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. (JEL: D83, L13, D12)

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

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1. Introduction

In many retail markets, 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. In pharmaceutical markets, prominence may be particularly important. Products are complex to understand for laymen (Bronnenberg et al., 2015) and the search effort involves a multitude of agents, including prescribers and pharmacists, opening a possibility of misaligned incentives and inefficiencies.

The role of prominence for consumer choice has been thoroughly documented in the context of online markets (Dinerstein et al., 2018; Ursu, 2018; Agarwal et al., 2011) and so has the importance of defaults across a wide range of markets where it is difficult for consumers to compare products (Madrian and Shea, 2001; Abaluck and Gruber, 2011; Agarwal et al., 2017). Empirically, the effect on prices is less

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well studied, but theoretically, prominence is an advantage which can result in both higher prices (Arbatskaya, 2007) or lower prices (Armstrong et al., 2009) depending on consumer preferences and search costs.

We study the role of prominence and defaults for equilibrium prices and market shares in pharmaceutical markets using a dataset covering all transactions and prices in Danish pharmacies between 2005 and 2016. Prominence arises in two ways. First, prescribing physicians in Denmark use a search engine to find drugs which presents results in alphabetical order, generating arbitrary variation in brand prominence for physicians across products.[1] Second, prescriptions determine which product is prominent to the consumer, meaning that physicians directly influence consumer choice.

We use this setting to estimate the causal effect of prominence on market shares and prices. We formulate and estimate a structural model of search, demand and equilibrium pricing. Our key counterfactual shows that sorting products by price rather than firm names enhances price competition and saves money for taxpayers and consumers.

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, and we can assume that the measured effects take into account adjustment of equilibrium prices and beliefs.

We find that alphabetical rank affects which drug brand 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. By including product fixed effects, our results are robust to any time-constant firm-level unobservables that might be correlated with name choice.[2]

While the reduced form results tell us the effect of prominence on prices under the given information structure, we need a model to quantify the relative importance of preferences and information frictions, and to evaluate counterfactual designs of the IT system.

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1. We discuss the issue of exogeneity in greater detail in Section 4. For now, simply note that we will include company and even product fixed effects, so variation in rank will be due to factors outside the firm's own control.

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

We build a structural econometric model of physician prescribing and consumer purchase. Physicians exert costly effort to browse through the list of available brands, trading off search costs against expected savings and consumer-product match value. The consumer takes the prescription to the pharmacy where the pharmacist by law is required to recommend the cheapest available product (a process called *generic substitution*). The consumer then decides whether to sequentially search for alternative products. Thus, the alphabetically first-ranked product is prominent to the prescribing physician, whereas the prescribed and the cheapest products are prominent to the consumer.

Estimation is made tractable using recent methodological breakthroughs in estimation of ordered search models. Armstrong (2017) and Choi et al. (2018) showed 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. (2021) overcome this by deriving a search cost distribution that implies a closed "logit" form for the choice probabilities. The computationally costly integration to obtain search cost distributions can then be done in a single step after estimation.

The estimated model shows that physicians are not ignorant about the induced effect on the consumer, but neither are they perfect search agents. 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. Physicians also respond 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 computed 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 rather than the prominent firm, forcing prominent firms to compete more aggressively. In this way, we show that information frictions can be used in the design of the search architecture to improve competition and market outcomes.

This insight is relevant more broadly for markets with complex products. Empirically, consumers often make systematic mistakes regarding health insurance (Abaluck and Gruber, 2011; Bhargava et al., 2017), retirement savings (Madrian and Shea, 2001; Benartzi and Thaler, 2007), and mortgage products (Agarwal et al., 2017). In such markets, it may be optimal to provide a default option (Benartzi and Thaler, 2013), and a recent literature explores the effects of alternative choice architectures on demand.[3] We provide evidence that the supply side also responds, and highlight the benefits from strengthened price competition that arise when prominence is awarded based on price.[4]

We conduct two further counterfactuals to provide a frame of reference for the magnitudes. We show that prohibiting physicians from prescribing original manufacturers' brands reduces costs by 3.2%, showing that prescriptions can explain part of the continued demand for high-priced branded drugs post patent expiration (Feng, 2019). Second, we simulate a system in which physicians are forced to prescribe the cheapest product. In duopoly markets, this reduces costs of 10.3%. This represents an upper bound to potential savings, but is not a realistic policy from a medical viewpoint.

We contribute to a literature on the importance of brands, prescriptions[5] and information frictions in pharmaceutical markets. Previous papers have studied the role of "expert consumers" (Bronnenberg et al., 2015; Janssen, 2019), advertising (Sinkinson and Starc, 2019), or consumer learning (Ching et al., 2019). In the US, a randomized experiment where physicians' IT systems where set to prescribe the cheapest by default, found a causal effect of physician prescriptions on demand (Patel et al., 2014), leading to an increase in generic consumption of 5.4%. We contribute by estimating the effect of generic prescribing on price competition.

Our paper also contributes to an empirical literature on the effect of search frictions on prices. While we study a centralized market, the previous literature has largely focused on decentralized markets such as mutual funds (Hortaçsu and Syverson, 2004), social security plans (Hastings et al., 2017), credit cards (Galenianos and Gavazza, 2018), mortgages (Allen et al., 2019), used books (Ellison and Ellison, 2018), and video games on eBay (Dinerstein et al., 2018). The key difference is that in decentralized markets, prices are typically not uniform across consumers.

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.

3. See e.g. Abaluck and Gruber (2016); Ericson and Sydnor (2017); Ketcham et al. (2019).

4. Two recent papers, Luco (2019) and Brown (2019), have also studied price responses to information provision, utilizing price disclosure websites. (Interestingly, they find opposite effects on average prices.) Dinerstein et al. (2018) study very related aspects of digital platform design for eBay, albeit in a decentralized market setting.

5. See Ching et al. (2019) for a recent survey on structural work in this context.

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 similar 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 is a set of products having the same substance, strength, dose and similar pack size.[6] All products that have a submitted price in the system are available for the consumer to purchase at that price, and a consumer is allowed to choose any product in the same substitution group as the product on her prescription.[7] Throughout, a *market* will refer to a substitution group and a *period* will refer to a 14-day price period.

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. When writing a prescription for the patient, the physician has no monetary incentives and 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.

As mentioned, our empirical strategy relies on variation in prominence generated by the alphabetical ranking of products. The alphabetical ranking arises due to 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 1.[8] This way, the name of the product becomes important.

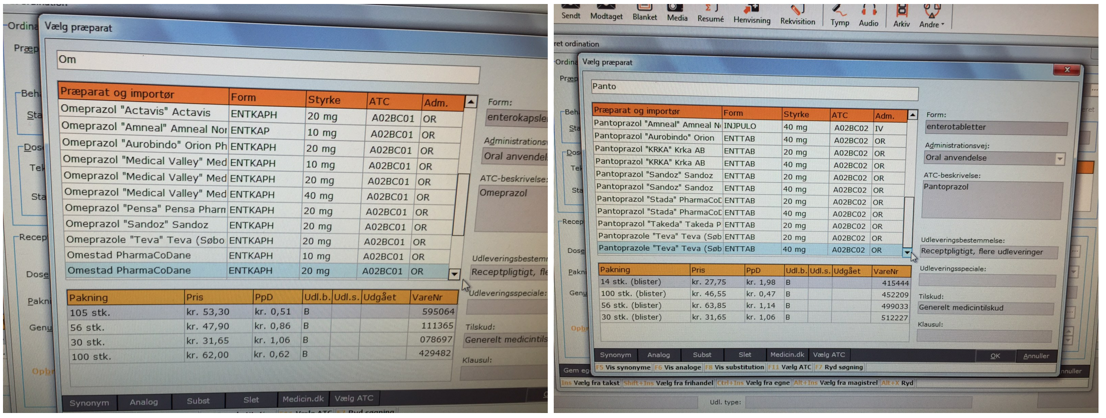
6. Pack size is measured in number of Defined Daily Dosages (DDDs). The definition of a substitution group allows for a variation of $\pm 10\%$ in DDD within the group. Products in a substition group are bioequivalent, but not necessarily chemically identical. In rare cases it is possible that this distinction makes a difference, for instance if consumers are allergic to the coating of one product but not the other. For the vast majority of consumers, products in a substitution group are for all practical purposes perfect substitutes, although our structural model does not assume this.

7. Technically, the consumer can also substitute, say, two 25 pill packages for one 50 pill package of the same package, so long as the quantity does not increase.

8. Physicians may then click on each product to view additional informaton such as the price, which is hidden in the default view. Anecdotally, we first became aware of the mechanism when an irritated physician explained how she spent time cliking through the list to find a cheap product to put on the prescription. Other physicians we have talked to have no reason to pick one product over another, expecting the pharmacist to help the consumer to find a cheaper alternative.

FIGURE 1. Search engine illustration

(A) Example 1: Omeprazole (B) Example 2: Pantroprazole



The ability of firms to change the names of 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 will define a product as being generic if the name follows category 2. This ensures that in the markets we study, the order of the generic firms in the search rank is determined by the company name. Conversely, 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.[9]

The pharmacist's role in the mechanism is to guide demand towards the cheapest product in the market. Pharmacists are legally mandated to recommend that the consumer buys the cheapest product in the substitution group.[10] This is referred to as *generic substitution* and appears in most countries in some version. As a result, when one firm undercuts another, even by a tiny amount, this makes them the recommendation made by all pharmacists. This explains the strong discontinuity in market demand at the minimum price that we will present later. We cover additional details regarding pharmacy regulations in Appendix B.

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

9. 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.

10. If multiple firms bid the lowest price, the pharmacist may choose which to recommend.

annual expenditure, starting at 0% and eventually reaching 100% for consumers with very high accumulated expenditures (see Appendix Figure B.1 for details). However, a consumer must pay the full price difference between the cheapest product and the chosen product out of her own pocket. This structure of insurance implies that the consumer receives a fixed subsidy regardless of which product she chooses and then pays the price difference down to the cheapest. This allows us to simplify the structural model and abstract from the subsidy. While some consumers have additional market-based health insurance, this insurance does not alter the relative prices.[11] Additional institutional details are in in Appendix B.

To summarize, the firm submitting the lowest price in a market – the “winner” – is rewarded in two ways in the mechanism: first, through the prominence resulting from the pharmacist’s recommendation, and second, through the subsidy structure. The physician’s decision to prescribe one product over another in the same market does not affect the consumer apart from making that product the de facto default. The alphabetical ordering affects the physician’s prescription probabilities, which in turn affects product prominence to the consumer through the default status.

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

11. Private health insurers offering supplementary coverage are also active in the Danish market, the largest such provider being “danmark”. The most common package in “danmark” covers an additional part of the out-of-pocket payment but, similarly to the public insurance, not the extra price differences from opting out of the cheapest. This means that the price differences between the available products are not affected by insurance. Since we do not have an outside option in our model, discrete choice probabilities will be numerically unaltered. We do not know much about the outside option because we do not observe prescriptions that are not filled.

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 0.01% subsample of transactions. Summary statistics for this sample are shown in Appendix Table A.2.

3. Descriptive evidence

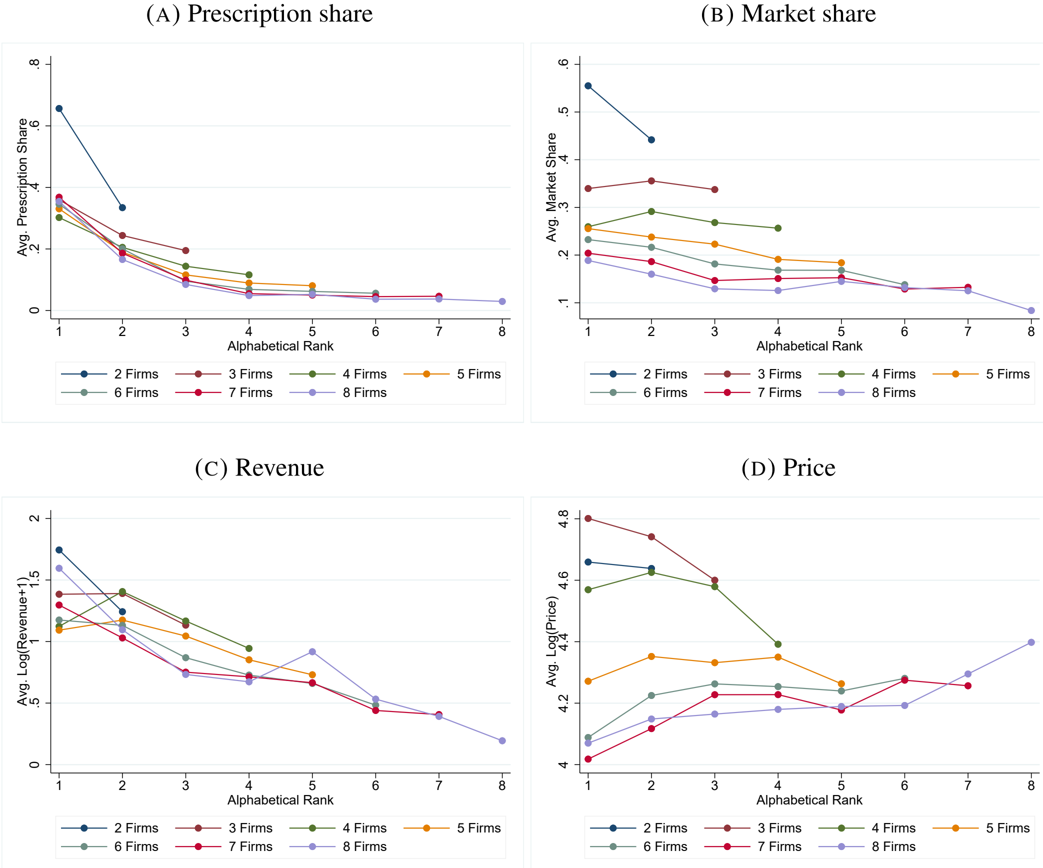
Figure 2 shows the relationship between the alphabetical rank of a product on the x-axis and the average or median of four different outcome variables on the y-axis, and as such display the raw associations in the data to provide an overview.

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 for generic pharmaceutical products in Figure 2a. 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.

Figures 2b and 2c 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 2d 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.

FIGURE 2. Alphabetical Rank and Market Outcomes for Generics



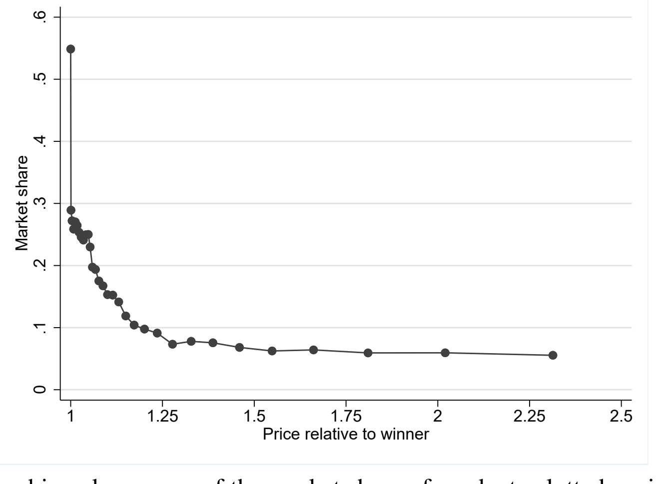
Note: All figures are constructed using our product-level dataset (i.e. an observation is a product-period) including only generic productrs. Since 5% of observations have zero revenue we add 1 to revenue (in 1000 DKK) before taking logs.

All the panels in Figure 2 are constructed using only observations for generic products, which are the ones that are ranked by the firm name. Original manufacturer products use the proprietary name, which can therefore be either first or last, as explained earlier.[12] Appendix Figure A.1 contains the same panels including all products. As expected, the first and last product looks different there. When we later turn to regressions, we can control for whether a product is generic to avoid to avoid such compositional changes, and our results are robust to running either on the full sample or only generics, so we have opted to use the most inclusive sample in the remainder of the paper.

12. In a few cases, packages can have non-generic names for other reasons (e.g. parallel imported generics). Appendix Figure A.3 shows the frequency with which a given product is a generic for each rank position.

Next, we turn to the shape of the demand curve, describing how patient purchase depends on price. Figure 3 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 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).

FIGURE 3. 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.

Finally, we will briefly comment on the sources of variation. Table A.3 presents variance decompositions of the key variables into the overall, between, and within variances. This shows that all variables have substantial variation within a product over time. For instance, the within-productc variance of market shares is greater than the between variance. Not surprisingly, all other variables have greater variance between than within, with the log prices showing the greatest disparity with 1.57 between but only 0.35 within. Still, that is not surprising given that there are both expensive original products and cheap generics in our broadest sample definition. Table A.4 shows the

Markov transition matrix for the winner status (being the cheapest product), which shows that only 72.1% of products winning in a given period t also win in period $t+1$, indicating that there is much more variation closer to the winning price. Table A.5 presents the transition rates for alphabetical rank positions, which are more stable but still have sufficient variation.

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.

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 1.

TABLE 1. Summary Statistics

	Mean	S.d.	P10	P50	P90
No. Firms	4.19	1.77	2.00	4.00	7.00
Log(Revenue+1)	1.89	1.49	0.12	1.66	3.97
Log(Price)	1.19	1.54	-0.46	0.92	3.12
Price relative to winner	1.83	3.81	1.00	1.04	2.31
Alphabetical Rank	2.34	1.53	1.00	2.00	5.00
Market Share	0.29	0.30	0.00	0.16	0.78
Prescription Share	0.29	0.27	0.02	0.19	0.73
Quantity sold (1000 packages)	0.37	1.28	0.00	0.05	0.79
Years since end of exclusivity	10.83	8.93	2.31	8.17	23.21
No. Generics (def. 1)	2.23	2.07	0.00	2.00	5.00
No. Generics (def. 2)	3.22	1.84	1.00	3.00	6.00
Original manufacturer ranked first	0.16	0.36	0.00	0.00	1.00
N (product-periods)					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.[13] We consider variations of the following regression model:

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

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 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.[14] 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

13. 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.

14. 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.

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 considering 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 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 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 2. Marginal Rank Effects and Market Structure

	Log Price	Prescription Share	Market Share	Revenue Share
$J = 2$	-0.047	-0.049	-0.024	-0.019
$J = 3$	-0.040	-0.043	-0.023	-0.017
$J = 4$	-0.032	-0.037	-0.021	-0.015
$J = 5$	-0.024	-0.031	-0.020	-0.013
$J = 6$	-0.017	-0.025	-0.018	-0.011
$J = 7$	-0.009	-0.019	-0.017	-0.010
$J = 8$	-0.001	-0.013	-0.015	-0.008

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 $\hat{\rho}_1 + \hat{\rho}_2 J$. The marginal effects are computed using our preferred regression specification, column (4), which uses fixed effects at the product and period level: $\eta_{jt} = \eta_j + \eta_t$.

Table 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 3. Prescription share

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.0319**	-0.0538***	-0.0564***	-0.0607***	-0.0587***
	(0.00995)	(0.00731)	(0.00797)	(0.00669)	(0.00843)
Alphabetical 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	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes both branded and generic products. "Company FE" are common for all products in the same pharmaceutical company's portfolio.

As shown in Table 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 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 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 5. Log price regressions

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.592***	-0.359***	-0.0444**	-0.0629***	-0.0506**
	(0.0609)	(0.0498)	(0.0159)	(0.0168)	(0.0166)
Alphabetical 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	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes both branded and generic products. "Company FE" are common for all products in the same pharmaceutical company's portfolio.

TABLE 4. Market share

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.0223***	-0.0379***	-0.0245***	-0.0274***	-0.0223***
	(0.00641)	(0.00581)	(0.00633)	(0.00553)	(0.00675)
Alphabetical 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	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes both branded and generic products. "Company FE" are common for all products in the same pharmaceutical company's portfolio.

Table 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 A.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 2 showed, the marginal effect of rank starts at 4.7% for duopoly markets, and is 0.1% with 8 firms.

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 6. The pattern similar to the one in Table 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 to the more common log revenue measure is the high prevalence of zero sales in our data. As a robustness, Table A.6 in the appendix presents regressions using $\log(\text{Revenue}+1)$ as outcome, which yields similar patterns qualitatively.

TABLE 6. Revenue share

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.0207**	-0.0328***	-0.0281***	-0.0225***	-0.0279***
	(0.00634)	(0.00588)	(0.00656)	(0.00543)	(0.00701)
Alphabetical Rank×No. Firms	0.00200	0.00347***	0.00299**	0.00184*	0.00294**
	(0.00103)	(0.000924)	(0.00100)	(0.000788)	(0.00108)
Drug age FE	Yes	Yes	Yes	Yes	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes both branded and generic products. "Company FE" are common for all products in the same pharmaceutical company's portfolio. We prefer this specification to one using log revenue due to the large number of zeros, but such a specification is given in Appendix Table A.6.

We now turn to robustness checks. 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, it might be a concern that branded and generic products are too dissimilar to compare. Therefore, as a robustness check, we 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 452,427 product-period observations over 1184 markets, and the results are presented in Appendix Section A.2. Additionally we present results with a very narrow definition of generics that results in 348,491 product-period observations over 711 markets in Appendix A.3. The qualitative picture is the same and all estimates are statistically significantly different from zero at the 5% level. In general, results are slightly larger in magnitude using in the narrowest definition and slightly smaller in magnitude using the widest definition.

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. Physicians will have to pay a higher search cost to learn about products further down the alphabetical list, whereas consumers pay a higher cost to learn about the products that are neither prescribed nor the recommended product by the pharmacist. Our exposition is an adaptation of the empirical framework developed by Moraga-Gonzalez et al. (2021) which has the advantage that estimation is straightforward, while the computationally demanding task can be done only after estimation.

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. The magnitude of $\omega_{ij}(p)$ relative to ε_{ij} will determine the relative balance of consumer expenditures and patient-drug match value heterogeneity in the physician's choice of prescription.

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. (2021), 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

$$\begin{aligned}\mathbb{E}\left(\max\{u_{ij},\overline{u}\}\right)-\overline{u}-c_{ij} &= \mathbb{E}_{\varepsilon}\left(\max\{\omega_{ij}(p^E)+\varepsilon-\overline{u},0\}\right)-c_{ij} \\ &\equiv H_{ij}(\overline{u})-c_{ij}.\end{aligned} \tag{2}$$

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

$$r_{ij}=H_{ij}^{-1}(c_{ij}). \tag{3}$$

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 Armstrong (2017); Choi et al. (2018) 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

$$w_{ij}=\min\{r_{ij},u_{ij}\} \tag{4}$$

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 (4) 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

$$\begin{aligned} F_{ij}^{w}(x) &= 1 - \left[1 - F_{ij}^{r}(x)\right]\left[1 - F_{ij}^{u}(x)\right] \\ &= 1 - F_{ij}^{c}\left[H(x)\right]\left[1 - F_{ij}^{u}(x)\right] \end{aligned} \tag{5}$$

Computing prescription probabilities involves solving a $J-1$ dimensional integral, but using the relationship in (5), this may be done straightforwardly using e.g. simulation techniques.

However, the key contribution by Moraga-Gonzalez et al. (2021) was to show that sufficient structure has already been assumed to make estimation even more convenient. Note that Equation (5) implies that given a distribution for the unobserved match values F_{ij}^{u}, there is a one-to-one relationship between the distribution of F_{ij}^{w} and F_{ij}^{c}. So instead of making parametric assumptions on F_{ij}^{c} and deriving the implications for choice probabilities and requiring simulation during estimation, we may instead make our (convenient) assumptions on F_{ij}^{w} and derive the implied distribution of search costs, F_{ij}^{c}. Thus, it is clearly convenient to assume that F_{ij}^{w} is T1EV with location parameter μ_{ij}, implying that the prescription choice probabilities take the form

$$\Pr(j \text{ prescribed}) = \frac{\exp\left[\omega_{ij}(p) - \mu_{ij}\right]}{\sum_{k=1}^{J} \exp\left[\omega_{ij}(p) - \mu_{ik}\right]}, \tag{6}$$

where we have made the assumption that physician price expectations are correct so $p^{E} = p$. Moraga-Gonzalez et al. (2021) show that under the assumption on F_{ij}^{w}, the corresponding distribution of search cost is

$$F_{ij}^{c}(c) = \frac{1 - \exp\left\{-\exp\left[-H_{ij}^{-1}(c) - \mu_{ij}\right]\right\}}{1 - \exp\left\{-\exp\left[-H_{ij}^{-1}(c)\right]\right\}}, \tag{7}$$

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.

Before proceeding, it is worth commenting on our choice to include the generic dummy in search costs and not in utility. Since both search and match value terms enter additively in (6), it is not possible to allow it to enter in both and infer relative magnitudes without separate data on search (Moraga-Gonzalez et al., 2021). Thus, we assume that any differences between generic and branded products are purely due to search costs. This is consistent with the fact that there is overwhelming medical evidence of no differences in clinical outcomes – the penultimate consumption value of pharmaceuticals – between branded and generic drugs with the same molecule (e.g. Manzoli et al., 2016). Our assumption is furthermore consistent with Bronnenberg et al. (2015), who show that "expert" consumers are far less likely to choose branded pharmaceuticals than regular consumers due to informational differences.[15]

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

15. Of course, one could argue that there are different *types* of information, whereas we interpret all informational differences as being due to search costs. For instance, one could argue that information such as brand awareness is a part of consumption utility, e.g. due to social status (something that is probably not relevant for pharmaceuticals as most consumers are quite private about medical issues).

prescription. Since we do not consider repeat purchases, i may also interchangeably refer to a transaction. Consumers maximize utility

$$v_{ij} = \beta_1^v \log(p_j) + e_{ij}, \quad e_{ij} \sim \text{IID Extreme Value} \tag{8}$$

Note that the consumer and physician error terms, e_{ij} and ε_{ij}, are independent. To learn the values of product j (p_j and e_{ij}), consumer i pays the random search cost $\zeta_{ij} \sim F_{ij}^{\zeta}$, where the distribution F_{ij}^{ζ} has location parameter κ_{ij}, interpreted as the average search cost. It is cheaper to search a product if it is on the prescription, and it is also cheaper to search the product if the pharmacist recommends it, i.e. if it is cheapest. The first channel is the only way the alphabetical rank can affect final product purchase, and the second channel is what will result in the discontinuity in demand at the minimum price (see Figure 3). We set

$$\kappa_{ij} = \beta_2^v \mathbf{1}_{p_j \in \mathscr{A}(p)} + \beta_3^v \mathbf{1}_{p_j \in \mathscr{B}(p)} + \mathbf{1}_{a_i = j} \left(\beta_4^v \mathbf{1}_{p_j \in \mathscr{A}(p)} + \beta_5^v \mathbf{1}_{p_j \in \mathscr{B}(p)} + \beta_6^v \mathbf{1}_{p_j \in \mathscr{C}(p)} \right) \tag{9}$$

where a_j indicates whether product j is on the prescription or not, p denotes the full vector of prices in the market, 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 among products available in the market.[16]

We identify consumer preferences, β_v^1, separately from the role of the pharmacist by the assumption that consumer utility is continuous in expenditure, whereas the pharmacist's recommendation is always the cheapest and thus discontinuous in price. Thereby, any discontinuities in final demand at the cutoffs must be due to the pharmacist affecting search costs. Most importantly among these is β_2^v: Figure 3 demonstrated a dramatic discontinuity at the minimum price where the average market share is nearly cut in half at even the smallest undercutting by a rival.

As mentioned in Section (2.1), the pharmacist's mandate to recommend the cheapest product changes both at the minimum price, but also at a price difference of 5%, giving rise to the three price regions, $\mathscr{A}, \mathscr{B}, \mathscr{C}$: for prices "near" the minimum, $p_j \in \mathscr{B}(p)$, the law merely *encourages* the pharmacist to recommend substitution, but for prices far above, $p_j \in \mathscr{C}(p)$, the pharmacist is *obliged* to recommend substitution. Thus, we allow the effect on search costs to vary with these regions.

The coefficients $(\beta_4^v, \beta_5^v, \beta_6^v)$ capture the effect of the prescription itself. Since the prescribed product is the default, we allow it to have lower search costs. Any effect of the alphabetical rank will work through this cannel by first making the physician more likely to prescribe the product, thereby making the product cheaper to search for the

16. Technically, the cutoff is not 5% everywhere but very nearly, so we present this for simplicity of exposition.

consumer, and who is then more likely to end up buying it. A large negative coefficient β_6^v, for instance, will imply that a product with a high price, $p_j \in \mathscr{C}(p)$, will (almost) sell nothing to consumers where it was not prescribed.

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 Danish public insurance system, which is fortunately structured in a way that makes this very nearly without loss of generality.[17]

Again, we follow Moraga-Gonzalez et al. (2021) and assume that the unobserved "Pandora's Rule" utility indices are distributed Extreme Value Type 1, so that the final consumption choice probabilities are

$$\Pr(j \text{ purchased}|a_i) = \frac{\exp\left[\beta_1^v \log(p_j) - \kappa_{ij}\right]}{\sum_{k=1}^J \exp\left[\beta_1^v \log(p_k) - \kappa_{ik}\right]}, \tag{10}$$

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

$$\mathbb{E}(p|a_i) = \sum_{j=1}^J \frac{\exp\left[\beta_1^v \log(p_j) - \kappa_{ij}\right]}{\sum_{k=1}^J \exp\left[\beta_1^v \log(p_k) - \kappa_{ik}\right]} p_j. \tag{11}$$

This is the measure we insert as physician preferences in one of the two specifications we use: $\omega_{ij}(p) = -\omega \log\left[\mathbb{E}(p|a_i)\right]$. 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.

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

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

with the corresponding choice probabilities given in (6) and (10). Note that the J-vector of prices, p_i, varies across transactions depending on the date of purchase

17. 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.

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 and consumer error terms, ε_{ij} and e_{ij}, are independent, and that the physician cannot condition a_j on the consumer's realization of, e_{ij}.[18]

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 identified by variation across consumers in prices and which product was prescribed. 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. As mentioned earlier, Appendix Table A.3 shows the variance decomposition for prices and winner status, which have substantial within-product variation over time.

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 (7). 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 search costs. The effect on the final choice probabilities is equivalent to a price change of more than a full log point, since the price coefficient is -1.32. 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

18. Allowing the physician to observe, partially or fully, the consumer's realization of e_{ij} means that we cannot use the Moraga-Gonzalez et al. (2021) approach and have to solve the full (double nested) dynamic search model.

TABLE 7. Consumer Choice Model

	Consumer choice
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	115,167

Note: Parameters estimated by maximum likelihood using the consumer choice probabilities in (10), where the outcome is the final product purchase choice. Summary statistics for the estimation sample are in Appendix Table A.2. The reference category is a product in the C category (most expensive), which is not on the prescription. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

dummy (1.47). This indicates that consumers place great importance in the physicians prescription, even though the effect of the alphabetical rank indicates that it is strongly influenced by medically irrelevant factors. Similarly, we note that while generics have higher search costs (0.22), this coefficient is much smaller. 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. However, we do not have variation to allow us to distinguish match utility from search costs for the patient, although this will not affect our counterfactuals.[19]

Physician model estimates. Estimates for the physician model are shown in Table 8. In our preferred specification (Column 1), alphabetical rank affects physician search costs in a logarithmic form, $\varphi(R_j) = \log(R_j)$, 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, search costs are higher for generics, 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.

19. We will in one counterfactual eliminate search frictions for the physician, but not for the consumer.

TABLE 8. Physician Choice Model

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Match value						
log(Expected Expense)	-0.57***		-0.64***		-0.56***	
	(0.04)		(0.04)		(0.04)	
log(Price)		-0.01*		-0.04***		-0.01
		(0.01)		(0.01)		(0.01)
Search costs						
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	115,167	115,167	115,167	115,167	115,167	115,167

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 (6).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

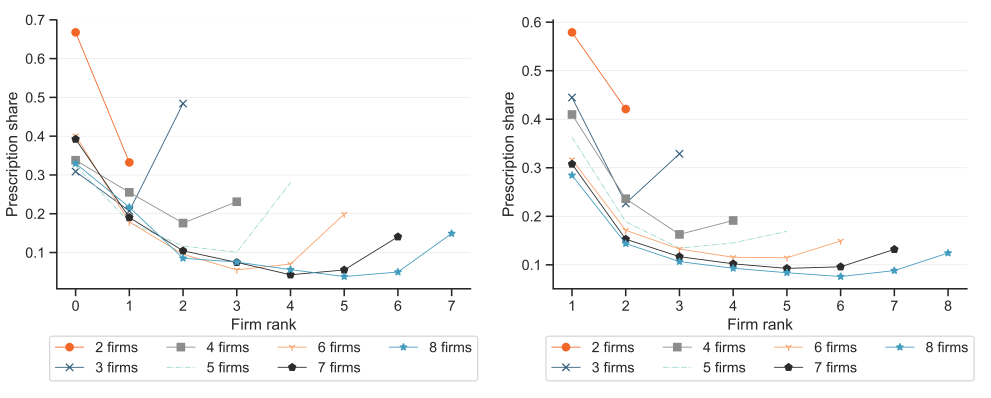
Table 8 also shows three other specifications where we change one or both of $\varphi(R_j)$ to be nonparametric (a full set of dummies), and $\omega_{ij}(p)$ to be the price directly, p_{ij}. Allowing rank to enter non-parametrically does not significantly change the coefficient on expected expense. 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 8 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 elderly might have a harder time navigating the system.

Model fit. Figure 4 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 4. Model Fit – Prescription Shares by Alphabetical Rank

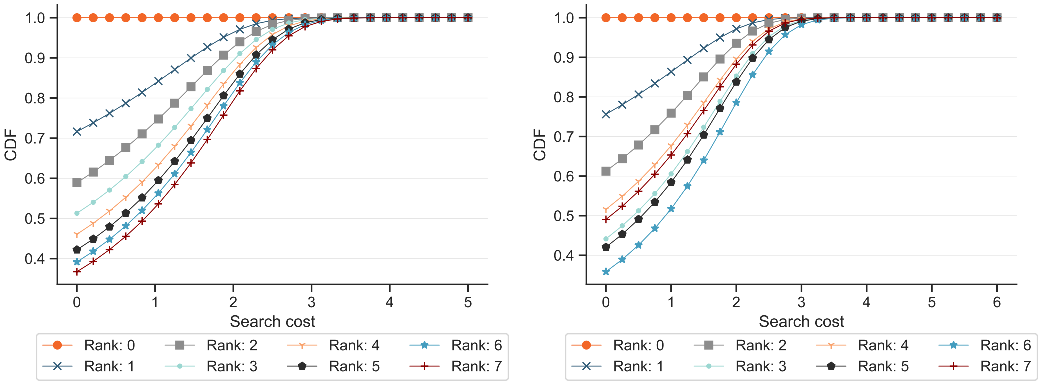
(A) Data (B) $G(R) = \log(R)$



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 (7) 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), 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. Implied Search Cost Distribution

(A) $\mu(R) = \log(R)$ (B) $\mu(R)$ non-parametric



Note: The distributions are computed using Equation (7).

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,[20]
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 the Price Equilibrium

We assume that firms maximize profits with a zero marginal cost. This is adequate for a market where the marginal production cost for a pill is virtually zero, while the bulk of costs are fixed in the form of compliance, packaging, etc. Since our model does not have an outside option, firms simply maximize

$$\pi_j(p_j) = \mathbb{E}_{p_{-j}}[s_j(p_j, p_{-j})p_j],$$

20. 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.

where market shares are given by

$$s_j(p_j, p_{-j}) = \int \Pr(a_i \text{ prescribed}) \Pr(j_i \text{ chosen}|a_i) \mathrm{d}F,$$

integrating out the distribution of consumers in the market, denoted by F. Note that $s_j(\cdot, p_{-j})$ has a discontinuity at $\min_{k \neq j} p_k$, due to the large estimate of β_2^v, which captures the generic substitution by the pharmacist. Empirically, we saw this discontinuity of demand in Figure 3. Intuitively, by undercutting a competitor, a firm can increase its market share by around 20%-points, which implies a discontinuous jump in profits.

The discontinuity in demand resulting from our sizeable estimate of β_2^v implies that the price equilibrium must be in mixed strategies. The reason is that by undercutting a rival by a tiny amount, the firm's product gets a substantially lower search cost (as it becomes the recommended product by pharmacists), and consequently profits increase discontinuously. This, combined with a non-zero demand at prices above the minimum, means that no pure strategy equilibrium can exist, as in Varian (1980). However, note that without generic substitution (if $\beta_k^v = 0$ for all $k > 1$), then the usual differentiated goods pure strategy price equilibrium would prevail.[21]

Appendix Tables A.3 and A.4 provide descriptive evidence that the dynamics of prices are indeed consistent with a mixed strategy equilibrium: for example, the empirical probability that the cheapest product is also cheapest in the next period is only 72.1%. Interestingly, the fact that the equilibrium is in mixed strategies also explains why we have sufficient price variation within products over time, and provides an argument why this price variation is exogenous, since firms are randomizing prices as part of the equilibrium.

Finding the Nash equilibrium of the game is thus non-standard due to two facts: first, that it is in mixed strategies, and second that firms are inherently asymmetric – due e.g. to their alphabetical rank. Therefore, we can neither solve the game analytically nor by simple algorithms such as iterated best response. Instead, we rely on a numerical algorithm called the "homotopy method," specifically the quantal response method implemented in `Gambit` (version 15.1.1). This is an iterative algorithm that converges to the unique Nash equilibrium (mixed or pure) if the game has a unique equilibrium that is locally stable.[22]

21. In this sense, it is the steering of demand towards the cheapest product that eliminates the pure strategy equilibrium. We posit that a similar effect would hold in any such centralized market. This is interesting as such "defaulting to the cheapest" mechanisms have been widely suggested, e.g. for health insurance markets (Abaluck and Gruber, 2016; Ericson and Sydnor, 2017; Ketcham et al., 2019) and retirement savings plans (Benartzi and Thaler, 2013).

22. The homotopy method involves solving a perturbed but computationally simpler game, and then iteratively reducing the pertubation. For a more precise description, we refer the reader to Herings and Peeters (2010) or Borkovsky et al. (2012).

Firms maximize revenue arising from the structural demand model, corresponding to an assumption of zero marginal cost.[23] Furthermore, we set all firms as generics. 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, it is not possible to truly undercut and then discretized game may have only pure strategy equilibria.

6.2. Counterfactual simulations with fixed prices

The results are shown in Table 9 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.

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23. 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.

TABLE 9. 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.[24]

Table 10 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 10 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 ambiguous 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

24. 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.

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 10. 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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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.

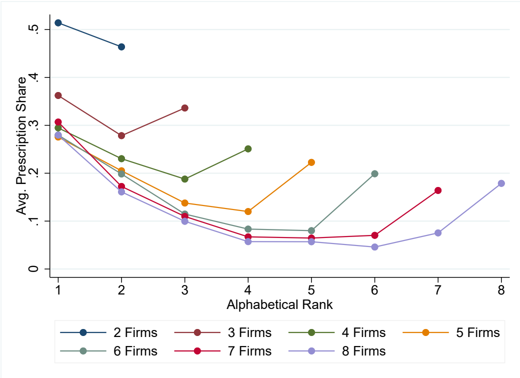
TABLE A.2. Summary Statistics – Transaction Sample

	Mean	Std.	P10	P50	P90
Income (log)	11.92	0.93	11.37	11.96	12.57
Age	60.43	16.85	37.00	63.00	81.00
1(Female)	0.55	0.50	0.00	1.00	1.00
1(Education post 2nd)	0.52	0.50	0.00	1.00	1.00
No. products	5.06	1.59	3.00	5.00	7.00
No. generic	3.93	1.66	2.00	4.00	6.00
1(Generic purchased)	0.83	0.38	0.00	1.00	1.00
1(Generic prescribed)	0.62	0.49	0.00	1.00	1.00
1(Prescribed purchased)	0.40	0.49	0.00	0.00	1.00
Observations (transactions)					115,167

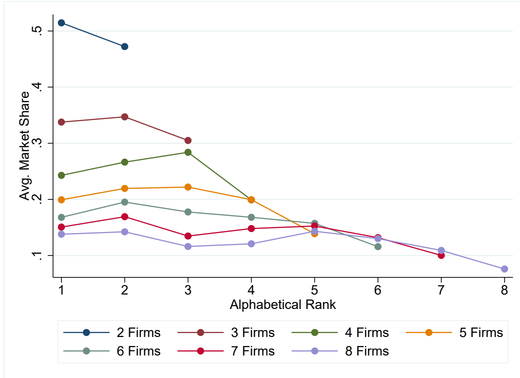
Note: This sample is used for estimation of the structural search model in Section 5.

FIGURE A.1. Alphabetical Rank and Market Outcomes

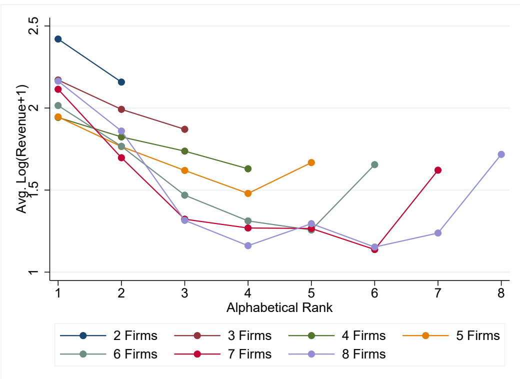
(A) Prescription share



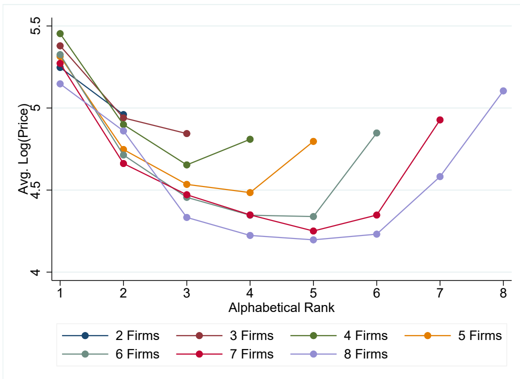
(B) Market share



(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 (in 1000 DKK) before taking logs.

TABLE A.3. Variance Decomposition: Within and Between Products

	Mean	Overall σ	Between σ	Within σ
Rank	2.34	1.53	1.52	0.54
Log(Price)	1.19	1.54	1.57	0.35
Log(Revenue)	5.61	2.62	2.25	1.48
Prescription share	0.286	0.27	0.24	0.12
Market share	0.287	0.30	0.20	0.23
Observations				697,636

Note: Computed based on 8,456 unique products over 82.50 price periods (on average). The Overall σ is the usual standard deviation, while the Between σ is the standard deviation of product averages, and the Within σ is the standard deviation within products over time.

Appendix A: Additional Results

A.1. Log Revenue

TABLE A.6. Outcome: $\log(\text{Revenue} + 1)$

	(1)	(2)	(3)	(4)	(5)

TABLE A.4. Markov Transitions for Winner Status

		$Winner_{t+1}$ 0	1
$Winner_t$	0	84.6%	15.4%
	1	27.9%	72.1%

Note: Winner Status is equal to 1 if the product has the minimum price in the market during that period (so multiple products can win if there is a tie). The table is based on all observations of products where two subsequent periods were observed for the same product (681,330 product-periods).

TABLE A.5. Markov Transitions for Alphabetical Rank

		$Rank_{t+1}$ 1	2	3	4	5	6	7	8
$Rank_t$	1	99.19	0.78	0.02	0.00	0.00	0.00	0.00	0.00
	2	1.21	96.65	2.02	0.10	0.01	0.00	0.00	0.00
	3	0.09	3.65	92.83	3.25	0.15	0.02	0.01	0.00
	4	0.01	0.31	5.25	90.37	3.85	0.17	0.02	0.01
	5	0.00	0.07	0.47	7.09	88.11	4.09	0.17	0.02
	6	0.00	0.04	0.10	0.67	8.77	86.10	4.18	0.14
	7	0.00	0.02	0.06	0.19	0.82	10.61	85.28	3.02
	8	0.00	0.04	0.00	0.12	0.39	1.43	13.30	84.72
	Total	39.01	25.87	14.74	9.68	5.83	3.09	1.40	0.37

Note: Table based on all observations of products where two subsequent periods were observed (681,330 product-periods).

A.2. Regressions using wider generic definition

This section includes a set of tables showing the results from estimating our primary regression specifications on a subsample consisting of generic products according to a *wide* definition. We include either products defined as generics according to the *narrow* definition (see Section A.3) or satisfying the following condition: the product must not have been available for purchase prior to patent expiration (and we only apply this in markets where at least one such product exists).

TABLE A.7. Prescription share: wide definition of generics

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.0424***	-0.0573***	-0.0683***	-0.0804***	-0.0754***
	(0.00801)	(0.00690)	(0.00777)	(0.00618)	(0.00847)
Alphabetical Rank×No. Firms	0.00183	0.00527***	0.00692***	0.00902***	0.00810***
	(0.00121)	(0.00101)	(0.00112)	(0.000774)	(0.00122)
Drug age FE	Yes	Yes	Yes	Yes	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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	1184	1184	1183	1171	1113
Observations	452427	452426	452425	452331	444884

Note: Standard errors clustered at the market level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes only generic products according to the "wider" definition. Furthermore, we remove observations where there are many non-generic firms present, defined as more than 2 or more than 50% of the products.

TABLE A.8. Market share: wide definition of generics

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.00161	-0.0243***	-0.0132*	-0.0190**	-0.0123
	(0.00654)	(0.00592)	(0.00636)	(0.00631)	(0.00690)
Alphabetical Rank×No. Firms	-0.00105	0.00214*	0.000972	0.000301	0.00100
	(0.00101)	(0.000891)	(0.000938)	(0.000852)	(0.00102)
Drug age FE	Yes	Yes	Yes	Yes	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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	1184	1184	1183	1171	1113
Observations	452427	452426	452425	452331	444884

Note: Standard errors clustered at the market level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes only generic products according to the "wider" definition. Furthermore, we remove observations where there are many non-generic firms present, defined as more than 2 or more than 50% of the products.

TABLE A.9. Revenue share: wide definition of generics

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.00647	-0.0236***	-0.0142*	-0.0187**	-0.0133*
	(0.00623)	(0.00566)	(0.00609)	(0.00582)	(0.00662)
Alphabetical Rank×No. Firms	-0.000213	0.00221**	0.00138	0.000795	0.00139
	(0.000946)	(0.000842)	(0.000884)	(0.000764)	(0.000964)
Drug age FE	Yes	Yes	Yes	Yes	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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	1184	1184	1183	1171	1113
Observations	452427	452426	452425	452331	444884

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.10. Log revenue: wide definition of generics

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.0497	-0.0332	0.00139	-0.0390	0.0154
	(0.0461)	(0.0454)	(0.0257)	(0.0300)	(0.0281)
Alphabetical Rank×No. Firms	-0.00571	-0.00434	-0.00512	-0.00357	-0.00659
	(0.00725)	(0.00693)	(0.00386)	(0.00358)	(0.00412)
Drug age FE	Yes	Yes	Yes	Yes	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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	1184	1184	1183	1171	1113
Observations	452427	452426	452425	452331	444884

Note: Standard errors clustered at the market level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes only generic products according to the "wider" definition. Furthermore, we remove observations where there are many non-generic firms present, defined as more than 2 or more than 50% of the products.

TABLE A.11. Log price: wide definition of generics

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.663***	-0.329***	-0.0282*	-0.0463*	-0.0286**
	(0.0693)	(0.0536)	(0.0110)	(0.0195)	(0.0101)
Alphabetical Rank×No. Firms	0.0847***	0.0366***	0.00329	0.00565*	0.00429*
	(0.0108)	(0.00894)	(0.00204)	(0.00232)	(0.00192)
Drug age FE	Yes	Yes	Yes	Yes	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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	1184	1184	1183	1171	1113
Observations	452427	452426	452425	452331	444884

Note: Standard errors clustered at the market level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes only generic products according to the “wider” definition. Furthermore, we remove observations where there are many non-generic firms present, defined as more than 2 or more than 50% of the products.

A.3. Regressions using narrow generic definition

This section presents a set of tables showing estimates from our primary specification on a subsample consisting of only products categorized as generic according to our *narrow* definition: the product’s name (in the IT system) must have quotation marks in it. This is only ever the case for generics, but there may be some generics that do not satisfy the condition, which are thus not included. However, products defined as generics according to the narrow definition will for sure be ranked alphabetically by firm name. Thus, this subsample is the one that behaves most in accordance with our theoretical model.

TABLE A.12. Prescription share: narrow definition of generics

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.136***	-0.113***	-0.155***	-0.112***	-0.176***
	(0.00948)	(0.00821)	(0.00848)	(0.00729)	(0.00979)
Alphabetical Rank × No. Firms	0.0137***	0.0124***	0.0170***	0.0131***	0.0196***
	(0.00142)	(0.00120)	(0.00121)	(0.000946)	(0.00135)
Drug age FE	Yes	Yes	Yes	Yes	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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	276157	276155	276155	276065	276155

Note: Standard errors clustered at the market level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes only generic products according to the "narrower" definition: i.e. there must be quotes in the name of the package. Furthermore, we remove observations where there are many non-generic firms present, defined as more than 2 or more than 50% of the products.

TABLE A.13. Market share: narrow definition of generics

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.0237**	-0.0278***	-0.0230**	-0.0110	-0.0211*
	(0.00856)	(0.00695)	(0.00792)	(0.00751)	(0.00924)
Alphabetical Rank × No. Firms	0.00169	0.00236*	0.00164	-0.000180	0.00161
	(0.00132)	(0.00107)	(0.00114)	(0.00103)	(0.00127)
Drug age FE	Yes	Yes	Yes	Yes	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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	276157	276155	276155	276065	276155

Note: Standard errors clustered at the market level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes only generic products according to the "narrower" definition: i.e. there must be quotes in the name of the package. Furthermore, we remove observations where there are many non-generic firms present, defined as more than 2 or more than 50% of the products.

TABLE A.14. Log price: narrow definition of generics

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.251***	-0.213***	-0.0408**	-0.0482*	-0.0416***
	(0.0415)	(0.0471)	(0.0156)	(0.0217)	(0.0124)
Alphabetical Rank × No. Firms	0.0402***	0.0299***	0.00821***	0.00841**	0.00860***
	(0.00665)	(0.00625)	(0.00227)	(0.00268)	(0.00194)
Drug age FE	Yes	Yes	Yes	Yes	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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	276157	276155	276155	276065	276155

Note: Standard errors clustered at the market level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes only generic products according to the "narrower" definition: i.e. there must be quotes in the name of the package. Furthermore, we remove observations where there are many non-generic firms present, defined as more than 2 or more than 50% of the products.

TABLE A.15. Revenue share: narrow definition of generics

	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.0253**	-0.0269***	-0.0251***	-0.0102	-0.0246**
	(0.00816)	(0.00649)	(0.00727)	(0.00688)	(0.00849)
Alphabetical Rank × No. Firms	0.00229	0.00257**	0.00230*	0.000199	0.00233*
	(0.00123)	(0.000968)	(0.00103)	(0.000907)	(0.00115)
Drug age FE	Yes	Yes	Yes	Yes	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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	276157	276155	276155	276065	276155

Note: Standard errors clustered at the market level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes only generic products according to the "narrower" definition: i.e. there must be quotes in the name of the package. Furthermore, we remove observations where there are many non-generic firms present, defined as more than 2 or more than 50% of the products.

TABLE A.16. Log revenue: narrow definition of generics

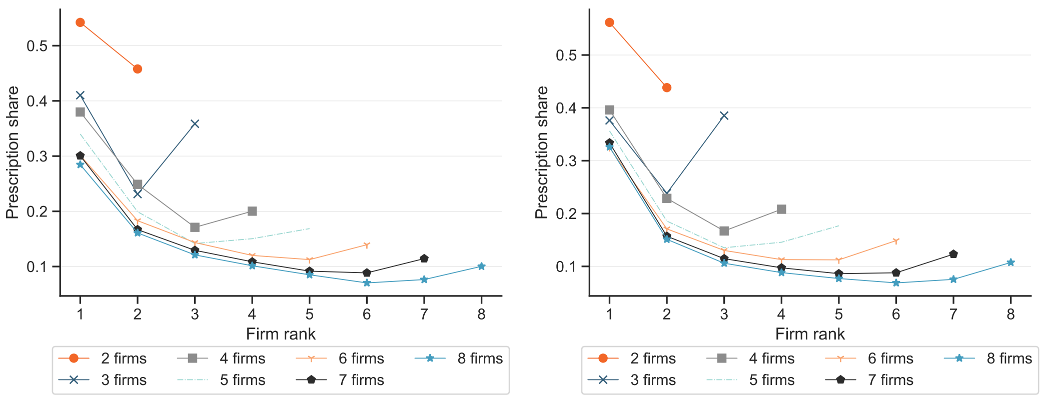
	(1)	(2)	(3)	(4)	(5)
Alphabetical Rank	-0.0510	-0.0235	-0.0373	-0.0133	-0.0192
	(0.0481)	(0.0502)	(0.0281)	(0.0328)	(0.0325)
Alphabetical Rank × No. Firms	-0.00498	-0.00515	-0.00431	-0.00614	-0.00645
	(0.00733)	(0.00669)	(0.00414)	(0.00383)	(0.00450)
Drug age FE	Yes	Yes	Yes	Yes	No
No. Firms FE	Yes	Yes	Yes	Yes	No
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	276157	276155	276155	276065	276155

Note: Standard errors clustered at the market level, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sample includes only generic products according to the “narrower” definition: i.e. there must be quotes in the name of the package. Furthermore, we remove observations where there are many non-generic firms present, defined as more than 2 or more than 50% of the products.

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

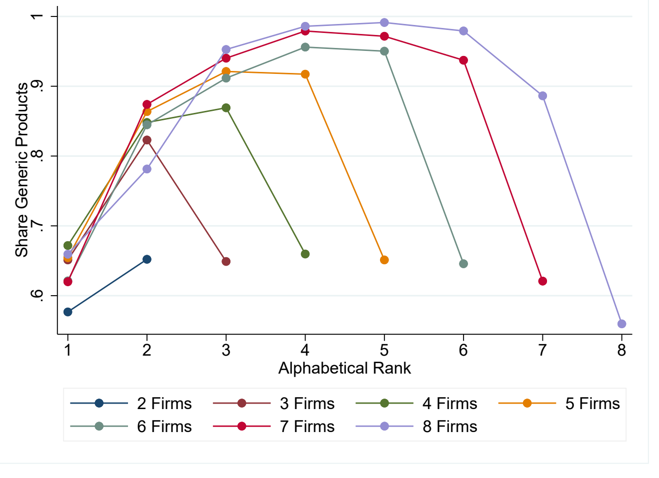
TABLE A.17. Equilibrium Expected Profit and Counterfactuals

		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.

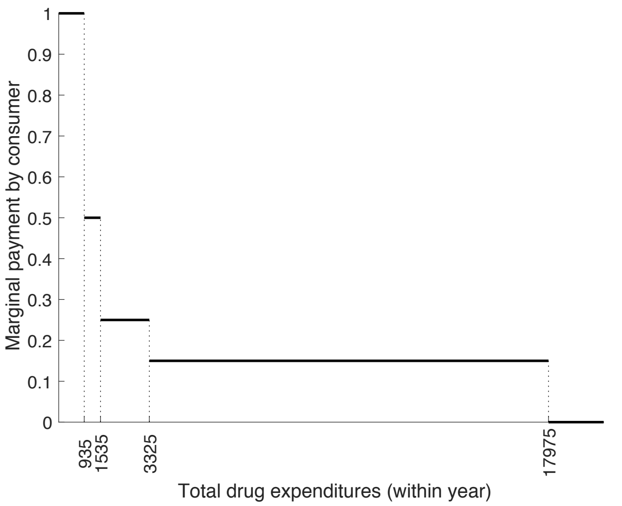
Appendix B: Institutional Details

This section covers additional institutional details for completeness.

Insurance: As mentioned in Section 2.1, all Danes are covered by public health insurance, which covers a part of the costs for the cheapest drug in the market. Figure B.1 shows the marginal co-payment rate for the consumer as a function of the total expenditures within a year. Each consumer's year begins at the first purchase and then lasts until the same date of the following year, so they are not synchronized across consumers.

Pharmacy regulation: 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. 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 pharmacy does this. The pharmacy industry as a whole is heavily regulated with respect to entry, margins and ownership structure (they must be owned by a pharmacologist, which for instance bars supermarket chains from entering the market). Additionally, pharmacies have an internal reallocation method whereby high revenue pharmacies, e.g. in high-demand areas like urban centres, have to pay a part of their revenue to those with lower revenues. In 2015, just as our sample ends, entry was deregulated, allowing free entry and deregulating ownership structure. Subsequently, the number of pharmacies greatly increased. Apart from lower waiting times at pharmacies, we do not expect that this greatly affected demand for prescription pharmaceuticals.

FIGURE B.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.