key contribution by Moraga-Gonzalez et al. (2018) was to show that sufficient structure has already been assumed to make estimation even more convenient. Note that Equation (5.4) implies that given a distribution for the unobserved match values F^u_{ij}, there is a one-to-one relationship between the distribution of F^w_{ij} and F^c_{ij}. So instead of making parametric assumptions on F^c_{ij} and deriving the implications for choice probabilities and requiring simulation during estimation, we may instead make our (convenient) assumptions on F^w_{ij} and derive the implied distribution of search costs, F^c_{ij}. Thus, it is clearly convenient to assume that F^w_{ij} is T1EV with location parameter μ_{ij}, implying that the prescription choice probabilities take the form

$$\Pr(j \text{ prescribed}) = \frac{\exp\left[\omega_{ij}(p) - \mu_{ij}\right]}{\sum_{k=1}^{J} \exp\left[\omega_{ij}(p) - \mu_{ik}\right]}, \tag{5.5}$$

where we have made the assumption that physician price expectations are correct so $p^E = p$. Moraga-Gonzalez et al. (2018) show that under the assumption on F^w_{ij}, the corresponding distribution of search cost is

$$F^c_{ij}(c) = \frac{1-\exp\left\{-\exp\left[-H^{-1}_{ij}(c) - \mu_{ij}\right]\right\}}{1-\exp\left\{-\exp\left[-H^{-1}_{ij}(c)\right]\right\}}, \tag{5.6}$$

from which it is clear that μ_{ij} is also a location-shifter for the search cost distribution. This means that the estimation of the structural ordered search model is done simply by estimating a conditional logit that additively includes both mean utility shifters (such as product price), and search cost shifters (such as alphabetical rank). Due to the simplicity and flexibility of this procedure, we use it as our main specification.

The term $\omega_{ij}(p)$ reflects the physician's perception of how her choice affects consumer utility. We investigate two different specifications of $\omega_{ij}(p)$. In the first one, we let physicians take into account the substitution at the pharmacy. To do so, we set $\omega_{ij}(p)$ equal to the (log of) expected consumer expenditure when product j is prescribed, computed from a consumer search model, which we will cover in the subsequent section. This model takes into account the generic substitution by the pharmacist, which implies that the variation in expected expenditures is much smaller than the variation in prices, since an expensive prescription is likely undone at the pharmacist's recommendation.

Our second specification simply sets $\omega_{ij}(p) = -\omega \log(p_j)$, so that physicians search directly for price. Since price is highly salient to the physician, it may be that physicians do not solve the complicated consumer-pharmacist decision problem, but rather conserve on mental effort and focus on what is immediately in front of them. Finally, we parameterize the location shifter for the search cost distribution for physicians as

$$\mu_{ij} = \beta_0 \varphi(R_j) + \beta_1 1_{\{j \text{ generic}\}} + z_i' \beta^u \times \varphi(R_j)$$

where $\varphi(\cdot)$ is a function that maps rank into search cost, and z_i denotes a vector of characteristics of the consumer. We will consider both a linear, logarithmic, and fully unrestricted functional form, setting respectively $\varphi(R_j) = R_j$, $\varphi(R_j) = \log(R_j)$ or $\varphi(R_j) = \sum_{r=1}^{J} \delta_r \mathbf{1}\{R_j = r\}$. The coefficient β_1 measures the difference in search cost between generic or branded products. The vector z_i includes gender, income and age which we interact with the product rank to measure how the physician search effort is affected by consumer characteristics.

5.2 The Consumer Choice

We model consumer choice using an ordered search model as well, but one where the prescription and pharmacy recommendations is what creates prominence (through low search costs) rather than the alphabetical ordering. Consumer i enters the pharmacy with a prescription and searches among the products that she can legally buy with her prescription. Since we do not consider repeat purchases, i may also interchangeably refer to a transaction. Consumers maximize utility

$$v_{ij} = \beta_1^v \log(p_j) + \varepsilon_{ij}. \tag{5.7}$$

To learn the values of product j (p_j and ε_{ij}), consumer i pays the random search cost $\zeta_{ij} \sim F_{ij}^{\zeta}$, where the distribution F_{ij}^{ζ} has location shifter κ_{ij}. It is cheaper to search a product if it is on the prescription, and it is also cheaper to search the product that the pharmacist is legally obliged to recommend to the consumer, so we set

$$\begin{aligned}\kappa_{ij} &= \kappa_j(p, a_i) \\ &= \beta_2^v \mathbf{1}_{p_j \in \mathscr{A}(p)} + \beta_3^v \mathbf{1}_{p_j \in \mathscr{B}(p)} + \mathbf{1}_{a_i = j}\left(\beta_4^v \mathbf{1}_{p_j \in \mathscr{A}(p)} + \beta_5^v \mathbf{1}_{p_j \in \mathscr{B}(p)} + \beta_6^v \mathbf{1}_{p_j \in \mathscr{C}(p)}\right).\end{aligned}$$

where a_j indicates whether product j is on the prescription or not, and $\mathscr{A}(p), \mathscr{B}(p), \mathscr{C}(p)$ define the three price regions described in Section 2.1, which determine whether or not the pharmacist is legally obliged to recommend substitution:

$$\mathscr{A}(p) = \{\underline{p}\}, \mathscr{B}(p) = (\underline{p}; 1.05\underline{p}], \mathscr{C}(p) = (1.05\underline{p}; \infty),$$

where $\underline{p} \equiv \min_k p_k$ is the lowest price in the market. We can separate consumer preferences from pharmacy recommendation by assuming that pharmacy recommendations only depend on which of the three discrete price regions the price is in, and thus discontinuous changes in demand around these price regions are solely attributed to pharmacy recommendations whereas continuous demand responses within a price region (e.g. the difference in demand between a cheap and expensive C product) are driven by consumer preferences. Since pharmacists are *obliged* to recommend substitution if $p_j \in \mathscr{C}(p)$ but only *encouraged* when $p_j \in \mathscr{B}(p)$, we allow for different effects of these, both in terms of the "recommendation" and "prescription" factors: β_2^v, β_3^v capture the recommendation effects from the pharmacist suggesting substitution towards a cheaper alternative. Specifically, β_2^v will help produce the discontinuous change in demand at the minimum price, which we see so clearly in the data. Conversely, $\beta_4^v, \beta_5^v, \beta_6^v$ are the prescription effects, which can explain the status quo bias towards the prescribed product, which is prominent to the consumer and thus easily searched. Note that our specification implies that κ_{ij} is affected by $\min_k p_k$ (though generic substitution), so search costs are affected by prices of competing products through the pharmacist's recommendation. Finally, we do not model the public insurance system, which is fortunately structured in a way that makes this very nearly without loss of generality.[8]

Again, we follow Moraga-Gonzalez et al. (2018) and assume that the unobserved "Pandora's Rule" utility indices are distributed Extreme Value Type 1, so that the final consumption choice probabilities are

$$\Pr(j \text{ purchased}|a_i) = \frac{\exp\left[\beta_1^v \log(p_j) - \kappa_{ij}\right]}{\sum_{k=1}^J \exp\left[\beta_1^v \log(p_k) - \kappa_{ik}\right]}, \tag{5.8}$$

and simultaneously implying that the consumer search cost distribution takes the form $F_{ij}^{\zeta}(\zeta) = \frac{1-\exp\left\{-\exp\left[-H_{ij}^{-1}(\zeta)-\kappa_{ij}\right]\right\}}{1-\exp\left\{-\exp\left[-H_{ij}^{-1}(\zeta)\right]\right\}}$. The expected patient expenditures induced by the physician's prescription can now be computed as

$$\mathbb{E}(p|a_i) = \sum_{j=1}^{J} \frac{\exp\left[\beta_1^v \log(p_j) - \kappa_{ij}\right]}{\sum_{k=1}^J \exp\left[\beta_1^v \log(p_k) - \kappa_{ik}\right]} p_j. \tag{5.9}$$

This is the measure we insert as physician preferences in one of the two specifications we use: $\omega_{ij}(p) = -\omega \log(\mathbb{E}(p|a_i))$. Since consumer utility depends only on price the difference between using expected expenditure and expected utility is whether we scale prices by the consumer marginal utility of money β_1^v. By not doing that we can compare directly how sensitive physicians are to patient expenses relative to patients themselves.

[8] In reality, the co-insurance rate is based on the *cheapest* product within a market, with the patient having to pay any excess above the minimum price, $\underline{p}$. Thus, it is as if patients have to pay $\tau_i \underline{p}$ regardless of the product they choose, where τ_i is out-of-pocked fraction for consumer i. Then the final out-of-pocket payment is $\tilde{p}_j = p_j - \underline{p} + \tau_i \underline{p}$, and it is as if we subtract $\beta_1^v(1-\tau_i)\underline{p}$ from all utilities. However, since we use log prices rather than prices in levels, this does not hold exactly.

5.3 Estimation and Identification

Let i denote a transaction with prescription a_i and final patient choice j_i. Then the likelihood function for observation i is

$$
\begin{aligned}
L_i(\theta) &= \Pr(a_i \text{ prescribed}) \Pr(j_i \text{ chosen}|a_i) \\
&= \frac{\exp\left[\omega_{ia_i}(p_i) - \mu_{ia_i}\right]}{\sum_{k=1}^{J} \exp\left[\omega_{ik}(p_i) - \mu_{ik}\right]} \frac{\exp\left[\beta_1^{\nu} \log(p_{ij_i}) - \kappa_{ij_i}\right]}{\sum_{k=1}^{J} \exp\left[\beta_1^{\nu} \log(p_{ik}) - \kappa_{ik}\right]}
\end{aligned}
$$

with the corresponding choice probabilities given in (5.5) and (5.8). Note that the J-vector of prices, p_i, varies across transactions depending on the date of purchase and the market, something we have suppressed in the notation previously. Under the assumptions we have made thus far, the likelihood function can be maximized by first estimating the consumer-pharmacist choice parameters in ν, and then inserting these in the physician utility function and estimating the physician search model. The key assumption allowing us to do this is that the physician cannot condition a_j on the realization of the consumer's utility, ε_{ij}.

Before turning to the results, it is worth briefly considering what type of behavior produces the identifying variation in the data for the two models. The parameters in the consumer conditional choice model are simply identified by variation across consumers in prices and prescriptions, both across and within markets or time. For instance, the coefficients on price regions interacted with the prescription dummy are identified by comparing consumers entering a pharmacy on the same date but having two different products prescribed: one where the second-cheapest is prescribed and one where a more expensive product is prescribed. For identification of the price parameters it is handy that the market mechanism has no pure strategy equilibrium due to the discontinuity stemming from pharmacy recommendations. We can therefore expect random within-product price variation stemming from the mixing equilibrium outcome. This means that we are actually able to study the demand under several random price outcomes.

The parameters of the physician search model is the search cost shifters, μ_{ij} which crucially depends on alphabetical rank, as well as the parameters indexing the physician utility post search, $\omega_{ij}(p)$ which mainly depends on the price. Identification then comes from a comparison of how prescription shares depend on alphabetical rank across markets with different realizations of prices. For instance, if we observe that the prescription shares do not change much whether the first price is much higher or just a little higher than the second price, then this indicates that search costs play a larger role relative to ω.

5.4 Results

Consumer model estimates Estimates for the consumer search model are presented in Table (5.1). The reference category is a product with a C price (most expensive region), which is not prescribed, and not generic. There is a substantial effect of being prescribed of 1.61 on latent utility, which is the equivalent of a drop in price of more than a full log point. In fact, the boost in demand is greater even than the effect of the pharmacist's recommendation as measured by the coefficient on the A-price dummy (1.47). Similarly, we note that the advantage to being a non-generic is 0.22 in utils, which is far smaller than any of the effects described above. This indicates that the market power of original manufacturers owes more to prominence and search frictions earned through physician prescriptions, than it does to brand value and other effects.

Physician model estimates Estimates for the physician model are shown in Table 5.2. In our preferred specification (Column 1), alphabetical rank affects physician search costs as $\varphi(R_j) = \log(R_j)$, and physicians are altruistic, $\omega_{ij}(p) = \omega \log(\mathbb{E}(p|a_i))$. The resulting model has three coefficients, which are all statistically significant. As expected, the physician attaches negative weight to expected patient expenditures, and search costs are higher for products further down the alphabetical list. Moreover, it is substantially easier to search non-generics, which is consistent with the fact that branded names are very prominent to physicians, some of whom have been prescribing for years prior to patent expiration when the branded was the sole option.

Table 5.2 also shows three other specifications where we change one or both of $\varphi(R_j)$

Table 5.1: Consumer Choice Model

	Model 1
Match value	
log(Price)	-1.32***
	(0.01)
Search costs	
1(Price A)	1.47***
	(0.00)
1(Price B)	0.89***
	(0.01)
1(Prescribed and A)	0.86***
	(0.01)
1(Prescribed and B)	1.03***
	(0.01)
1(Prescribed and C)	1.61***
	(0.01)
1(Generic)	-0.22***
	(0.00)
Observations	590488

Note: Parameters estimated by maximum likelihood using the consumer choice probabilities in (5.8). The reference category is a product in the C category (most expensive), which is not on the prescription. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

to be nonparametric (a full set of dummies), and $\omega_{ij}(p)$ to be the price directly, p_{ij}. Allowing rank to enter non-parametrically does not significantly change the coefficient on expected expense. On the other hand, there is naturally a very large difference between price and expected expense, owing to the fact that the expected expense varies much less over alternatives than the product price, because the consumer is not forced to buy what the physician prescribes. In other words, there is much greater variation in product price across alternatives than in expected expense.

In the final two columns in Table 5.2 we allow physician search costs to depend on patient characteristics. We do this by including interactions between the log of alphabetical rank and log patient income, a gender dummy and and age variable. The results imply that physicians search more for female and for poor consumers. The effect of age, on the other hand, is a precisely estimated zero. This heterogeneity in search cost can be interpreted as the physician rationing search effort across consumers according to some preference ordering. The fact that poor consumers receive more attention is evidence of pro-social preferences, while the lack of an effect of age may seem surprising given a prior that the

Table 5.2: Physician Choice Model

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
log(Price)		-0.01*		-0.04***		-0.01
		(0.01)		(0.01)		(0.01)
log(Expected Expense)	-0.57***		-0.64***		-0.56***	
	(0.04)		(0.04)		(0.04)	
log(Rank)	-0.51***	-0.52***			-0.30***	-0.29***
	(0.00)	(0.00)			(0.06)	(0.06)
1(Generic)	-0.89***	-0.84***	-0.86***	-0.83***	-0.89***	-0.84***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
log(Rank)*Age					-0.00	-0.00
					(0.00)	(0.00)
log(Rank)*1(Female)					0.07***	0.07***
					(0.01)	(0.01)
log(Rank)*log(Income)					-0.02***	-0.02***
					(0.01)	(0.01)
1(Rank=2)			-0.41***	-0.41***		
			(0.01)	(0.01)		
1(Rank=3)			-0.57***	-0.58***		
			(0.01)	(0.01)		
1(Rank=4)			-0.86***	-0.86***		
			(0.01)	(0.01)		
1(Rank=5)			-0.74***	-0.75***		
			(0.01)	(0.01)		
1(Rank=6)			-0.92***	-0.93***		
			(0.02)	(0.02)		
1(Rank=7)			-0.98***	-0.98***		
			(0.02)	(0.02)		
1(Rank=8)			-0.67***	-0.64***		
			(0.03)	(0.03)		
Observations	115167	115167	115167	115167	115167	115167

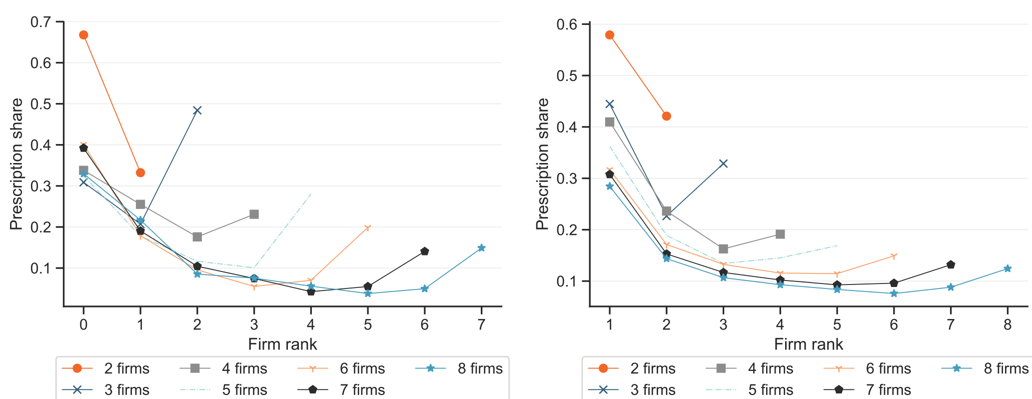
Note: The table presents estimates from the model of the physician's choice of what brand to prescribe. The estimator is Maximum Likelihood using choice probabilities from equation (5.5).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

elderly might have a harder time navigating the system.

Model fit Figure 5.1 shows a comparison of the model prediction of the relationship between prescription share and rank. As seen in panel (a), the data exhibits a sharp decrease in prescription share in rank after rank one. In general we see a small bump in market share in the end of the list, reflecting that branded products are typically either first or last in the markets we study. Panel (b) shows the corresponding predictions from our preferred specification. The model is largely able to reproduce the relationship seen between rank and prescription share seen in the data. In Figure A.2 we show models where the search cost is linear in rank or with rank dummies respectively, producing very similar fits. The most notable misfit is the 3rd ranked product in 3-firm markets: here, the data shows a large upwards tick, which is not reproduced by any model.

Figure 5.1: Model Fit

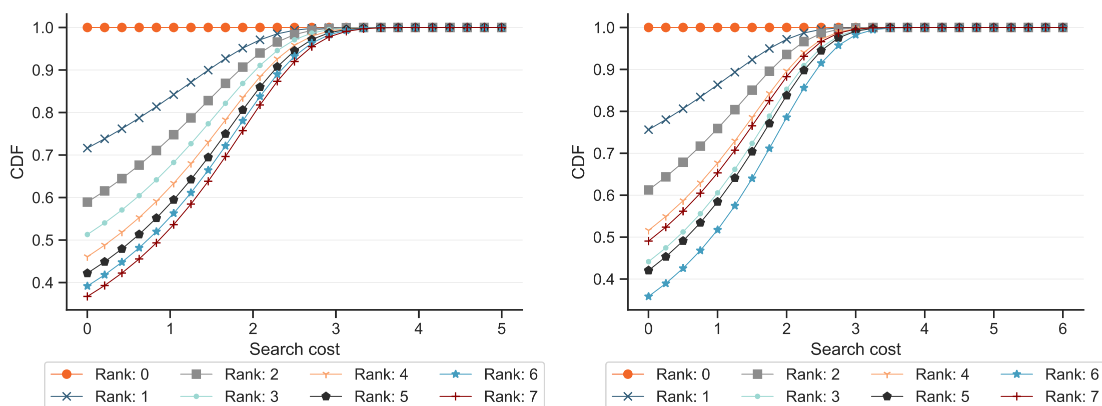
(a) Data (b) $G(R) = \log(R)$



Implied search cost distribution Using estimates from our three different model specifications of the relation between search cost and rank, we can use the search cost distribution in Equation (5.6) to work backwards from our conditional logit estimates to construct estimates of the structural search cost distribution that physicians face. We show results for two different specifications in Figure (5.2), where we have used two different assumptions for the relationship between rank and the search cost location parameter μ. Both specifications imply that $\mu(1) = 0$, so that the location for rank one products is 0. This implies that the search cost distribution for the first ranked product is degenerate with 100% mass at a search cost equal to zero. This is a convenient property since it is common to assume that consumers search one product for free when there is no outside option.

Figure 5.2: Implied Search Cost Distribution

(a) $\mu(R) = \log(R)$ (b) $\mu(R)$ non-parametric



Note: The distributions are computed using Equation (5.6).

6 Counterfactual Simulations

Using our structural estimates we conduct a series of counterfactual simulations to both investigate the role of search costs in consumer choice and to assess the impact of counterfactual designs of the physician search architecture. To do this, we will explore the following three counterfactuals:

1. Free physician search: setting $\mu(R_j) = 0$ for all j and allowing either *a)* the full choiceset, or *b)* only generics to be prescribed,

2. Price ranking: rank products according to price and allow either *a)* all products, or *b)* only generics to be prescribed,[9]

[9] For price ranking, we need to take a stand on how to handle ties. When two firms submit the same price, we assign each the average of the two ranks in question.

3. Prescribe cheapest: forcing the physician to always prescribe the cheapest product.

We will both conduct counterfactual simulations in which we keep prices fixed, and where we allow firms to adjust prices in response to the new demand system.

6.1 Solving for Equilibrium Price

Two features of our model complicates the question of counterfactual equilibrium prices: first, the demand model has a strong discontinuity at the minimum price – implied by the A-region dummy in Table 5.1. This discontinuity together with a non-zero demand at higher prices eliminates pure strategy equilibria by the same arguments as in Varian (1980). Second, firms are inherently asymmetric due to their alphabetical rank and the implications for prescription shares so it does not make sense to restrict attention to symmetric equilibria.

Therefore, we cannot solve the pricing equilibrium analytically but rely on a numerical algorithm to solve for the static mixed strategy equilibrium. We discretize the price space and compute equilibrium strategy vectors using the quantal response homotopy method implemented in `Gambit` (version 15.1.1). This is an algorithm which iteratively updates player strategies in a manner that converges to the unique Nash equilibrium if the game has a unique equilibrium that is locally stable. Firms maximize revenue arising from the structural demand model, corresponding to an assumption of zero marginal cost.[10] The computational complexity of finding an equilibrium does not allow us to study games with more than 4 players if we are to use a reasonable grid size. Having a large number of grid points is important because when there are too few, the algorithm can only find pure strategy equilibria.

[10]Naturally, this is an approximation. However, pharmaceutical products are characterized by high fixed and low variable costs. Moreover, the price differences across firms of different alphabetical rank that we documented earlier are consistent with market power rather than differences in marginal cost.

6.2 Counterfactual simulations with fixed prices

The results are shown in Table 6.1 and are all normalized relative to the equilibrium in the baseline. Row 1a shows that the direct cost-savings from removing search frictions holding prices fixed are numerically small, even displaying a tiny increase of 0.1%. This is partly due to the relative importance of price vis-a-vis idiosyncratic match value in physician search, and partly due to the fixed prices, which will become more clear once we also solve for equilibrium prices. Comparing 1a to 1b shows that if we in addition prohibit non-generic prescriptions, the effect is a cost reduction of 3.2% relative to baseline. This larger effect reflects the fact that a prescription is most valuable to a product with a price far above the minimum and non-generics tend to keep their prices high after patent expiration.

In the second counterfactual we explore price ranking of products. When we simply assume that products are ranked according to price (row 2a), the cost savings are 1.7% relative to baseline. If we additionally prohibit physicians from writing branded products on the prescription (row 2b), the average cost savings amount to 4.4% relative to baseline. This once again shows the importance of physician prescribing in driving costs related to patients' continued purchase of high-priced branded products even after patent expiration.

Finally and as expected, the third counterfactual results in a substantial reduction in cost, since the status quo is then always the cheapest. Forcing the physician to prescribe the cheapest product results in a reduction in average cost of of 9.4%, holding prices fixed. However, such a dramatic change is unrealistic in practice as the physician may have in some cases have medical reasons behind prescription choices such as allergies, captured by the idiosyncratic match values in our model. Thus, this counterfactual should just be viewed as an upper bound on the cost savings that can be attained from altering physician choice.

Table 6.1: Counterfactual Simulations: Holding Prices Fixed

	2 Firms	3 Firms	4 Firms	5 Firms	6 Firms	7 Firms	8 Firms	Total
Baseline (Index)	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
1a: Free search	99.9	99.9	100.1	100.2	100.1	100.4	100.4	100.2
2a: Price Ranking	99.6	99.1	98.5	98.2	97.8	97.9	97.7	98.3
3: Prescribe Cheapest	98.2	94.8	91.4	89.4	88.5	87.9	86.4	90.4
Prohibiting prescriptions of branded products								
1b: Free search	99.9	97.1	96.3	96.0	96.8	97.1	97.2	96.8
2b: Price ranking	99.6	96.7	95.5	94.7	95.2	95.3	95.1	95.6

Note: The table presents normalized average consumer expenses under Five different model assumptions for physician search. In this counterfactual exercise, we hold the prices fixed at the observed values. Each column uses only observations from markets with the corresponding number of active firms, and the column "Total" is a pooled average.

6.3 Counterfactual simulations with equilibrium prices

We now turn to counterfactuals in which we solve for the counterfactual price equilibrium. Throughout this, we ignore brands and instead assume that all products in the market are generic. We do this because branded products often price several times above generic products at a level that is unlikely to be fully understood using the estimated demand system for the Danish market. Instead, the pricing of branded firms likely reflects an intention to affect international reference prices which is beyond the scope of this paper.[11]

Table 6.2 presents average prices by rank and total expenditures for our three counterfactuals. The results labeled "baseline" show the implied model prices and expenditures when we solve for the mixed strategy equilibrium using the baseline estimated model. Table 6.2 shows that the model-implied equilibrium prices are (weakly) decreasing in rank, which is consistent with the empirical relation that we documented in Section 4. Furthermore, the magnitudes are relatively close to our preferred fixed effects estimates from Section 4, in the range of 2% to 6% per rank position.

In the first counterfactual, we see that removing physician search frictions has an am-

[11]Reference pricing is when a country determines the price of pharmaceuticals based on a basket of other countries. Denmark is a reference country in many other markets, which may incentivize original manufacturers to keep Danish prices high post patent expiration regardless of local market conditions.

biguous effect on equilibrium prices. In this counterfactual equilibrium, firms are symmetric and, reassuringly, we find a symmetric equilibrium. In two-firm markets, prices are lower for both firms, but with three or four firms, the unique price is higher for the last-ranked firms. As a result, expenditures decrease the most in two-firm markets.

In the second counterfactual with price ranking, the downwards pressure on prices is stronger than under free search because the lowest-priced firm wins a lot of prescriptions, which is a competitive advantage. This implies cost-reductions of just over 5%, 6%, and 4% for markets with two, three and four firms respectively. This result implies that the effect of changing the IT ranking from name-based to price-based is more effective than removing search frictions altogether. We see that compared to our counterfactual with frozen prices, the savings in 2 and 3 firm markets are larger after price adjustments while they are slightly smaller in 4 firm markets.

The third and final counterfactual removes physician choice altogether, always assigning the cheapest product on the prescription. Again, this makes firms symmetric and the algorithm converges to a symmetric price equilibrium. Unsurprisingly, this counterfactual results in the largest cost savings, amounting to 10%, 7% and 7% for markets with two, three and four firms, respectively. These numbers may be thought of as an upper bound on how much demand can be directed towards the cheapest product because physicians sometimes do have medical reasoning behind their prescription decisions, e.g. when a particular patient is allergic to one but not another product.

However, the symmetric equilibrium in the third counterfactual reveals another interesting insight: Expected prices and expenditures are both increasing in competition. This is a striking contrast to the fact that when we hold market structure fixed, expenditures are decreasing from counterfactual 1 to 2 to 3, i.e. in the prominence of the cheapest product. While seemingly at odds with many standard economic models of competition, this can occur in theoretical search models, e.g. Janssen and Moraga-González (2004). Intuitively, when the competition for the searching segment of consumers becomes too intense, firms can instead choose to exploit the inelastic non-searching consumers they encounter.

If a firm is not prominent, it will likely only encounter desperate and thus inelastic consumers. In other words, when firms are faced with a tradeoff between business stealing and exploitation, the effect of competition can be ambiguous.

Table 6.2: Counterfactuals: Prices in Equilibrium

		Prices				
		Rank 1	Rank 2	Rank 3	Rank 4	Expenditures
2 Firms	Baseline	1.17	1.15			1.16
	1a: Free Search	1.14	1.14			1.14
	2a: Price Ranking	1.11	1.11			1.10
	3: Prescribe Cheapest	1.05	1.05			1.04
3 Firms	Baseline	1.20	1.12	1.11		1.13
	1a: Free Search	1.14	1.14	1.14		1.13
	2a: Price Ranking	1.10	1.10	1.1		1.08
	3: Prescribe Cheapest	1.08	1.08	1.08		1.05
4 Firms	Baseline	1.20	1.20	1.11	1.1	1.14
	1a: Free Search	1.14	1.14	1.14	1.14	1.13
	2a: Price Ranking	1.11	1.11	1.11	1.11	1.09
	3: Prescribe Cheapest	1.10	1.10	1.1	1.1	1.06

Note: The table presents average prices and expenditures across rank and under different market structures. To compute the equilibria we discretize the price grid and compute the equilibrium using `Gambit` (version 15). We use the homotopy method using the logit correspondance.

7 Conclusion

We estimate the effect of product prominence on market shares and prices in pharmaceutical markets. Prominence arises from the ease with which physician may find products on their computer, which clearly affects the likelihood that a product ends up on the prescription. We show that prescribing a product has a strong effect on patient purchasing behavior and ultimately prices, highlighting the importance of the physician for pharmaceutical demand. While it may seem surprising that physician prescriptions affect demand so heavily, inattention by the consumer could be rational given that an expert has already made a recommendation in the form of the prescription.

Our structural model shows that putting the cheapest product on the prescription would save up to 10% in expenses. Given that the system already has strong generic substitution in place at the pharmacy, savings of this magnitude are important. It is particularly interesting that the savings from this improvement in the information architecture are larger than those arising from a removal of information frictions. Our results highlight that a fully effective generic substitution ought to start already at the prescribing physician in order to gain maximum effect.

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Appendix Intended for Online Publication

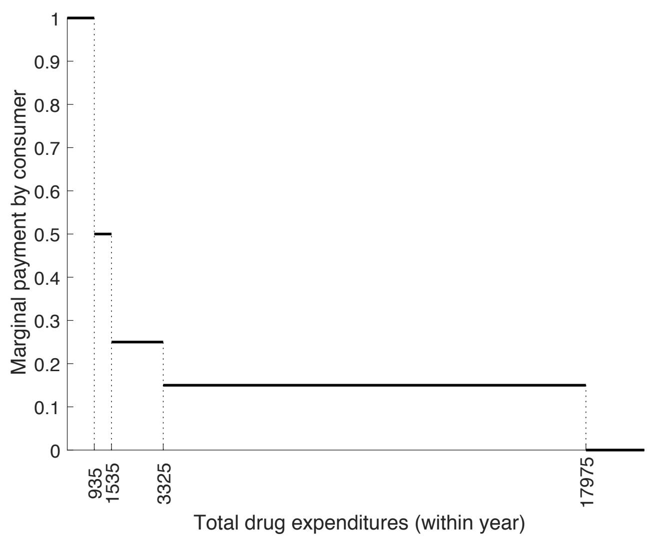
A Appendix

Table A.1: Sample Selection

Selection	Product-Periods	Transactions
Raw Data	3,162,223	869,804,625
A: After 2005	1,776,331	501,049,110
B: A & Off Patent	1,066,805	364,806,655
C: B & $2 \leq J \leq 8$	749,072	245,345,025
D: C & package name observed	704,731	218,958,275
E: D & market share not missing	697,636	218,958,040
F: E & max. 2 branded	348,494	99,491,700
G: F & year $\leq$ 2013	207,918	60,136,270
H: G & age, gender & inc observed	172,502	60,080,895

Note: The sample "F" is our product-level panel, used in Section 4, and "H" is our transaction-level sample used in Section 5. The selection to periods prior to 2014 ("G") is income is not in our data after 2013.

Figure A.1: Out of pocket payment under the public health insurance



Note: The plot depicts the fraction of the transaction price that must be paid out of pocket by the consumer. The spending thresholds are as of 2015 and subject to an annual inflation adjustments. Each consumer will have asynchronous drug expenditures years: the first time a consumer makes a purchase, an expenditure year is initiated. During the year, expenditures mount and the marginal payment starts to fall. Then, precisely a year later, total expenditures are reset to zero. The next year does not begin until the next time the consumer makes a purchase.

A.1 Log Revenue

Table A.2: Log (revenue+1) regressions: linear

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Alphabetical Rank	0.285**	0.167	0.0434	0.109	0.0679
	(0.0884)	(0.0874)	(0.0521)	(0.0665)	(0.0552)
Alphabetical Rank×No. Firms	-0.0754***	-0.0503***	-0.0267**	-0.0426***	-0.0310**
	(0.0152)	(0.0148)	(0.00906)	(0.00966)	(0.00958)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	1552	1552	1547	1540	1475
Observations	697636	697635	697630	697511	685368

Note: Standard errors clustered at the market level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.2 Regressions using broader generic definition

Table A.3: Prescription share: wide definition of generics

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.0689***	-0.0714***	-0.0775***	-0.0951***	-0.0786***
	(0.0125)	(0.00892)	(0.00901)	(0.00758)	(0.00919)
Rank×No. Firms	0.00521**	0.00725***	0.00835***	0.00990***	0.00866***
	(0.00181)	(0.00126)	(0.00125)	(0.000942)	(0.00127)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	711	711	711	700	711
Observations	348494	348491	348491	348354	348491

Note: Standard errors clustered at the market level. We use a broader definition of generic, that is a product that have quotes in the name or satisfies that the product was first observed after the patent expired. We use markets where no more than 2 or 50 percent of products are non-generic according to this definition. *p<0.05, **p<0.01, *** p<0.001

Table A.4: Market share: wide definition of generics

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.0212**	-0.0234***	-0.0243***	-0.0139*	-0.0246***
	(0.00793)	(0.00595)	(0.00599)	(0.00670)	(0.00608)
Rank×No. Firms	0.00186	0.00223*	0.00248**	0.0000665	0.00255**
	(0.00118)	(0.000886)	(0.000885)	(0.000876)	(0.000892)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	711	711	711	700	711
Observations	348494	348491	348491	348354	348491

Note: Standard errors clustered at the market level. We use a broader definition of generic, that is a product that have quotes in the name or satisfies that the product was first observed after the patent expired. We use markets where no more than 2 or 50 percent of products are non-generic according to this definition. *p<0.05, **p<0.01, *** p<0.001

Table A.5: Revenue share: wide definition of generics

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.0197**	-0.0255***	-0.0289***	-0.0107	-0.0301***
	(0.00760)	(0.00629)	(0.00645)	(0.00660)	(0.00658)
Rank×No. Firms	0.00145	0.00240*	0.00293**	0.0000307	0.00309**
	(0.00118)	(0.000953)	(0.000950)	(0.000914)	(0.000957)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	711	711	711	700	711
Observations	348494	348491	348491	348354	348491

Note: Standard errors clustered at the market level. We use a broader definition of generic, that is a product that have quotes in the name or satisfies that the product was first observed after the patent expired. We use markets where no more than 2 or 50 percent of products are non-generic according to this definition. *p<0.05, **p<0.01, *** p<0.001

Table A.6: Log revenue: wide definition of generics

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	0.000334	-0.00785	-0.0361	-0.0364	-0.0368
	(0.0265)	(0.0255)	(0.0222)	(0.0260)	(0.0227)
Rank×No. Firms	-0.00760	-0.00511	-0.00126	-0.00125	-0.00106
	(0.00478)	(0.00392)	(0.00373)	(0.00321)	(0.00380)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	711	711	711	700	711
Observations	348494	348491	348491	348354	348491

Note: Standard errors clustered at the market level. We use a broader definition of generic, that is a product that have quotes in the name or satisfies that the product was first observed after the patent expired. We use markets where no more than 2 or 50 percent of products are non-generic according to this definition. *p<0.05, **p<0.01, *** p<0.001

Table A.7: Log price: wide definition of generics

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.0377	-0.0674*	-0.0574**	-0.0415*	-0.0613**
	(0.0289)	(0.0262)	(0.0185)	(0.0210)	(0.0187)
Rank×No. Firms	0.00646	0.00841*	0.00725*	0.00692**	0.00802**
	(0.00542)	(0.00402)	(0.00299)	(0.00236)	(0.00298)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	711	711	711	700	711
Observations	348494	348491	348491	348354	348491

Note: Standard errors clustered at the market level. We use a broader definition of generic, that is a product that have quotes in the name or satisfies that the product was first observed after the patent expired. We use markets where no more than 2 or 50 percent of products are non-generic according to this definition. *p<0.05, **p<0.01, *** p<0.001

A.3 Regressions using narrow generic definition

Table A.8: Prescription share: narrow definition of generics

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.0689***	-0.0714***	-0.0775***	-0.0951***	-0.0786***
	(0.0125)	(0.00892)	(0.00901)	(0.00758)	(0.00919)
Rank × No. Firms	0.00521**	0.00725***	0.00835***	0.00990***	0.00866***
	(0.00181)	(0.00126)	(0.00125)	(0.000942)	(0.00127)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	711	711	711	700	711
Observations	348494	348491	348491	348354	348491

Note: Standard errors clustered at the market level. We define a generic narrowly as a product with quotes in the name and use markets where no more than 2 or 50 percent of products are non-generic. *p<0.05, **p<0.01, *** p<0.001

Table A.9: Market share: narrow definition of generics

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.0212**	-0.0234***	-0.0243***	-0.0139*	-0.0246***
	(0.00793)	(0.00595)	(0.00599)	(0.00670)	(0.00608)
Rank × No. Firms	0.00186	0.00223*	0.00248**	0.0000665	0.00255**
	(0.00118)	(0.000886)	(0.000885)	(0.000876)	(0.000892)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	711	711	711	700	711
Observations	348494	348491	348491	348354	348491

Note: Standard errors clustered at the market level. We define a generic narrowly as a product with quotes in the name and use markets where no more than 2 or 50 percent of products are non-generic. *p<0.05, **p<0.01, *** p<0.001

Table A.10: Log price: narrow definition of generics

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.0377	-0.0674*	-0.0574**	-0.0415*	-0.0613**
	(0.0289)	(0.0262)	(0.0185)	(0.0210)	(0.0187)
Rank × No. Firms	0.00646	0.00841*	0.00725*	0.00692**	0.00802**
	(0.00542)	(0.00402)	(0.00299)	(0.00236)	(0.00298)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	711	711	711	700	711
Observations	348494	348491	348491	348354	348491

Note: Standard errors clustered at the market level. We define a generic narrowly as a product with quotes in the name and use markets where no more than 2 or 50 percent of products are non-generic. *p<0.05, **p<0.01, *** p<0.001

Table A.11: Revenue share: narrow definition of generics

	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	-0.0197**	-0.0255***	-0.0289***	-0.0107	-0.0301***
	(0.00760)	(0.00629)	(0.00645)	(0.00660)	(0.00658)
Rank × No. Firms	0.00145	0.00240*	0.00293**	0.0000307	0.00309**
	(0.00118)	(0.000953)	(0.000950)	(0.000914)	(0.000957)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	711	711	711	700	711
Observations	348494	348491	348491	348354	348491

Table A.12: Log revenue: narrow definition of generics

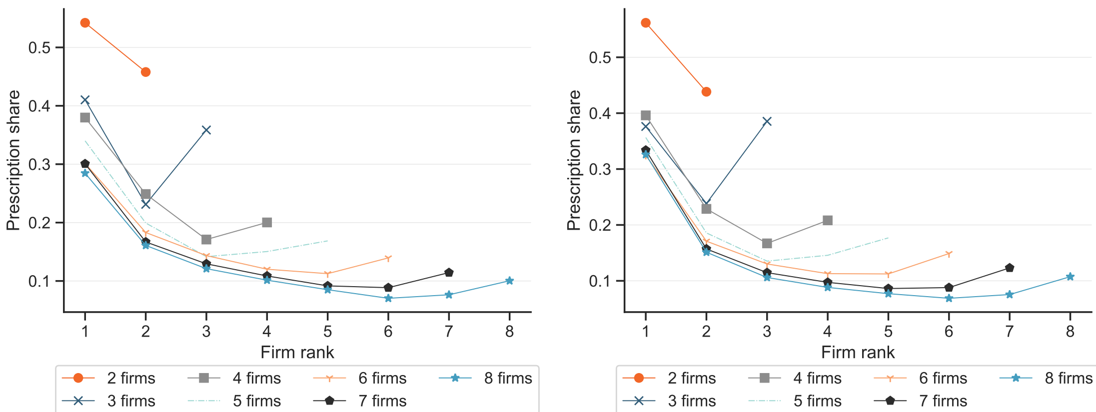
	(1) OLS	(2) Company FE	(3) Market+Company FE	(4) Product FE	(5) Market-by-date FE
Rank	0.000334	-0.00785	-0.0361	-0.0364	-0.0368
	(0.0265)	(0.0255)	(0.0222)	(0.0260)	(0.0227)
Rank × No. Firms	-0.00760	-0.00511	-0.00126	-0.00125	-0.00106
	(0.00478)	(0.00392)	(0.00373)	(0.00321)	(0.00380)
Drug age FE	Yes	Yes	Yes	Yes	Yes
No. Firms FE	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	No	Yes
Period FE	No	Yes	Yes	Yes	No
Market FE	No	No	Yes	No	No
Product FE	No	No	No	Yes	No
Market-by-date FE	No	No	No	No	Yes
Clusters	711	711	711	700	711
Observations	348494	348491	348491	348354	348491

Note: Standard errors clustered at the market level. We define a generic narrowly as a product with quotes in the name and use markets where no more than 2 or 50 percent of products are non-generic. *p<0.05, **p<0.01, *** p<0.001

A.4 Model Fit: Linear and Non-Parametric Specifications

Figure A.2: Model Fit

(a) $G(R) = R$ (b) $G(R)$ non parametric



A.5 Structural Model Simulations

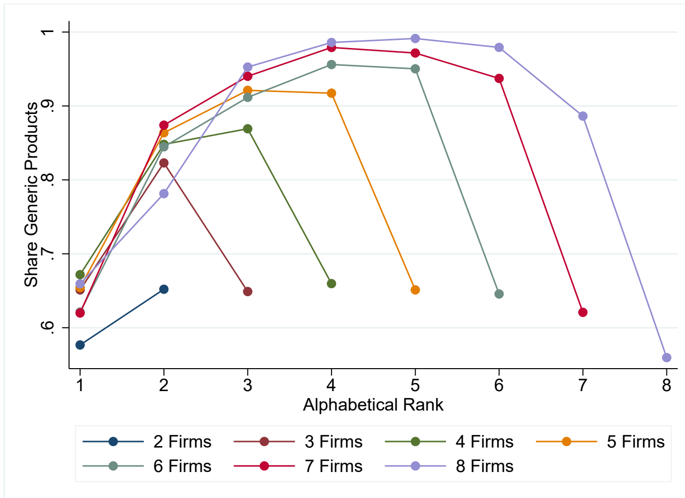
Table A.13: Equilibrium Expected Profit and Counterfactuals

		Rank 1	Rank 2	Rank 3	Rank 4	Total
2 Firms	Baseline	0.09	0.07			0.16
	Counterfactual: Free Search	0.07	0.07			0.14
	Counterfactual: Price Ranking	0.05	0.05			0.10
	Counterfactual: Prescribe Cheapest	0.02	0.02			0.04
3 Firms	Baseline	0.06	0.04	0.04		0.13
	Counterfactual: Free Search	0.04	0.04	0.04		0.13
	Counterfactual: Price Ranking	0.03	0.03	0.03		0.08
	Counterfactual: Prescribe Cheapest	0.02	0.02	0.02		0.05
4 Firms	Baseline	0.05	0.03	0.03	0.03	0.14
	Counterfactual: Free Search	0.03	0.03	0.03	0.03	0.13
	Counterfactual: Price Ranking	0.02	0.02	0.02	0.02	0.09
	Counterfactual: Prescribe Cheapest	0.01	0.01	0.01	0.01	0.06

Note: The tables present average revenue across rank and under different market structure using equilibrium price distributions. To compute the equilibria we discretize the price grid and compute the equilibrium using `Gambit` *(version 15). We use the homotopy method using the logit correspondance.*

A.6 Generic Status by Rank

Figure A.3: Generic share (Wide definition) by rank



Note: The figure is constructed using our product-level dataset (i.e. an observation is a product-period) including all products both branded and generic. Note that there can be multiple branded in a given market, although there is most typically only one.