Preemption in spatial competition: Evidence from the retail pharmacy market*

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Preliminary and incomplete

Abstract

We study the entry decisions of the three retail pharmacy chains in Norway over the period from 2004 to 2012. Following a deregulation of entry, the market grew rapidly, doubling the number of pharmacies. We document that repeated entry by an already present incumbent chain occurs with non-trivial frequency and set out to investigate whether preemptive motives play a key role. We propose and estimate a highly flexible spatial demand model with overlapping sets of consumers across space. While the estimates imply substantial demand heterogeneity, we reject the hypothesis that the repeated incumbent entries can be explained by market segmentation by store format differentiation. Instead we propose that *private information* about local market conditions may play a role. Indeed, we find that an incumbent chain is significantly more likely to respond to local market heterogeneity than competing chains.

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1 Introduction

In recent years, urbanization and urban-rural inequality is putting spatial policies on the forefront of the political debate. However, optimal policy design requires a solid understanding of the intricacies of location decisions by households and firms.

This paper presents an empirical study of entry among pharmacy chains in Norway, focusing on the question of preemption in entry. Preemption in spatial competition has been studied theoretically since at least (Schmalensee, 1978; Eaton and Lipsey, 1979; Judd, 1985). However, empirical studies have been lacking behind until fairly recently. In this paper, we will provide new evidence on what drives an incumbent chain to enter with additional stores. Our data will allow us to go further in terms of the flexibility of demand than in most prior work on preemption, but ultimately we will show that product differentiation is not the primary driver.

Instead, we will present evidence that private information about local market demand appears to be a strong predictor of incumbent chains entering multiple times in the same local market. In our setting, a single pharmacy store can perfectly cope with an overly large market, it just requires consumers to accept long queues. Therefore, entry by an incumbent that observes the local market to be above-average is simply that firm reacting to private information. This, we argue, is a very clean example of a type of preemptive entry.

Our dataset combines two sources: the universe of all transactions of prescription pharmaceuticals in Norway, and the locations of households decomposed into demographic groups. This allows us to formulate and estimate a rich demand model in the spirit of Ellickson et al. (2020) with overlapping consumer choicesets across space. Pharmacy stores are also located in space with different distances to the consumer locations and with different characteristics such as being located in a mall or near one of the government-regulated liquor stores, the ”wine monopoly.”

To estimate this demand model, our data gives us an advantage over what is typically used in the literature: we observe store-level sales disaggregated finely by consumer segments, whereas most prior work only observes aggregated sales. This extra level of detail allows us to observe whether two neighboring pharmacy stores with identical aggregate sales have the same mix of customers or if there is no overlap. This allows us a lot of precision in terms of modeling the cannibalization versus business stealing motives for entry.

There are two key advantage of the market for prescription pharmaceuticals. First, demand is largely driven by factors that are unrelated to pharmacy entry. That is, there is virtually no effect on total demand from the entry of additional pharmacies. Second, there is no scope for price competition, and all pharmacies must stock all products. While there are other sales, e.g. of shampoo, that component of sales is much smaller than for example in the US. Therefore, pharmacies can largely only compete in where they locate, which is precisely what we wish to study.

Given our estimates, we set out to study the entry events occurring in our data. We classify entries based on whether the entering chain was incumbent, which we define as the chain being the owner of the nearest existing pharmacy. Incumbent entry events are the ones that are potentially preemptive, since the incumbent cannibalizes the sales of her nearby store and must see a greater reward elsewhere to offset this.

The first hypothesis we test is whether incumbent entry events are simply due to market segmentation by store format differentiation. Our estimated demand model implies that there is a surprisingly large amount of heterogeneity across consumer segments in terms of preferences for store characteristics. For example, the younger households tend to prefer pharmacies that are located in large malls and close to a wine monopoly, whereas the elderly prefer pharmacies located elsewhere. Similarly, while all households dislike traveling, the elderly have half and twice as strong disutility for travel distance, for males and females respectively. Given preference heterogeneity, incumbent entry events might simply be product differentiation. If that were the primary driver, we would expect to see incumbents entering with significantly different characteristics from entrants. However, we find that the store characteristics are indistinguishable.

Next, we turn to our key contribution: the role of private information. We argue that incumbents have an easier time learning about local market demand, simply by observing their own sales in the market. Thus, they can tell if the consumers in a local region are buying more than their characteristics would suggest.

Such demand residuals might be common or private information. In fact, Igami and Yang (2016) precisely argue that if there are common information market-level shocks, then that can explain seemingly preemptive entry simply as a result of local demand being higher and being able to support more firms. However, their argument implies that *all chains* are equally likely to enter if residual demand is high. We instead propose that if the shocks are *private* information, then the incumbent firm will be more likely to respond to positive demand residuals than competing firms. And that is precisely what we find.

We firstly show the result using raw averages. We construct an event study where we compute the average demand residuals for the nearest pharmacy to the entrant before and after entry. For the events where the new pharmacy belongs to the same chain as the nearest existing one – the incumbent entry events – we see that demand residuals are substantially larger before and even after entry compared to the entrant chain events.

Next, we use a linear probability model to control for differences in observable characteristics relating to the events, and the result still holds: a significant conditional correlation between the demand residual and an indicator for the new pharmacy belonging to the same chain. This is consistent with the private information hypothesis in the sense that the incumbent chain responds to the local demand residual in a way that competing chains do not.

We outline a model of dynamic entry competition in the spirit of Igami and Yang (2016). They estimate their model using choice probability inversion and using techniques for integrating out unobserved market-level heterogeneity in the process. We make a simple extension of their model whereby a scalar parameter, ρ, captures the degree to which information is common ($\rho = 0$) or private ($\rho = 1$).

Another closely related paper is Zheng (2016), who studies preemptive entry decisions among two large retailers in the US. Zheng finds a large loss of productive efficiency due to preemptive entry.

Our approach differs from the two papers and much of the preceding literature on retail entry terms of our demand model. Crucially, we do not make any assumptions regarding the configuration of local markets. Instead, we follow Ellickson et al. (2020) in assuming that consumers are located across space according to register data at fine disaggregation.[1] Consumers dislike traveling but are be heterogeneous in their preferences for individual store formats. Ellickson et al. (2020) show that such a demand model is able to capture rich substitution patterns that better capture the nature of spatial competition.

The importance of differentiation for location decisions was demonstrated by Orhun (2013), who solves a static discrete location choice game among retail supermarkets. Orhun demonstrates that local market heterogeneity, which is assumed to be common information to players, plays an important role in shaping spatial competition. Our contribution in this regard is to attempt to distinguish whether information is common or private.

We are related to a large empirical literature on entry games (e.g. Bresnahan and Reiss, 1991; Berry, 1992; Seim, 2006; Aguirregabiria et al., 2007), and in

[1]Zheng (2016) also avoids making assumptions on local markets by using clustering methods to infer market boundaries.

particular spatial competition; see e.g. the recent survey by Aguirregabiria and Suzuki (2016). Specifically, the part that emphasizes the chain-affiliation aspects (Jia, 2008; Aguirregabiria and Vicentini, 2016). However, another strand has emphasized network effects induced e.g. by logistic concerns (Holmes, 2011; Ellickson et al., 2013). Finally, we are related to a methodological literature aimed at the estimation of dynamic games (Bajari et al., 2007; Aguirregabiria et al., 2007; Arcidiacono et al., 2016; Iskhakov et al., 2016).

The paper is organized as follows: Section 2 describes our data and institutional setting, and Section 3 provides descriptive evidence regarding entry patterns. Section 4 presents out model for demand and competition, and 5 presents estimates from the demand model. Section 6 presents evidence regarding incumbent entry decisions, and Section 7 concludes.

2 Data and Institutional Setting

2.1 Data

We rely on two datasets: one regarding pharmacy sales and one regarding consumers.

Our data on pharmacies has the universe of all daily prescription transactions at the pharmacy-level. For each transaction, we observe the total amount purchased, the number of packages, as well as demographic characteristics of the purchasing consumer. Unfortunately, we are not able to identify the individual in a way that could be matched to demographic registers and in particular, we do not observe the residential location of the consumer.

Next, we want to aggregate transactions at the pharmacy-period level within consumer segments. To do so, we discretize consumers into groups based on their gender as well as six age categories. Table 1 shows summary statistics for the

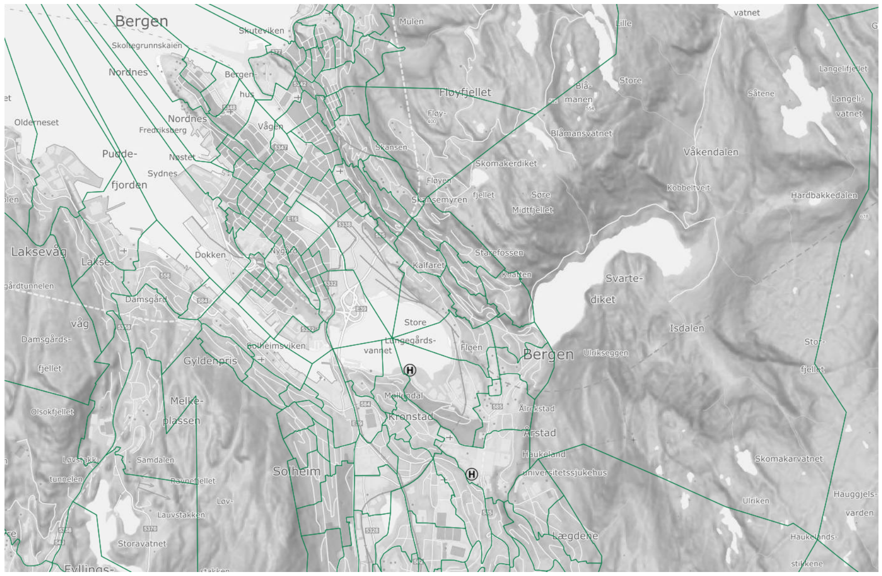


Figure 1: Basic Units in the City of Bergen

transactions and the aggregate demographic composition of sales.

For the same discretization of demographics, we count the number of individuals living in each *location*. Throughout the paper, location will refer to a *Basic Unit (BU)*. A BU is a zone defined by Statistics Norway, which is far smaller than a zip code area - there are 12,164 BUs across Norway. Figure 1 shows the BUs in the city of Bergen. For each such location, we compute the number of residing consumers of each demographic type. For the purpose of distance calculations, we will use centroids. Table 2 shows summary statistics for the demographic characteristics across the 12,164 locations. For example, we see that there are several locations where only a single segment resides.

We likewise find the location of all pharmacies and also attribute them to the corresponding centroid. We then compute the travel distances in minutes by car from all consumer locations to pharmacy coordinates, including any tolls that would be incurred during the shortest path of travel.

2.2 Institutional Setting

2.2.1 Entry (de)regulation

Sale of pharmaceuticals in Norway is highly regulated and only permitted at licensed pharmacies, with the exception of a few deregulated over-the-counter drugs that can be sold in grocery stores.[2] Until 2001, pharmacies were subject to a strict licensing scheme, where only licensed pharmacists (equivalent to M.Sc. in pharmacology) could own a pharmacy, and the number and location of pharmacies were decided by the Ministry of Health Care and Services. In 2001, ownership and establishment of pharmacies were deregulated, allowing both individuals and companies to own multiple pharmacies. The new regulation lead to the establishment of three pharmacy chains, based on existing groups of pharmacies engaging in cooperation particularly over purchases, where pharmacies were bought up by the new chains, in addition to a noticeable and persistent increase in establishment of new pharmacies. The pharmacy chains became vertically integrated with three large, existing pharmaceutical and health product wholesalers. The majority of pharmacies, both existing and newly established, have since belonged to one of the three chains, with a smaller number of independent, private pharmacies and on-site, publicly owned pharmacies at the larger hospitals. Even though anyone can establish and own a pharmacy, each pharmacy outlet is required to have a licensed pharmacist at the location to manage and oversee the operations.

On the wholesaler side, only full-line wholesalers are allowed to sell to pharmacies, meaning that they need to carry all prescription drugs that have marketing permission in Norway, while more specialized, medical wholesalers can only sell to hospitals and the full-line wholesalers. This regulatory feature together with scale economies in standardized product logistics is a likely explanation for the low and stable number of vertically integrated pharmaceutical chains over time.

[2]E.g., tablets with paracetamol up to 500 mg or ibuprofen up to 200 mg with limitations on package size, and nasal sprays containing fluticasone, mometasone, triamcinolone and budesonide.

2.2.2 Price regulation, reimbursement and generic substitution

Prices of prescription drugs are subject to reference price regulation, where the maximum price is set based on international averages, which is almost always binding for branded drugs, likely due to both high degree of reimbursement and low elasticity of demand for most pharmaceutical treatments.[3] Norway has a single-payer health care system, where drugs used in treatment of chronic conditions (treatments longer than 3 months) are reimbursed with a coinsurance rate of 36%, where copayments are capped at approximately 50 EUR per 3 months and total medical copayments are capped at 200 EUR per year (including copayments for doctor consultations, pharmaceuticals and laboratory services), while treatment of most contagious diseases are fully reimbursed. After generic entry, the maximum reimbursement is regulated down over time according to a common, pre-specified schedule tied to the maximum price at the time of generic entry. Pharmacies are required to have at least one generic option that is priced no higher than the maximum reimbursed price, and to suggest substitution to the cheapest generic substitute if the prescription specifies the brand name of the drug. If the customer refuses generic substitution, their reimbursement is calculated according to the maximum reimbursed price, while the remaining price is covered fully out-of-pocket.

Technically, the price regulation features a maximum price from the wholesaler to the pharmacy and a maximum pharmacy margin, which together determine the maximum price to consumer. From the perspective of an integrated pharmacy chain, the maximum margin is only a matter of accounting, while the relevant margin is given by the difference between the consumer price and the wholesale price paid to the manufacturer, where the latter is not subject to regulation. For independent pharmacies, the maximum margin itself can play a role in determining

[3] Specifically, the maximum is set as the average of the three lowest prices from Sweden, Finland, Denmark, Germany, UK, Netherlands, Austria, Belgium and Ireland.

Table 1: Summary statistics: transactions

Transactions	
Observations (million transactions)	144.6
Total amount (NOK)	485
No. packages	1.25
Gender composition	
Male	0.436
Female	0.564
Age composition	
0-24	0.064
25-45	0.103
46-59	0.182
60-74	0.297
75-89	0.280
90+	0.074

Note: For each transaction in our dataset, we observe the demographics of the purchasing individual, since this gets recorded as the transaction is encoded. The table shows averages computed over all transactions unweighted.

profitability and the relative importance of prescription drug sales versus over-the-counter drugs and other products, and is likely a contributing factor to the majority of new establishments being undertaken by chains.

3 Descriptive Evidence

Figure 2 shows the number of active pharmacies over time. The figure shows a broader period around our sample period (2004-2012) to provide context. We clearly see a rapid growth following the liberalization of entry in 2001, with an almost constant growth of between 20 and 30 pharmacies per year. A constant growth rate is indicative of firms facing some form of constraints in the number of pharmacies they can open per year.

Table 3 presents descriptive statistics for entry events. Out of the full set of

Table 2: Summary statistics by location (basic unit, BU)

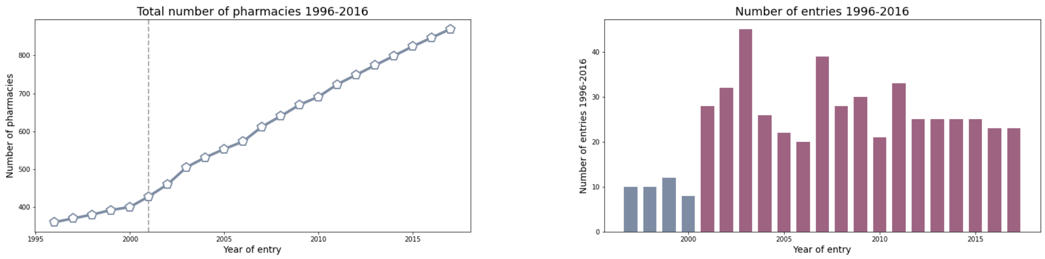
	Mean	St.dev.	Min	Max
Gender composition				
Male	0.510	0.064	0.000	1
Female	0.490	0.058	0.000	1
Age composition				
0-24	0.312	0.082	0.002	1
25-45	0.277	0.090	0.004	1
46-59	0.208	0.062	0.004	1
60-74	0.143	0.073	0.001	1
75-89	0.071	0.060	0.000	1
90+	0.013	0.023	0.000	0.412
Observations (basic units)				12,164

Note: For each location (BU), we compute each statistic based on all residing individuals and take the average over all periods in our sample. The source for the demographic data is the Norwegian register data.

entry events, we restrict attention to a subset that are most relevant for our study, resulting in 225 events in our final dataset. Out of these, 55 (24%) are by the same chain as the nearest pharmacy. Given that there are three chains, this is a remarkably high propensity, given that such pharmacies will be cannibalizing the chain's own sales.

To better understand these 55 events, we show the empirical distribution of the density to the nearest existing pharmacy at the time of entry separately for the 55 same-chain entries and the 170 competing-chain entries in Figure 3. The graph clearly shows a tendency for incumbents to locate further away from the nearest existing pharmacy than a competitor would. This is consistent with the broad intuition from the classic Hotelling (1929) model of competition, where one locates as close as possible to a competitor to maximize business stealing.

Figure 2: Entry over time



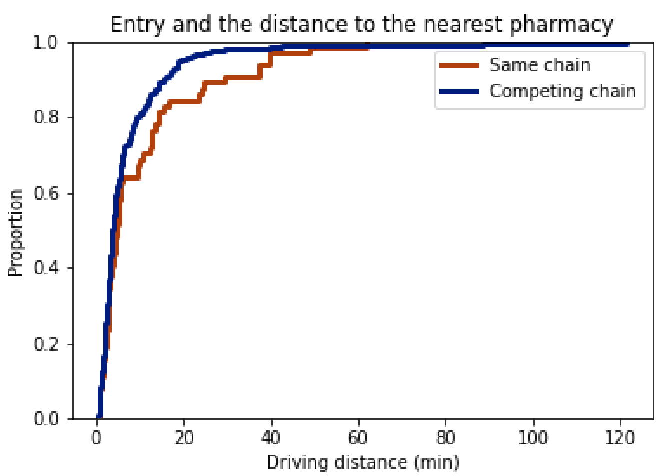
Note: The dashed line indicates the entry deregulation in 2001.

Table 3: Descriptive statistics for entry events

		Closest pharmacy to entrant	
	Total	Same chain	Competing chain
Distance to neighbor (driving min.)	8.0	10.5	7.2
Center	47.6%(107)	56.4%(31)	44.7%(76)
Shopping mall	32.0%(72)	29.1%(16)	32.9%(56)
Wine monopoly	7.6%(17)	3.6%(2)	8.8%(15)
Number of entries	225	55	170

Note: The numbers in parentheses are frequencies corresponding to the fractions.

Figure 3: Distance to nearest existing pharmacy



Note: The graph shows the empirical CDF of the driving distance from an entering pharmacy to the nearest pharmacy operating at the time of entry. That is, an observation is an entry. There are two lines, one conditioning on the nearest pharmacy belonging to the same chain, and one where it belongs to a competing chain.

4 Model

4.1 Consumer Choice

Our model of consumer demand builds on Ellickson et al. (2020). Fundamentally, we assume that quantity demanded, q_{it}, varies across consumers, but does not respond to the entry decisions of firms. That is, total quantity sold at pharmacy j in period t is

$$Q_{jt} = \sum_{i \in I_t} \Pr(j|it) q_{it},$$

where I_t is the set of consumers and $\Pr(j|it)$ is the probability that consumer i visits pharmacy j in period t.

Consumers choose only which pharmacy to visit. Consumer i residing at location $\ell \in \mathcal{L}^c$ and belonging to demographic group k in period t gets indirect utility

$$\begin{aligned} u_{i\ell ktj} &= v_{i\ell ktj} + \varepsilon_{i\ell kt}, & (1) \\ v_{i\ell ktj} &= \gamma_0^k + \gamma_1^k d(j, \ell_{it}) + \theta^k \mathbf{1}\{\text{toll}(j, \ell_{it}) > 0\} + \mathbf{x}_j' \boldsymbol{\beta}^k + \eta_{f_j}^k. & (2) \end{aligned}$$

where $\eta_{f_j}^k$ is a set of dummies for the chain affiliation pharmacy j, where $f \in \{1,2,3\}$, j, $\varepsilon_{i\ell ktj}$ is IID Extreme Value Type I, and $\mathbf{x}_j$ is a vector of pharmacy characteristics including dummies for being located in a mall, a large mall, next to a wine monopoly, and interactions of large mall and wine monopoly.[4] Given this, the probability that consumers living in region ℓ buys from pharmacy j take the usual logit form,

$$\Pr(j|\ell, k, t) \equiv \frac{\exp(v_{\ell ktj})}{\sum_{j' \in \mathcal{J}_t} \exp(v_{\ell ktj'})}.$$

[4] In Norway, sale of alcohol is restricted to the so-called wine monopoly stores.

The quantity purchased is parameterized as

$$q_{it} = \beta_0^{k_i} + \beta_1^{k_i} t + \sum_{m=2}^{1} 2\beta_{2m}^{k_i} \mathbf{1}\{\text{month}(t) = m\} + \xi_{\ell_i t} + \xi_{it}.$$

where ℓ_i denotes i's location of residence, and $k_i \in \{1, ..., K\}$ is the demographic group to which i belongs. This specification allows demand to vary by discrete demographic groups, k, and both to be drifting over time within demographic groups and to have seasonal variation, of which there is a lot, e.g. due to the seasonal flu. The group unobservables, $\xi_{\ell t}$, will play an important role later. It determines the value of being present in the local market and we will argue that the assumption that incumbent firms have private information about $\xi_{\ell t}$ will be crucial.

4.2 Firm Choice

Firms have to decide make entry decisions across Norway. The state space is categorized by a discrete set of locations in space, $\mathcal{J}$, which will be distinct from the consumer locations. We will denote locations by j, since a pharmacy and its location are indistinguishable given that at most one pharmacy can be located at any given point in space.

We will assume that the set of pharmacies present in the final year of our data is the absorbing state, known in advance to firms. At each location at a point in time, there can be one of the three pharmacy chains or no pharmacy currently present. We denote this by $s_{jt} \in \{0, 1, 2, 3\}$, where $s_{jt} = 0$ denotes no present pharmacy at location j in period t. By our assumption that the final configuration is absorbing, $s_{jT} \neq 0$ for all $j \in \mathcal{J}$.

The flow profit from a pharmacy at location j takes the form

$$\pi_{jt} = R_{jt} - VC_j(Q_{jt}),$$

where R_{jt} is the total revenue earned at pharmacy j in period t, and $VC_j(Q)$ is total variable cost for Q transactions. Revenue depends on the composition of sales

$$R_{jt} = \sum_{i \in I_t} q_{it} \Pr(j|it) p_{k_i t},$$

and p_{kt} is the average earnings per transaction for a consumer of segment k.

Firms make entry decisions dynamically in order to maximize expected discounted profits. However, we assume that entry decisions are sequential and that firms are restricted to make precisely one entry per choice occasion. This is in order to match Figure 2 which showed that entry events occurred at a virtually constant rate over time. Such a pattern may arise due to choice restrictions due to e.g. borrowing constraints or arbitrary budgeting rules.

Given this restriction, if chain c in period t has the right to move, it simply has to decide where to open a new pharmacy. Let $S_t \equiv \{s_{jt}\}_{j \in \mathcal{J}}$ be the state variable at period t. Then the choiceset for the moving firm is the set of locations where no other chain has yet opened a pharmacy:

$$\mathcal{D}(S_t) = \{j \in \mathcal{J} | s_{jt} = 0\}.$$

To simplify the numerical solution of the game further, we further assume that $\mathcal{D}(S_t)$ consists of only the locations j where an actual pharmacy opened within a window of 6 months. This also captures the fact that maybe some locations, e.g. malls, were not physically available earlier on in the data.

The dynamic problem then takes the form

$$\max_{d_1,\ldots,d_T} \sum_{t=1}^{T} \delta^t \mathbb{E}[\Pi_{ct}(S_t, d_t)],$$

where the chain-level profits are simply

$$\Pi_{ct}(S_t, d_t) = \sum_{j \in \mathcal{J}} \Big[\mathbf{1}\{s_{jt} = c\} \pi_{jt} \Big] - FC(d_t) + \omega_{ct}(d_t),$$

where $FC(d)$ is the entry cost of opening a pharmacy in the chosen location, d, and ω_{ct} is a vector of IID Extreme Value error terms.

4.3 Information structure and timing

The game is sequential move with random move order. When a firm (a chain) has the right to move, it immediately observes the current-period idiosyncratic shocks to all currently available locations, $\{\omega_{ct}(d)\}_{d \in \mathcal{D}(S_t)}$.

The most important common value variable is the state of local demand $\xi_{\ell t}$ at all consumer locations $\ell \in \mathcal{L}$. This variable is unobserved to the econometrician, and we may think of it as decomposed into two parts,

$$\xi_{\ell t} = \rho \xi^1_{\ell t} + (1 - \rho) \xi^2_{\ell t}, \quad \rho \in [0; 1],$$

where $\xi^1_{\ell t}$ is commonly observed by all firms and $\xi^2_{\ell t}$ is privately observed by the incumbent firm. We define the incumbent chain c at location ℓ to be the firm that operates the pharmacy closest to ℓ. The parameter ρ controls the extent to which market-level excess demand is common ($\rho \to 1$) or private ($\rho \to 0$) information.

Let us now consider the issue of identification of ρ. Intuitively, we can obtain the residuals, $\xi_{\ell t}$, using demand data, but we cannot further decompose those residuals based on demand data alone. That is, we can only hope to learn about ρ from the entry decisions that firms make.

In the ideal experiment, the initial firm network is exogenously given and orthogonal to $(\xi^1_{\ell t}, \xi^2_{\ell t})$, which are furthermore independent across locations ℓ. We can start by noting that we should observe more entry where $\xi_{\ell t}$ is large. Identification of ρ then boils down to whether the incumbent firm is more likely to enter close to ℓ compared to a competitor, all else equal.

Our framework nests that of Igami and Yang (2016), who implicitly assume that the market-level unobservable is common information, $\rho = 1$. While this will indeed explain why an incumbent chain chooses to enter again in a nearby location, a competing chain will also know this information and should have an even stronger incentive to enter. This is because the incumbent chain will to a large extent be cannibalizing its own sales.

Before presenting our results, it is worth briefly discussing what preemptive entry is in this setting. First off, let us note that given that there is no outside option for consumers, the game is zero-sum. Basically, we are assuming that consumers have to get their medicine regardless of how long it takes to drive, so a single pharmacy would have been sufficient to supply Norway. While this assumption is extreme, it is empirically relevant given the large growth in the number of pharmacies presented earlier.

5 Demand

5.1 Econometric Methodology

Given that we do not observe the locations of the consumers for all transactions, our data leaves us unable to estimate by maximum likelihood. Instead, we predict purchases from consumers at all locations (BUs) and match it to the sales to each demographic at all pharmacies. Estimation is then conducted using the method of simulated moments.

To be precise, we observe q^{data}_{jkt}, the total sales to demographic group k at pharmacy j in period t. The corresponding predicted quantity from our model is obtained as

$$q_{jkt}(\theta) = \sum_{\ell \in \mathcal{L}} N_{\ell kt} q_{\ell kt}(\theta) \Pr(j|\ell,k,t;\theta),$$

where $N_{\ell kt}$ is the number of consumers in demographic k residing at location ℓ. This equation also illustrates the problem: we are predicting demand at the pharmacy-level (j), but we observe consumers at the location-level (ℓ). For simplicity, we assume that demand has fully died out after 1 hour of driving, so we impose a probability of zero mechanically thereafter.

Hence, our estimator is

$$\hat{\theta} = \arg\min_{\theta} \sum_{j \in \mathcal{J}_t} \sum_{t=1}^{T} \sum_{k=1}^{K} \left[q_{jkt}^{\text{data}} - q_{jkt}(\theta) \right]^2.$$

That is, we minimize the squared residuals of observed and predicted pharmacy-level transactions for each demographic segment in all periods.

5.2 Results

In this section, we present and discuss the estimates of the parameters in our demand model. There are two sets of parameter estimates: those affecting pharmacy choice and those affecting quantity purchased. Table 4 presents estimates regarding the parameters affecting the pharmacy choice, i.e. equation (2). We start with the common patterns across all demographic groups and before looking the aspects that are heterogenous across consumers.

With the exception of one of the 12 demographic groups, all consumers dislike distance and travel costs. Consumers all prefer larger pharmacies and all but one group dislike pharmacy locations to be in either the center or in a small mall. Regarding location in a large mall or close to a liquor store (”wine monopoly”), we see substantial heterogeneity: younger households prefer pharmacies located in a large mall, while older households dislike it. Similarly, most households and particularly females are attracted to pharmacies located near to a wine monopoly, although there are interesting differences depending on whether it is in a mall or not: again, the elderly appear to be discouraged by mall locations whereas it has the opposite effect for younger households.

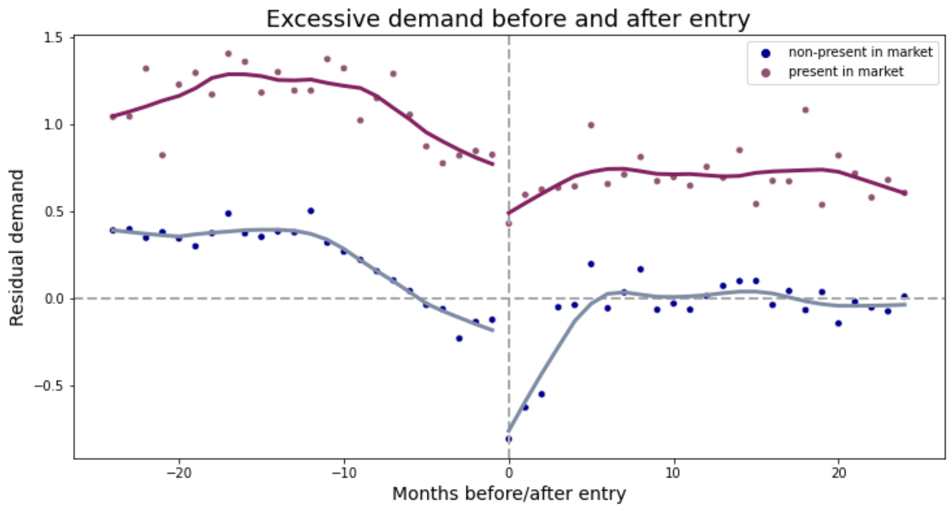
The second part of parameters indexing consumer demand are those that affect quantity, i.e. those in equation (4.1). Those results are presented in Table 5. Those estimates are available upon request from the authors and left out of the paper for brevity. The results are as one might expect: demand is higher during the winter months, e.g. due to the seasonal flu.

6 Investigating Entry Decisions

In this section, we investigate entry decisions in lieu of our demand model. Specifically, we want to focus on the events where an incumbent firm in a location enters with another pharmacy – such entry events are the ones that can potentially be viewed as *preemptive*. To do so, we restrict attention to the set of such entry events that are the cleanest examples: monopoly to duopoly transitions. That is, locations (BUs) where a single pharmacy is present prior and then another pharmacy enters with the same chain affiliation as the incumbent.

Figure 6 shows an event study around firm entry, with a separate line drawn for the entry events depending on whether the chain of the entrant was present in the market prior or not. For chains that were not previously in the market, residual demand was near zero just prior to entry, but then returned to zero after a few months of low demand. For the chains that were already present, however, residual demand was much higher prior to entry, but remains substantially above zero even after.

If taken at face value, this result is consistent with the hypothesis that incumbent firms choose to enter in a market if their private information tells them that



local demand is high. However, the graph merely presents raw averages, so there may be confounders between entry events in markets where the incumbent is already present versus ones where it is not.

To control for differences, we instead pursue a linear regression specification:

$$\mathbf{1}\{\text{same chain}\}_e = \alpha\hat{\xi}_e + x_e\beta + \text{error}_e,$$

where e denotes entry events, and $\hat{\xi}_e$ is the predicted demand residual averaged over the 3, 6, or 12 months prior to the entry (in separate columns), and where x_e is a vector of characteristics of the entry event, including chain dummies, characteristics of the store, and the market size.

The results are shown in Table 6. We find statistically significant estimates of the coefficient on residual demand, α. Furthermore, the estimates are remarkably similar whether we average over 3, 6, or 12 months prior to entry. This is consistent with the graphical evidence in Figure 6, where residual demand was fairly stable in many months before entry.

One important alternative hypothesis that might explain what we see is network effects. As suggested by e.g. Holmes (2011); Ellickson et al. (2013), there can be various reasons for economies of density such as logistic networks. We run the risk of attributing both network effects and private information shocks to only the latter, just as the prior literature has attributed both to network effects. However, given the complexity in solving for the single agent logistic problem of rolling out stores, we leave the integration of both strands for future work.

7 Conclusion

In this paper, we studied the entry decisions of retail pharmacy chains in Norway following a deregulation of entry. We documented that incumbent pharmacies enter with non-trivial frequency. Therefore, we set out to investigate whether such entry decisions should best be viewed as preemptive.

In this paper, we have formulated and estimated a rich model of demand in the retail pharmacy market. Our model features rich heterogeneity across consumer segments and thus scope for differentiation across retail store formats. Our first hypothesis was thus that incumbent entry events were simply market segmentation due to differentiation in store format. However, we found evidence against this hypothesis.

Next, we proposed that unobservable market-level heterogeneity in demand might play a role. This has been emphasized previously by e.g. Igami and Yang (2016); Orhun (2013). Next, we proposed that such unobservables might be either private or common information to the players of the game. We then presented evidence that such unoboservables are likely private information to a larger extent. This is because large demand residuals are more likely to attract pharmacies with nearby chains compared to competing chains.

In conclusion, we find evidence for preemptive motives based on private information about local market attractiveness.

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Table 4: Demand Estimates Part I: Pharmacy Choice

			Female			
	F0-24	F25-45	F46-59	F60-74	F75-89	F90+
Distance	-0.352***	-0.287***	-0.280***	-0.311***	-0.722***	-1.208
	(0.003)	(0.003)	(0.002)	(0.004)	(0.011)	(2.266)
Travel cost	-0.025***	-0.018***	-0.015***	-0.018***	-0.004*	0.824
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(1.582)
Distance x pop.density	0.000***	0.000***	0.000***	-0.000***	0.000***	-0.341
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.634)
Pharmacy size m^2	0.001***	0.001***	0.001***	0.001***	0.003***	2.091
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(3.885)
Center	0.008	-0.077***	-0.072***	-0.080***	0.189***	-0.965
	(0.009)	(0.007)	(0.007)	(0.008)	(0.021)	(10.02)
Mall	-0.269***	-0.269***	-0.164***	-0.186***	-0.426***	0.140
	(0.013)	(0.011)	(0.009)	(0.010)	(0.022)	(19.65)
Large mall	0.563***	0.407***	0.220***	0.078***	-0.485***	0.018
	(0.009)	(0.007)	(0.008)	(0.009)	(0.023)	(8.932)
Wine monopoly	0.094***	-0.084***	0.193***	0.193***	0.442***	-0.077
	(0.027)	(0.023)	(0.021)	(0.025)	(0.064)	(19.35)
Wine monopoly x large mall	0.554***	0.319***	0.291***	0.253***	-0.473***	-1.046
	(0.007)	(0.006)	(0.006)	(0.007)	(0.017)	(9.024)
			Male			
	M0-24	M25-45	M46-59	M60-74	M75-89	M90+
Distance	-0.033***	-0.39***	0.300	-0.309***	-0.449***	-11.410
	(0.001)	(0.004)	(0.257)	(0.004)	(0.01)	(10.85)
Travel cost	0.002***	-0.057***	-1.588***	-0.024***	-0.065***	-35.73
	(0.000)	(0.002)	(0.544)	(0.001)	(0.004)	(34.04)
Distance x pop.density	0.000***	0.000***	-0.971***	-0.000***	-0.000***	-0.581
	(0.000)	(0.000)	(0.335)	(0.000)	(0.000)	(0.550)
Pharmacy size (m^2)	0.001***	0.001***	0.216***	0.001***	0.002***	1.317
	(0.000)	(0.000)	(0.074)	(0.000)	(0.000)	(1.246)
Center	-0.169***	-0.076***	0.006	-0.132***	-0.076***	-3.366
	(0.006)	(0.009)	(0.879)	(0.008)	(0.015)	(4.445)
Mall	-0.127***	-0.366***	0.059	-0.233***	-0.312***	2.712
	(0.010)	(0.013)	(2.497)	(0.010)	(0.017)	(8.180)
Large mall	0.282***	0.231***	-0.091	-0.080***	-0.362***	3.244
	(0.008)	(0.009)	(1.162)	(0.009)	(0.017)	(6.830)
Wine monopoly	0.114***	-0.217***	-0.078	0.084***	0.239***	-2.560
	(0.021)	(0.029)	(1.586)	(0.026)	(0.047)	(105.5)
Wine monopoly x large mall	0.400***	0.155***	-0.153	0.138***	-0.201***	-5.944
	(0.006)	(0.008)	(0.608)	(0.007)	(0.012)	(6.717)
Observations (pharmacy-months)						55,285

Note: Standard errors are in parentheses. Significance levels are *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.
The data contains 724 pharmaices and predicted demand comes from 31,569,626 pharmacy-month-location tuples.
There are 29 parameters per demographic group.

Table 5: Demand Estimates part II: Quantity

	M0-24	M25-45	M46-59	M60-74	M75-89	M90+	F0-24	F25-45	F46-59	F60-74	F75-89	F90+
Const	0.748***	0.968***	1.658***	6.804***	13.268***	56.611***	0.629***	1.419***	2.976***	7.231***	9.257***	19.31***
	(0.006)	(0.008)	(0.024)	(0.055)	(0.164)	(0.903)	(0.006)	(0.011)	(0.024)	(0.056)	(0.178)	(0.563)
Time trend	0.321***	0.529***	1.183***	2.183***	5.209***	-37.617***	0.556***	0.515***	1.837***	2.081***	9.712***	-10.088***
	(0.005)	(0.008)	(0.022)	(0.05)	(0.154)	(0.806)	(0.006)	(0.01)	(0.022)	(0.051)	(0.17)	(0.509)
January	-0.39***	-0.457***	-0.699***	-2.588***	-4.665***	-8.356***	-0.243***	-0.665***	-1.418***	-2.678***	-3.267***	-0.834***
	(0.007)	(0.011)	(0.032)	(0.071)	(0.219)	(1.148)	(0.008)	(0.014)	(0.032)	(0.073)	(0.241)	(0.725)
February	-0.374***	-0.452***	-0.601***	-1.995***	-3.502***	-7.151***	-0.274***	-0.632***	-1.174***	-2.099***	-2.57***	-0.389
	(0.007)	(0.011)	(0.032)	(0.071)	(0.219)	(1.148)	(0.008)	(0.014)	(0.032)	(0.073)	(0.241)	(0.725)
March	-0.236***	-0.265***	-0.206***	-0.479***	-0.619**	-2.232*	-0.165***	-0.357***	-0.478***	-0.549***	-0.403*	1.768**
	(0.007)	(0.011)	(0.032)	(0.071)	(0.219)	(1.149)	(0.008)	(0.014)	(0.032)	(0.073)	(0.241)	(0.725)
April	-0.064***	-0.092***	-0.219***	-1.005***	-1.917***	-5.519***	-0.047***	-0.096***	-0.407***	-1.04***	-1.77***	-0.442
	(0.007)	(0.011)	(0.032)	(0.071)	(0.22)	(1.149)	(0.008)	(0.014)	(0.032)	(0.073)	(0.241)	(0.725)
May	0.031***	0.029**	-0.094**	-0.483***	-0.751	-2.058	0.031***	0.042**	-0.179***	-0.458***	-0.773**	1.041
	(0.007)	(0.011)	(0.033)	(0.071)	(0.22)	(1.149)	(0.008)	(0.014)	(0.032)	(0.073)	(0.241)	(0.725)
July	-0.286***	-0.207***	-0.331***	-1.009***	-1.498***	-2.698**	-0.239***	-0.321***	-0.689***	-1.194***	-1.395***	1.052
	(0.007)	(0.011)	(0.031)	(0.069)	(0.211)	(1.121)	(0.008)	(0.014)	(0.031)	(0.071)	(0.23)	(0.706)
August	-0.392***	-0.33***	-0.329***	-0.573***	-0.457**	-0.626	-0.263***	-0.437***	-0.68***	-0.679***	-0.625**	2.155***
	(0.007)	(0.011)	(0.031)	(0.069)	(0.211)	(1.122)	(0.008)	(0.014)	(0.031)	(0.071)	(0.231)	(0.706)
September	-0.35***	-0.325	-0.218	-0.189	-0.093	0.359	-0.237	-0.407	-0.49	-0.302	-0.296	2.147
	(0.007)	(0.011)	(0.031)	(0.07)	(0.212)	(1.122)	(0.008)	(0.014)	(0.031)	(0.071)	(0.231)	(0.706)
October	-0.346***	-0.313***	-0.212***	-0.239***	-0.165	0.685	-0.249***	-0.403***	-0.479***	-0.357***	-0.439*	1.989**
	(0.007)	(0.011)	(0.031)	(0.07)	(0.212)	(1.124)	(0.008)	(0.014)	(0.031)	(0.071)	(0.231)	(0.706)
November	-0.316***	-0.3***	-0.172***	-0.071	0.251	1.623	-0.212***	-0.372***	-0.383***	-0.12	-0.051	2.341***
	(0.007)	(0.011)	(0.031)	(0.07)	(0.212)	(1.125)	(0.008)	(0.014)	(0.031)	(0.071)	(0.232)	(0.707)
December	-0.224***	-0.107***	0.454***	2.657***	4.456***	5.38***	-0.145***	-0.043**	0.704***	2.22***	1.734***	2.546***
	(0.007)	(0.011)	(0.031)	(0.07)	(0.213)	(1.127)	(0.008)	(0.014)	(0.031)	(0.071)	(0.233)	(0.708)

Note: Standard errors are in parentheses. Significance levels are * - $p < 0.1$, ** - $p < 0.05$, *** - $p < 0.01$. Base categories are June and Apotek 1.
Number of pharmacies - 724. Number of pharmacy-month pairs - 55285. Number of pharmacy-month-BUs - 31569626. Number of parameters per group - 29.

Table 6: Preliminary Regressions

	Dep. Var.: Same/competing chain entry			
	I	II	III	IV
Intercept	-0.12	-0.01	-0.06	-0.17
	(0.22)	(0.21)	(0.21)	(0.22)
Apotek 1	0.50**	0.50***	0.54***	0.49**
	(0.19)	(0.18)	(0.17)	(0.19)
Boots	0.12	0.04	0.09	0.08
	(0.19)	(0.18)	(0.18)	(0.19)
Vitus	0.15	0.10	0.15	0.15
	(0.20)	(0.19)	(0.18)	(0.20)
Ditt apotek	0.15	0.07	0.06	0.09
	(0.20)	(0.19)	(0.19)	(0.20)
Center	0.12	0.11	0.12	0.15
	(0.14)	(0.13)	(0.13)	(0.15)
Small mall	0.33	0.41*	0.60**	0.72**
	(0.24)	(0.22)	(0.26)	(0.27)
Wine mon. in small mall	-0.25	-0.19	-0.20	-0.28
	(0.25)	(0.22)	(0.22)	(0.27)
Large mall	0.15	0.08	-0.03	0.06
	(0.15)	(0.14)	(0.14)	(0.15)
Wine mon. large mall	0.04	-0.00	-0.02	0.05
	(0.16)	(0.15)	(0.15)	(0.16)
Market size	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Residuals prior 3 months		0.13***		
		(0.03)		
Residuals prior 6 months			0.12***	
			(0.04)	
Residuals prior 12 months				0.13**
				(0.06)
Obs.	53	53	53	53