Finnish Competition
and Consumer Authority

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Working Papers 1/2025

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Publication: Working Papers 1/2025: Free Entry and Social Inefficiency in Regulated Pharmacy Markets

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Postal address: Finnish Competition and Consumer Authority, POB 5, 00531 Helsinki, Finland
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kkv.fi

ISSN 2954-1859

Free Entry and Social Inefficiency in Regulated Pharmacy Markets *

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Abstract

We study entry deregulation in the Finnish pharmacy market where prices, markups, and the number and location of pharmacies are regulated. Our counterfactual simulations show that the number of pharmacies increases substantially, particularly in urban areas. Although almost all consumers benefit, rural areas and areas with older populations benefit less. The increase in aggregate consumer surplus is dominated by significant decreases in pharmacy profits and government tax revenue. As a result, free entry turns out to be socially excessive. The prevailing entry restrictions may thus work reasonably well from a total welfare perspective, but with distributional consequences: They benefit incumbent pharmacists at the expense of customers.

Keywords: *entry regulation, deregulation, pharmacies, pharmaceuticals, welfare*
JEL-Classification: *L43, L81, R12*

*Author contributions: Jaakko Markkanen and Antto Jokelainen contributed equally to this work and are listed as co-first authors. The remaining authors are listed in alphabetical order. Antto Jokelainen: Aalto U. and Helsinki GSE, `antto.jokelainen@aalto.fi`. Jaakko Markkanen: ETLA, Aalto U. and Helsinki GSE., `jaakko.markkanen@etla.fi`. Samuli Leppälä: FCCA, `samuli.leppala@kkv.fi`. Markku Siikanen VATT and Helsinki GSE, `markku.siikanen@vatt.fi`. Matti Sipiläinen: FCCA, `matti.sipilainen@kkv.fi`. Otto Toivanen: Aalto U., Helsinki GSE and CEPR, `otto.toivanen@aalto.fi`. We thank Chris Conlon, Olli Ropponen, Paul T. Scott, Nelli Valmari, and seminar audiences at ETLA and NYU for comments. We thank Elsa Saario and Patrik Björkqvist for their outstanding research assistance and the OP Group Research Foundation for financial support. All errors are ours.

1 Introduction

The economic literature classifies barriers to entry as a distinct source of market distortions. However, the benefits of free entry depend on the intensity of competition. In markets where competition is limited, perhaps due to government intervention (e.g., price regulation), the potential gains from free entry may not be fully realized. Conversely, if each new entrant incurs fixed costs, restricting entry may be socially efficient, especially when increased entry does not lead to significant market expansion. Additionally, free entry may have distributional effects, increasing inequality by altering the division of economic rents—both between the industry and consumers and within firms and across different consumer segments. This is especially the case when firms are horizontally differentiated and consumers have heterogeneous preferences. In such markets, regulation of entry may benefit consumer segments that would be left without provision under free entry equilibrium.

We study the effects of removing entry barriers in a highly regulated industry: The Finnish pharmacy sector. As in many other countries, it is subject to strict regulations covering, for example, entry, pricing and markups, ownership, professional qualifications, and pharmacy locations. The presence of both entry and price regulation enables us to examine the effects of entry restrictions in a setting with limited price competition between pharmacies. We explore how the pharmacy network would change if existing entry restrictions were lifted while keeping other regulations intact and identify and measure the associated trade-offs. We also demonstrate how different demographic groups (old vs. young) and geographic areas (urban vs. rural) would be affected by deregulation.

We estimate a model of demand and supply that allows us to simulate a counterfactual where existing entry restrictions have been relaxed. First, we estimate a spatial demand model of pharmacy choice. We build on the model of Ellickson, Grieco and Khvastunov (2020) and tailor it to the Finnish pharmacy sector. Our most relevant changes are i) allowing unobserved heterogeneity in the distaste for travel through random coefficients, ii) using travel time as the measure for distance, and iii) including demographic variation in market potential. Second, as in Verboven and Yontcheva (2024), we use a production function approach to model variable costs of operating a pharmacy business and estimate fixed entry costs following Eizenberg (2014). In the third part of our empirical analysis, we simulate a counterfactual scenario in which we relax entry restrictions.

Our demand estimates show that consumers dislike longer travel times but with significant heterogeneity across consumers. This suggests that entry into neighboring markets can attract less distance-sensitive consumers away from their local market. Furthermore, we find that substitution to and from the outside option is limited. This implies that new entry to the market results mainly in business stealing with relatively little market expansion. Out of the models we consider, a random coefficients nested logit (RCNL) model produces the most flexible substitution patterns: It allows for closer substitution between pharmacies compared to the outside good, and it relaxes the assumption of independence of irrelevant alternatives (IIA) of standard logit and nested logit (NL) models.

On the supply side, we estimate pharmacies' variable costs using a Leontief-form production function with labor and material costs as inputs. We deal with the potential endogeneity between unobserved productivity shocks and revenue by using predicted revenues from the demand model as an instrument. Our instrumental variable (IV) estimates imply non-negligible economies of scale for the labor inputs. To estimate pharmacies' fixed costs, we follow Eizenberg (2014) and use observed entry and exit decisions to back out the range of fixed costs that rationalize these decisions. However, because regulated entry results in a very low number of entries or exits, we instead rely on the incumbents' decision to remain in the market to estimate upper bounds of the fixed costs. We do this separately for urban and rural pharmacies and use different percentiles of the estimated distribution of (the upper bound of) fixed costs in our counterfactual simulation.

Our counterfactual simulation shows that the number of pharmacies increases substantially with free entry. In the regulated regime, there were 822 pharmacies in Finland in 2021 (Association of Finnish Pharmacies 2021). In the free entry scenario, we end up with 2 276 pharmacies, an increase of 180%. However, there is significant variation in entry rates between regions. Most of the new entry is focused on densely populated urban areas with already existing pharmacies. For most rural areas, the relaxation of entry restrictions does not result in significant changes in their pharmacy network. However, there are some sparsely populated rural areas that lose access to nearby pharmacy services.

Almost all consumers benefit from entry deregulation as consumer surplus (CS) increases for 98% of the population. However, the benefits are unevenly distributed between different consumer groups and geographical areas, with young consumers and urban areas gaining the most. When we cross-tabulate changes in welfare and market concentration—measured by Herfindahl–Hirschman index (HHI)—we find that almost 1% of the population face a decrease in welfare despite having a simultaneous decrease in market concentration. This phenomenon can occur when consumers lose their local services and must travel to areas that are further away but also exhibit more competition within that area. On the other hand, for nearly 3% of consumers, both CS and market concentration increase, suggesting an opposite effect with the introduction of new local pharmacies. These findings illustrate that decreases in market concentration do not always imply improvements in consumer welfare, nor vice versa.

Although our simulations show that almost all consumers benefit from free entry, total welfare does not increase. Three main mechanisms explain why: First, most consumers do benefit but these benefits are small, with the average increase in CS being a modest 14%.[1] Second, each new pharmacy incurs an additional fixed cost, leading to a 188% increase in total fixed costs. Third, new entry induces very limited market expansion (the number of pharmacies increases by 178% whereas sales increase by only 8%), which leads to a significant decrease in average sales per pharmacy. This decrease results in the loss of economies of scale, causing further welfare losses. Our counterfactual leads to significant redistribution of surplus: Although the pharmacy industry suffers, the government bears most of the loss through lost tax revenue. Total annual welfare decreases by 76 million euros (7%), with consumers gaining 68 million (14%), pharmacies losing 42 million (28%), and the government losing 103 million (24%).

The primary motivation for entry regulation—ensuring sufficient access to pharmacies for all consumers—is not supported by our analysis: Entry regulation

1. Our CS calculation does not include welfare gains or losses from increased pharmaceutical use implied by market expansion. On one hand, one may argue that the increase is overconsumption from a medical perspective, but on the other hand, one could also interpret the increase to be pharmacologically effective use by distance-sensitive consumers who would otherwise forego their medical treatments.

does not necessarily produce a more equitable pharmacy network than free entry. However, it does appear to prevent the welfare loss caused by excessive entry. This efficiency gain coincides with a significant reallocation of surplus: Pharmacists and the government benefit from entry restrictions at the expense of consumers. As an alternative to entry regulation, excessive entry could be addressed through adjustments to pharmacy markups or taxation. Under price regulation, improving consumer welfare is challenging without inducing losses for the industry or the government. Allowing price competition could improve consumer and total welfare, but the outcome would depend on the specifics of the deregulation.

The regulation of the Finnish pharmacy sector is representative of the pharmacy regulations found in many other developed countries. In the European Union (EU), 18 member states regulate pharmacies in a way that resembles the Finnish system.[2] Furthermore, the type of counterfactual that we conduct—relaxing entry restrictions while keeping price controls in place—is a scenario that is based on actual pharmacy deregulation reforms in Europe during the 21st century (e.g., the deregulation of the Swedish pharmacy market in 2009).[3] Our results focus on a regulated market but they may also be relevant for regimes without entry regulation but with perceived problems with the geographical coverage of pharmacies, such as the United States of America (US), where an active discussion exists regarding so-called "pharmacy deserts" (e.g., Ying, Kahn and Mathis 2022; Catalano, Khan, Chatzipanagiotou and Pawlik 2024; Wittenauer, Shah, Bacci and Stergachis 2024). In addition, our results are not strictly limited to pharmacy markets. Any market that exhibits limited market expansion from competition, e.g., due to price controls or the absence of prices, may be susceptible to excessive entry. These types of markets can be found, for example, from sectors such as education, healthcare, energy, or infrastructure.

Our work is related to three strands of literature. We contribute foremost to the literature on entry and especially on restricted entry and deregulation. Previous empirical and theoretical analyses have documented that free entry can be excessive when firms have market power. Competition from an additional entrant may reduce

2. See Online Appendix Table B.1 for details on restrictions related to the number of pharmacies, the ownership of pharmacies, and horizontal and vertical integration in the EU.

3. See Online Appendix Table B.2 for a list of EU countries with deregulated entry but with remaining price controls.

prices due to increased competition (when prices are not regulated, as in our case); however, the new entrant may capture customers from incumbent firms, leading to social inefficiency through business stealing by increasing the industry's total costs via higher fixed costs and reduced economies of scale. Spence (1976), Dixit and Stiglitz (1977) and Mankiw and Whinston (1986) theoretically examine excessive entry. Berry and Waldfogel (1999) and Hsieh and Moretti (2003) are classical empirical analyzes documenting welfare distortions arising from free entry in the radio advertising and real estate markets. However, restricted entry has received less attention. Ferrari and Verboven (2010) provide a brief overview of empirical applications and modeling choices of restricted entry.

Three articles are particularly relevant to our work. Schaumans and Verboven (2008) study the Belgian pharmacy market using data on the number and location of pharmacies. They find more pharmacies and lower regulated markups when entry restrictions are removed. Although their context is similar, we use revenue and production cost data coupled with a flexible demand specification and focus on entry restrictions without price changes. Seim and Waldfogel (2013) and Verboven and Yontcheva (2024) examine market configurations after changes in entry restrictions. Seim and Waldfogel (2013) analyze the retail alcohol market in Pennsylvania, whereas Verboven and Yontcheva (2024) study the Latin notary profession in Belgium. Both find that entry regulation shifts surplus from the consumers to the industry, and that deregulation would increase total welfare. In contrast, our findings demonstrate that in markets where market expansion is limited, the gains for consumers may be smaller than the losses of the industry, implying a decrease in total welfare.

We contribute to the methodological entry game literature on simulating spatial entry games by developing a backward version of the Seim and Waldfogel (2013) sequential myopic entry (SME) algorithm. We call this the backward sequential myopic entry (BSME) algorithm. It produces outcomes that satisfy the same conditions as the original algorithm, but is at least an order of magnitude faster for large-scale problems. Although neither algorithm guarantees a Nash equilibrium, we evaluate the counterfactual market structure and find that, conditional on the locations of other players, only 1.4% of the entrants would prefer to switch locations. This robustness check represents an improvement to existing practices in the literature by providing a more systematic evaluation of the equilibrium properties of entry outcomes.

The second literature to which we contribute is deregulation. Previous work has found that deregulation can increase efficiency, reduce costs, boost economic growth, and increase consumer welfare (Winston 1993, 1998). Our contribution to existing industry studies on deregulation is that we study the distributional implications of relaxing a policy that is designed to protect consumers from harm.

Finally, our work is also closely related to the literature on local public good provision. Regulated pharmacies are responsible for providing essential public health services. This institutional setup has many similarities with the school and hospital network consolidation literature. School consolidation can force students to travel longer distances, and demand reallocation can lead to network changes with adverse impacts on student outcomes (Engberg, Gill, Zamarro and Zimmer 2012; Brummet 2014; Beuchert, Humlum, Nielsen and Smith 2018). Similarly, the previous literature has found that hospital service network consolidations can have heterogeneous impacts on patient outcomes. Consolidation can improve the quality of care, but increasing travel distances can reduce health outcomes (Fischer, Royer and White 2024; Avdic, Lundborg and Vikström 2024; Avdic 2016; Bertoli and Grembi 2017).

The remainder of the article is structured as follows. In Section 2, we present the relevant institutions and regulations. We introduce the data and present descriptive statistics in Section 3 and our demand model in Section 4. We devote Section 5 to presenting our supply model. Sections 6 and 7 present the entry game and the entry game results. We offer conclusions in Section 8.

2 Institutions

In this section, we explain the institutional background and market regulations related to pharmaceutical pricing and reimbursement in Finland. Finland is a sparsely populated Nordic country with a population of 5.55 million and a population density of 18 people per square kilometer (48 people per square mile). In Finland, consumers can buy pharmaceuticals (both prescription (RX) and over-the-counter (OTC) products) only from pharmacies.[4] Like many other EU countries, Finland regulates entry into the pharmaceutical retail sector. These restrictions are intended to ensure equitable access to healthcare services by maintaining the availability and quality of pharmacy services, particularly in rural areas.

Pharmacy regulation. Our definition of pharmacies includes only community pharmacies: We exclude hospital pharmacies.[5] Pharmacies are subject to strict quantity and location regulations that are applied throughout the country. We refer to these rules as the entry regulation. The Finnish Medicines Agency (Fimea), the regulator, decides the number of pharmacies in each municipality and the geographical locations where pharmacists can operate their pharmacies.

A pharmacy must be owned by an independent pharmacist who meets the educational (M.Sc. in Pharmacy) and work experience requirements set by the regulator. Each pharmacist may operate only one main pharmacy and up to three subsidiary pharmacies at a time. The regulator may permit pharmacists to own subsidiary pharmacies in situations where the regulator considers some area to require pharmacy services, but for which there are no prerequisites for an independent pharmacy.[6] In some cases, a pharmacy license can be conditional on the operation of a subsidiary pharmacy in a designated rural area. The legal status of being a main or a subsidiary pharmacy does not directly affect the quality of the pharmacy services. However, it may be correlated with other factors, such as shelf space or opening hours, that can affect the perceived quality by consumers. When the regulator identifies the need to establish a new pharmacy, it asks qualified pharmacists to apply and selects the most qualified pharmacist for the task.[7]

The vertical and horizontal organization of the pharmacy market in Finland is also highly regulated. Vertical integration between pharmacies, wholesalers, and/or

4. Pharmacies are brick-and-mortar stores but they can also sell pharmaceuticals through online delivery. However, the role of the online channel is very limited in this market: According to Kokko, Hyvärinen and Reinikainen (2024), the share of online sales was only 0.5% of all pharmacy sales in Finland. Therefore, we do not model this channel in our analysis.

5. Hospital pharmacies cannot sell pharmaceuticals; they can administer drugs free of charge for immediate use or for the start of outpatient care. See Finnish Medicines Act Section 7 65 §.

6. For detail on subsidiary pharmacies, see the Finnish Medicines Act 395/1987 52§.

7. The application form and basic rules can be found on the web-page of the regulator, Fimea. The key categories are 1) previous experience in pharmacies and pharmaceutical services and 2) relevant studies and management skills. The available materials do not give any indication on how the various aspects are weighed in the choice of the pharmacist.

pharmaceutical manufacturers is prohibited, and pharmacies are not allowed to form chains. The only exceptions to this rule are the Universities of Helsinki and Eastern Finland, which are permitted to operate their own pharmacy chains due to historical reasons and their role in providing pharmacy education.

An important institutional feature is the dual role of pharmacists. As the owner, a pharmacist is the residual claimant. In addition, a pharmacist can work in the pharmacy as a staff member. This dual role is particularly significant for small pharmacies, where the labor input from the owner can result in relatively low reported labor costs relative to turnover.

During our observation period (2021), pharmacists faced regulated markups: The retail prices of RX and OTC pharmaceuticals were given by a government-dictated piecewise linear function of the wholesale prices.[8] Implicitly, price competition for pharmaceuticals occurs at the wholesale level. For non-pharmaceutical products and services, pharmacies are allowed to set prices freely. In 2022, non-pharmaceutical sales were around 7% of the total private pharmacy turnover excluding Value Added Tax (VAT) (Kokko, Hyvärinen and Reinikainen 2024).

Pharmacies are not subject to the standard corporate tax; instead, they are taxed through a revenue-based pharmacy tax. The pharmacy tax applies to the total revenue from all pharmacies owned by the same pharmacist, including the main pharmacy and its subsidiaries. We demonstrate the differences between standard business taxation and pharmacy taxation in Appendix A.1. In addition to pharmacy tax, pharmaceutical sales are subject to 10% VAT. Pharmacists can engage in legal tax planning by establishing a limited liability company as a side-business for selling non-pharmaceutical products and services. In 2024, 38% pharmacists had established such a side-business. In our analyses, we do not model the tax effects of these side-businesses.

All in all, Finnish pharmacy regulations are in line with the international practice: Of the 27 EU countries, 19 (70%) regulate the number, 22 (81%) the location, 11 (41%) the ownership, nine (33%) the horizontal and 16 (59%) the vertical structure of pharmacies, and all but two the education of the pharmacy owner. We illustrate

8. Table A.1 in Appendix A.1 describes the pricing formula used during the year of our study. Since April 2022, the pricing of OTC products has been partly deregulated with a maximum retail markup instead of a direct pricing formula.

in Online Appendix B.2 Table B.1 that the pharmacy regulations currently used in Finland are also commonly used in other EU countries.

Wholesale price regulation. Pharmaceutical manufacturers compete with each other in the wholesale market. Manufacturers face a product-specific maximum wholesale price for reimbursed pharmaceuticals, but are allowed to freely set wholesale prices for OTC and RX drugs that are not included in the reimbursement system.[9] Manufacturers have to commit to uniform national wholesale prices. The purpose of the uniform prices is to guarantee equal prices throughout the country. Together these uniform wholesale prices and regulated pharmacy markups imply uniform retail prices for pharmaceuticals across pharmacies.

Reimbursement policy. In Finland, pharmaceuticals are reimbursed. Consumers can receive a reimbursement of 40%, 65%, or 100% of the retail price of the product, and the annual out-of-pocket (OOP) expenditure on reimbursed pharmaceuticals is capped. During our sample period (2021), price regulation incentivized consumers to substitute to an identical but cheaper product.[10]

3 Data

3.1 Data Sources

Our data come from several sources. Most of the spatial information is derived from the Statistics Finland Grid Database, which we refer to as "the grid data". This data divides Finland into 250m×250m cells and includes information on the population and age structure of the entire country. We assume that the representative consumers in our demand model and simulations reside at the centroid of the cells.

Our data on pharmacies and their financial statements are obtained from Fimea. The data contain standard accounting information on pharmacy profits and sales of RX and OTC pharmaceuticals. The balance sheet information also contains information on the cost structure and cost components of individual pharmacies.

9. We present a more detailed overview of the regulations in Appendix Section A.1.

10. Kortelainen, Markkanen, Siikanen and Toivanen (2023) provides further details on pharmaceutical price regulation in Finland.

The data allow us to distinguish between labor, rental, and pharmaceutical wholesale purchases. We obtain pharmacy locations from the addresses reported in Fimea's pharmacy registry, and geocode these addresses to coordinates with OpenStreetMap data. We complement pharmacy data with pharmacy visit and expenditure data at the postal code level from the Finnish Social Insurance Institution (Kela).

We supplement these data with several publicly available data sets. First, we use cell-level information on the community structure and urban/rural classification from Finnish Environment Institute (SYKE). Second, we use open access information on local amenities (e.g., nearby grocery stores and health centers) from various OpenStreetMap contributors. These data are complemented with postal code-level population data from Statistics Finland's Paavo database. We allocate pharmaceutical expenditures evenly into cells within each postal code area. Lastly, for the geographical presentation of our results, we use country boundaries from EuroGeographics, a 1 km $\times$ 1 km population grid from Statistics Finland, and the Helsinki metropolitan area map from the city survey services of Helsinki, Espoo, Vantaa and Kauniainen. We present the full list of our data sources in the Online Appendix Section B.3.

We calculate the distances between cells, pharmacies, and potential entry locations using travel time by car, measured in minutes.[11] Therefore, throughout the article, 'distance' refers to travel time.

3.2 Descriptive Statistics

Table 1 presents descriptive statistics in two panels. Panel A displays cell-level information on consumers. On average, the cells are sparsely populated rural areas with middle-aged residents. We define the choice set of a cell to include all pharmacies within 45 minutes of the cell.[12] The average driving time to the nearest pharmacy is about 13 minutes and the average choice set size is close to 20 pharmacies. Kela expenditure is the per capita expenditure on RX drugs which we observe at a postal code level. We use the Kela expenditure to bring geographical

11. Using distance rather than travel time has been a concern in the literature on pharmacy deserts (Ying, Kahn and Mathis 2022).

12. See Online Appendix Subsection B.4 for further details on travel time computation.

(and implicitly demographic) variation in market potential to our demand model.[13]

Note that all of these variables exhibit large variation and skewed distributions. To pick a few examples and comparing the 10th percentile to the 90th, population increases 33 times; expenditures double; and the number of pharmacies within the choice set increases by a factor of 23. Only 9% of cells are urban.

Table 1 Panel B summarizes the key characteristics of the existing pharmacies.[14] Most pharmacies are located in sparsely populated areas, as indicated by the average population density being double the median population density. Although job density in pharmacy cells is lower than population density, nearby jobs could potentially increase the demand for some pharmacies. 35% of existing pharmacies are located in an inner city area and almost 60% of the pharmacies have a supermarket nearby. Most of the existing pharmacies are main rather than subsidiary pharmacies and only 2% of the pharmacies belong to the Yliopiston Apteekki (YA) chain operated by the University of Helsinki.[15] Only 20% of the pharmacies have a nearby mall and 26% of pharmacies have a nearby health center. The average pharmacy sold pharmaceuticals worth 3.32 million euros, but the variation is large.

Table 1 panel C summarizes the key financial characteristics of the existing pharmacies used in production function estimation. This sample only contains roughly half of the existing pharmacies because pharmacies report their financials (excluding sales) together for the main pharmacy and the subsidiaries (see Section 2 for additional details). Therefore, we have limited our sample to only those pharmacies that have no subsidiaries.[16] The pharmacies in our sample also have slightly higher average sales than the entire population. Table 1 panel C shows that for an average pharmacy, material costs, which mainly consists of wholesale costs of pharmaceuticals, are the largest cost component, whereas labor and capital costs are much more modest. Material costs increase more rapidly than labor or capital costs when comparing distribution tails (P10 versus P90). Average profits net of

13. In the demand model, we also add a fixed 50 euros to Kela expenditure to represent the missing OTC expenditure. This also helps us deal with areas where Kela expenditure is zero.

14. Note that the locations of existing pharmacies are strictly regulated by Fimea, so it may be possible that the existing locations are not the most profitable locations for pharmacy operations.

15. The University of Eastern Finland Pharmacy is also included in the YA dummy.

16. We also exclude pharmacies that have significant amount of non-consumer sales, had an entry, exit or ownership change during the year, report zero capital or labor costs, or are one of the university pharmacies.

material costs are slightly above €1M; profits net of labor and capital costs, as well as taxes, are €0.15M. The price-cost margin, defined as (Pharmaceutical sales - Material costs)/Pharmaceutical sales, is, on average, close to 30%. Deducting (variable) labor and capital costs leads to an average price-cost margin of 14%.

Figure 1a shows the structure of the current pharmacy network in Finland and Figure 1b provides a detailed view of the pharmacy network in the Helsinki (capital) area, the most densely populated area of the country. Pharmacies are evenly distributed throughout the country (Figure 1a), except in Northern and Eastern Finland, which are sparsely populated areas. Large cities have many pharmacies. Most pharmacies in Helsinki are located in densely populated areas with good access to different modes of transport (Figure 1b).[17]

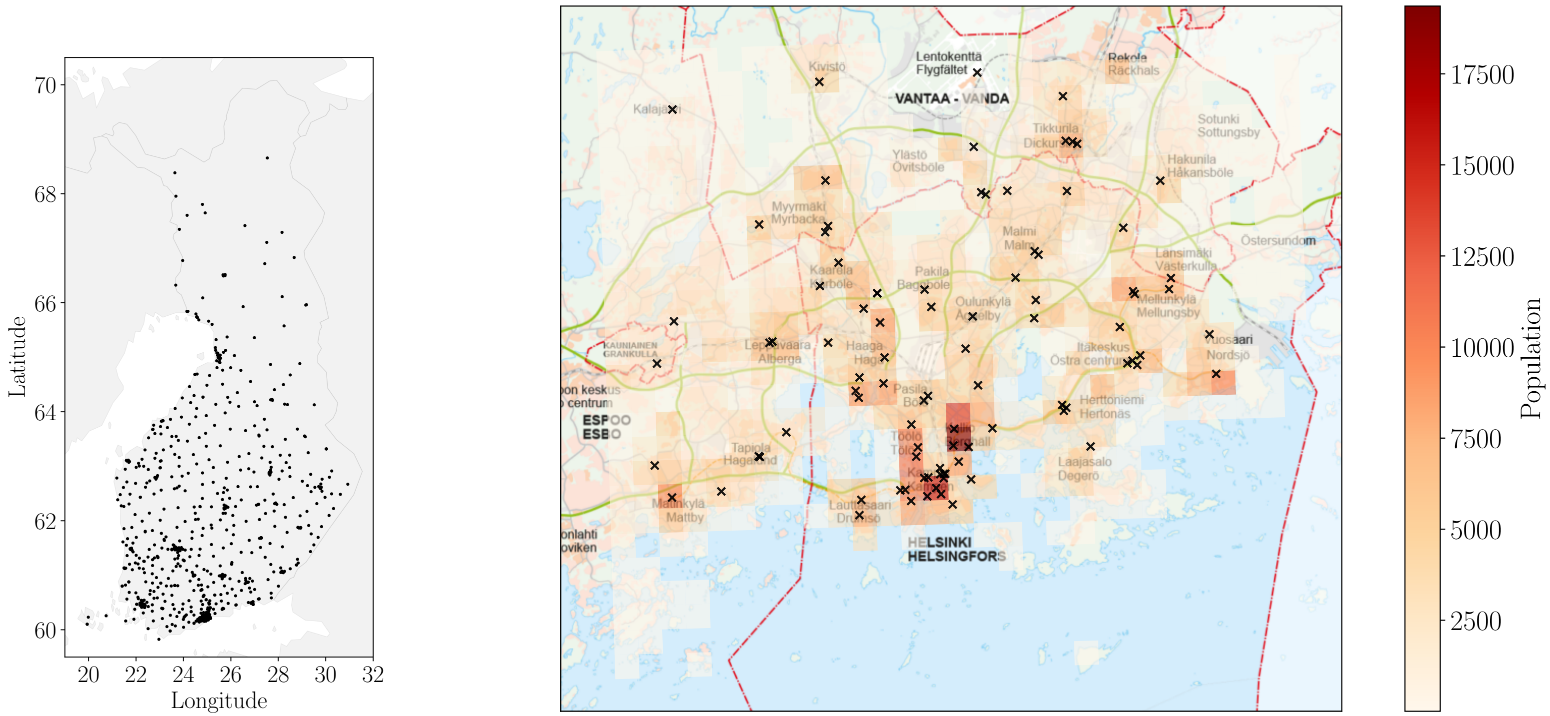
17. We exclude the pharmacy at Helsinki International Airport and any pharmacies that were founded during the calendar year, resulting in an incomplete accounting year, from the sample.

Table 1: Descriptive Statistics

Variable	**Mean**	**Std. Dev.**	**P10**	**P50**	**P90**	**N**
			Panel A: Cell characteristics			
Population	17.02	60.18	1.00	3.00	33.00	321950
City area	0.09	0.29	0.00	0.00	0.00	321950
Distance	13.18	12.23	3.63	10.91	24.13	321950
Choice set size	19.66	21.79	3.00	13.00	46.00	321950
Kela expenditure	453.52	139.49	306.90	440.63	601.08	321950
Market potential	604.23	167.39	428.28	588.76	781.29	321950
			Panel B: Pharmacy characteristics (Demand model)			
Pharmaceutical sales	3.32	3.21	0.72	2.45	6.61	818
Inner city	0.35	0.48	0.00	0.00	1.00	818
Outer city	0.13	0.33	0.00	0.00	1.00	818
Rural center	0.08	0.27	0.00	0.00	0.00	818
Supermarket nearby	0.59	0.49	0.00	1.00	1.00	818
Mall nearby	0.21	0.41	0.00	0.00	1.00	818
Healthcare nearby	0.26	0.44	0.00	0.00	1.00	818
Public transport nearby	0.07	0.25	0.00	0.00	0.00	818
Population density	2.14	2.70	0.28	0.99	6.12	818
Jobs density	1.82	4.24	0.11	0.53	4.23	818
Main pharmacy	0.79	0.41	0.00	1.00	1.00	818
YA	0.02	0.15	0.00	0.00	0.00	818
			Panel C: Pharmacy characteristics (Cost estimation)			
Pharmaceutical sales	3.85	2.21	1.45	3.48	6.74	402
Material costs	2.77	1.62	1.01	2.53	4.99	402
Gross profits	1.08	0.66	0.40	0.96	1.94	402
Price-cost margin	27.98	10.82	25.41	27.69	30.37	402
Labor costs	0.45	0.23	0.18	0.42	0.75	402
Capital costs	0.09	0.07	0.03	0.07	0.18	402
Net profits	0.15	0.08	0.06	0.14	0.25	402

Notes: This table presents descriptive statistics for consumer home cells (Panel A) and pharmacies (Panels B and C). Panel B includes the pharmacies used for estimating consumers' pharmacy choice, and Panel C the pharmacies used for estimating pharmacy cost function. All figures in Panel C, except the Price-cost margin, are in millions of euros.

Figure 1: Existing Pharmacy Network



(a) Pharmacies in Finland

(b) Pharmacies in Helsinki

Notes: The figure on the left plots the locations of all pharmacies in Finland. The figure on the right shows the locations of pharmacies and population densities in Helsinki. Sources for the maps: Fimea (2021), Nominatim and OpenStreetMap contributors (2024), Statistics Finland (2023), Helsinki City Survey Services, Cities of Espoo, Vantaa, and Kauniainen (2022) and EuroGeographics (2024).

4 Demand Model

We now develop and estimate a spatial model of pharmacy choice in Finland. We use the estimates of the model to rationalize the entry decisions of pharmacies in our counterfactual simulations.

4.1 A Spatial Model of Demand of Pharmacy Choice

We extend the discrete choice model of Ellickson, Grieco and Khvastunov (2020) by incorporating random coefficients. This extension is important for our entry counterfactual, as it relaxes the common IIA assumption. Our second extension is that we weigh the market potential with the postal code-level pharmaceutical expenditure data from Kela. This reflects the fact that some areas, mostly due to the age of residents, have significantly higher expenditure on pharmaceuticals. The weighting procedure allows our model to capture the exogenous variation in market potential and hence allows the model to match actual consumption patterns more closely.

A representative consumer i living at the centroid of cell t obtains indirect utility from spending at pharmacy s:

$$u_{ist} = \delta_{st} + \mu_{ist} + \varepsilon_{ist}, \quad u_{i0t} = \varepsilon_{i0t} \tag{1}$$

where we have normalized the mean utility of the outside good, u_{i0t}, to zero. With a NL specification,

$$\varepsilon_{ist} = \bar{\varepsilon}_{ih(s)t} + \left(1 - \rho_{h(s)}\right) \bar{\varepsilon}_{ist} \tag{2}$$

where $h(s)$ denotes the nests in the model where all inside goods are in the same nest and $\rho_{h(s)}$ is the nesting parameter to be estimated. This assumption implies that inside goods are closer substitutes to each other than to the outside good.[18] The common utility component in equation (1) is defined as

$$\delta_{st} = x'_{st}\beta_0 + \xi_{st}. \tag{3}$$

18. Values of $\rho_{h(s)}$ are consistent with utility maximizing behaviour when $0 \leq \rho_{h(s)} < 1$ holds. If $\rho_{h(s)}$ takes value 0, then the model collapses to a plain logit model.

We can further split x_{st} into factors related to the consumers' home cell t and factors related to the location of the pharmacy s. In our richest specification, the home cell specific variables in x_{st} include a constant, distance to the pharmacy (driving time), an indicator for whether cell t is an urban area or not, and interaction of the distance and the urban dummy.[19] For pharmacy-specific characteristics, we include a dummy for whether there is a supermarket, mall, health center, or public transport hub close to the pharmacy; population and job density in the pharmacy's vicinity; and dummies for the pharmacy being a main pharmacy or a university pharmacy.[20] In addition to the included variables, other potential pharmacy quality measures, such as pharmacy opening hours, waiting times, or service offerings, could also influence consumer utility. However, due to the lack of available data on these factors, we have not incorporated them into our analysis. We assume that the unobserved term ξ_{st} is orthogonal to all x_{st}.

Because, due to regulation, product-level pharmaceutical prices are uniform across all pharmacies, x_{st} does not include prices. Excluding prices from x_{st} only changes the size of the constant included to x_{st}. However, most pharmacies also sell non-pharmaceutical products, such as shampoo and cosmetics. Because we do not have detailed sales data on these products from pharmacies or other retailers, we make the crucial assumption that the choice probabilities of visiting a pharmacy are determined solely by pharmaceutical demand, with all other sales considered spillovers from that market segment. Throughout this article, when we refer to revenues R, we define them as pharmaceutical sales of OTC and RX products. We discuss the implications of this assumption in Subsection 4.2 and in Section 6.

The heterogeneous utility component is defined as:

$$\mu_{ist} = x'_{st} \left(\Sigma_0 \nu_{it} \right). \tag{4}$$

The indirect utility can also be written as $u_{ist} = x_{st}\beta_{it} + \varepsilon_{ist}$ with $\beta_{it} \sim \mathcal{N}(\beta_0, \Sigma_0)$. The additive ε_{ist} term is assumed to be i.i.d., drawn from a standard Type 1 extreme value distribution. This yields the familiar mixed multinomial logit model for the

19. Distance to the pharmacy is measured in minutes of travel time by car.

20. An amenity is considered to be near a pharmacy if it is within 200 meters of the pharmacy. Population and job density are calculated as an average of the cells within 500 meters of the pharmacy, and they are scaled to thousand inhabitants or jobs per one square kilometer.

choice probabilities:

$$
\begin{aligned}
p_{st}(\theta) &= \int \frac{\exp\left(\delta_{st}+\mu_{ist}\right)}{\sum_{k\in C_t}\exp\left(\delta_{kt}+\mu_{ikt}\right)} dF\left(\beta_{it}\right) \\
&= \int \frac{\exp\left(\delta_{st}+\mu_{ist}\right)}{\exp\left(u_{i0t}\right)+\sum_{k\in S_t}\exp\left(\delta_{kt}+\mu_{ikt}\right)} dF\left(\beta_{it}\right),
\end{aligned}
\tag{5}
$$

with $\theta = (\beta_0, \Sigma_0)$. In equation (5), we define the choice set C_t of consumers in cell t as $C_t = S_t \cup 0$ where $S_t = \{s : d_{ts} \leq D\}$[21]. This means that the choice set of a consumers consists of i) pharmacies at most distance D away from the centroid of their home cell t, and ii) the outside good. D is defined in terms of travel time in minutes. The outside good corresponds to the consumer not buying pharmaceuticals from any pharmacy.

For our RCNL model, the choice probabilities are given by equation (6):

$$
p_{st}(\theta) = \int \underbrace{\frac{\exp\left(\left(\delta_{st}+\mu_{ist}\right)/\left(1-\rho_{h(s)}\right)\right)}{\exp\left(I_{ih(s)}/\left(1-\rho_{h(s)}\right)\right)}}_{\text{Within nest probability}} \times \underbrace{\frac{\exp\left(I_{ih(s)}\right)}{\exp\left(I_i\right)}}_{\substack{\text{Probability of} \\ \text{choosing nest } h(s)}} \; dF\left(\beta_{it}\right) \tag{6}
$$

with

$$
I_{ih(s)} = \left(1-\rho_{h(s)}\right) \ln \sum_k \exp\left(\left(\delta_{kt}+\mu_{ikt}\right)/\left(1-\rho_{h(s)}\right)\right) \tag{7}
$$

and

$$
I_i = \ln\left(\exp\left(u_{i0t}\right) + \sum_h \exp\left(I_{ih(s)}\right)\right) \tag{8}
$$

denoting the inclusive value term (Train 2009; Grigolon and Verboven 2014). The set $C_{t,h(s)} = \{q \in C_t : h(s) = h(q)\}$ is the set of pharmacies that are in the same nest per each choice set. In our RCNL setting, where one nest contains all pharmacies and the other contains only the outside option, $I_i = \ln\left(\exp\left(u_{i0t}\right) + \exp\left(I_{ih(s)}\right)\right)$. With the choice probabilities computed, the revenue that pharmacy s receives from consumers in cell t can be expressed as

21. In our estimations, we impose a minimum size of three for the choice sets.

$$\hat{R}_{st}(\theta, \alpha) = g(\alpha, r_t) \times N_t \times p_{st}(\theta), \tag{9}$$

where N_t is the number of consumers in cell t, and the term $g(\alpha, r_t)$ represents the potential per capita expenditure on pharmaceuticals. This means that consumers can spend up to $g(\alpha, r_t)$ euros on pharmaceuticals, and this spending is then divided into the inside goods and the outside good. Hence, the amount of pharmaceutical spending that we observe in the data is $g(\alpha, r_t)$ times the market share of inside goods. Our data and model would allow us to treat $g(\alpha, r_t)$ either as data, a parameter to be estimated, or both. We choose the latter approach, where we define $g(\alpha, r_t) = \alpha \times r_t$. We estimate α which represents market potential as a factor of observed pharmaceutical spending.[22]

Importantly, our choice model considers the utility of a single one-way trip to a pharmacy. Therefore, our welfare calculations are adjusted for the fact that consumers make multiple two-way trips to pharmacies. We incorporate this by using external data on the number of pharmacy visits displayed in the Online Appendix Subsection A.3. However, our model and interpretation are consistent a representative consumer visiting a pharmacy n_t times a year, because for each visit, they choose a specific pharmacy with the same probability $p_{st}(\theta)$. To see this, let us consider the following case: During visit j, representative consumer t spends an amount r_{jt}, with $j \in \{1, 2, ..., n_t\}$. The expected revenue for pharmacy s from cell t is $p_{st}(\theta) \times r_{1t} + p_{st}(\theta) \times r_{2t} + ... + p_{st}(\theta) \times r_{nt} = p_{st}(\theta) \times r_t$, where $r_t = \sum_j^{n_t} r_{jt}$. This example demonstrates how our expenditure data r_t can capture the variation in both the number of visits n_t and the expenditure per visit r_{jt}.

Defining $L_s = \{t : s \in C_t\} = \{t : d_{st} \leq D\}$ as the set of cells that have pharmacy s in their choice set, we can express the total revenue of the pharmacy as

$$\hat{R}_s(\theta, \alpha) = \sum_{t \in L_s} \hat{R}_{st}(\theta, \alpha). \tag{10}$$

The econometrician observes the revenues with a multiplicative measurement error e^{ζ_s}:

22. Term r_t includes the RX spending from Kela data added with a fixed 50 euros that reflect the share of OTC spending.

$$R_s = \exp(\zeta_s) \times \hat{R}_s(\theta_0, \alpha_0), \tag{11}$$

where θ_0, α_0 denote the true parameter values of the model. We estimate the model with non-linear least squares by minimizing the squared log-difference of the predicted revenue and the observed revenue:

$$(\hat{\theta}, \hat{\alpha}) = \underset{\theta,\alpha}{\operatorname{argmin}} \sum_s \left(\log\left(\hat{R}_s(\theta, \alpha)\right) - \log(R_s) \right)^2 . \tag{12}$$

4.2 Demand Model Identification

The identification of our model parameters is based on the variation in the geographical distribution of population, demographics, pharmacy characteristics, and pharmacy revenues. We assume that consumers take their own and the pharmacy locations as given and that $(\epsilon_{its}, \zeta_s)$ are independent of pharmacy location and characteristics around the pharmacy, as well as consumer location and consumer location characteristics.

In the original Ellickson, Grieco and Khvastunov (2020) framework, the parameter α—denoting the expenditure share of total income potentially allocated to pharmacy purchases—is identified from variation in the total number of pharmacies in otherwise identical markets. In our application α denotes a multiplying factor such that the product of alpha and observed pharmaceutical expenditure is the amount of euros that a consumer could potentially spend on pharmaceuticals. So, if alpha is 1.5, then cells with observed expenditure of €100 and €200 have a market potential of €150 and €300, respectively. α is identified from the variation in the total number of pharmacies in observationally identical markets (consumer choice sets) and by observing the change in total revenue across all pharmacies. Increasing the number of pharmacies within choice sets may lead to substitution from the outside to inside goods and to redistribution of revenues between pharmacies. The identification of the demand parameters and the nesting parameter is similar to Ellickson, Grieco and Khvastunov (2020) and follows from the variation in pharmacy and consumer characteristics.

We estimate both the simple logit model with $\Sigma_0 = 0$, and the logit model with a random coefficient on the distance term. The random coefficient terms, σ, are

Table 2: Demand Model Main Results

Utility specification Model	Logit (1)	NL (2)	RC (3)	RCNL (4)
β Intercept	10.6436 ***		5.1818 ***	
	(2.6244)		(1.0359)	
β Distance	-0.2008 ***	-0.0288 ***	-0.2689 ***	-0.0341 ***
	(0.0165)	(0.0062)	(0.0268)	(0.0082)
β Dist. $\times$ Urban	-0.0310	-0.0032	-0.0224	-0.0003
	(0.0369)	(0.0052)	(0.0440)	(0.0056)
β Urban	-9.4842 ***	-0.4733 ***	-5.1704 ***	-0.5888 ***
	(2.6645)	(0.1170)	(0.9579)	(0.1245)
σ Distance			0.1381 ***	0.0149 **
			(0.0306)	(0.0049)
ρ		0.8651 ***		0.8706 ***
		(0.0296)		(0.0312)
α	1.0106 ***	2.0839 ***	1.1220 ***	2.1538 ***
	(0.0184)	(0.0371)	(0.0430)	(0.0450)
AIC	2410	2402	2403	2393
BIC	989	980	995	985
MSE	5.10e12	5.08e12	5.05e12	5.03e12

Notes: Distance refers to travel time by car. Model statistics: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Mean Squared Error (MSE). Robust standard errors are presented in parenthesis; * p< 0.1, ** p< 0.05, *** p< 0.01.

identified from the variation in pharmacy locations between different cells and from the demographic variation surrounding pharmacy and consumer cells.

4.3 Demand Model Results

We present our demand model results in Tables 2 and 3, with Table 2 containing our main parameter estimates, including the constant, an indicator for urban cells, interaction between distance and urban cell indicator and the rest of the distance -related parameters, the estimates for the expenditure parameter α, and nesting parameter ρ and Table 3 the β pharmacy-level demand characteristics.

We estimate four models: 1) a standard logit model, 2) a NL model where all inside goods are in one nest and the outside good in another, 3) a random coefficients logit (RC) model with a random coefficient on the distance term, and 4) a RCNL model that incorporates both a nesting structure and a random coefficient on the distance term. As shown in Table 2, all specifications yield precise and negative estimates for the distance term. The RC model provides the most negative estimate at -0.269, with a corresponding random coefficient estimate of 0.138. The logit model yields an estimate of -0.201. The nested models show significantly smaller effects, with the NL estimate at -0.029 and the RCNL estimate at -0.034. The RCNL model's σ parameter is estimated at 0.015. The absolute ratio between the mean and standard deviation estimates (β and σ) is approximately 1.9 in the standard RC model and 2.3 in the RCNL model, indicating that RCNL has slightly fatter tails, implying stronger heterogeneity in consumers' distaste for distance.[23] The difference in the magnitude of parameter estimates between the nested and non-nested models is likely due to the nesting structure and limited substitution to the outside good. Consequently, the nesting parameter ρ obtains relatively high values at 0.865 for the standard NL model and 0.871 for the RCNL model.

Additionally, consumers living in urban areas have a higher probability of choosing the outside good. Because urban consumers have significantly larger choice sets than rural consumers, the model mechanically forces them to spend more on inside goods (due to non-zero choice probabilities). As a result, the urban dummy probably negates some of the effect of market expansion in urban areas caused by large choice sets. At the same time, estimates for the interaction of distance with a dummy variable for the consumer's home cell being in an urban area are small and imprecise across all models, implying that there is little difference in the average distaste for travel time between consumers in urban and rural areas. The AIC, BIC, and MSE metrics indicate that the RCNL model performs the best. We use its parameter estimates for our post-estimation statistics and as the basis for our entry game.

The market potential of a consumer is defined by the term $g(\alpha, r_t) = \alpha \times r_t$

23. The share of positive individual distance parameters $P(\beta_i > 0)$ for consumers in rural areas is $P\left(Z > \frac{0.2689}{0.1381} = 1.947\right) \approx 0.0258$ (2.58%) for the RCs model and $P\left(Z > \frac{0.0341}{0.0149} = 2.289\right) \approx 0.0111$ (1.11%) for the RCNL model. For consumers in urban areas, the share is a bit smaller due to negative interaction term between distance and urban dummy.

where r_t is the observed per capita pharmaceutical spending at the postal code level. Thus, the α's in Table 2 represent a multiplying factor for the size of the market potential. The standard logit model yields the smallest factor, 1.01, implying that the market potential is 1.01 times the observed pharmaceutical sales. The RC model has the second smallest value at 1.12. The two nested models provide significantly larger estimates, with the NL estimate for α at 2.1 and the RCNL estimate at 2.2. This is likely explained by the small substitution from the outside good to the inside goods imposed by the nesting structure and the large estimated nesting parameter.

We present the rest of our demand model estimates in Table 3. All models produce estimates that are robust across models, with the exception that nested models have systematically smaller magnitude than non-nested models, as was also the case with our main estimates. Furthermore, all of our estimates are consistent with economic intuition. First, consumers prefer pharmacies located near a supermarket, mall, health center, or public transit hub. Second, consumers dislike pharmacies located in densely populated areas or in areas with many workplaces. This could reflect that consumers do not want to visit pharmacies in city centers or commercial districts, but rather those pharmacies that are better accessible by car. Third, consumers prefer main pharmacies over subsidiaries, probably because main pharmacies are generally larger. Lastly, consumers have a strong preference for university pharmacies. This is expected, given that these pharmacies are part of the only significant pharmacy chain with a well-established brand.

We also calculate several post-estimation results based on our demand model.[24] We provide descriptive statistics at the representative consumer level on distance elasticities and HHI in Table 4. On average, the own distance elasticities are negative, around -3.6. The cross-elasticities for distance are positive but small, with a mean of 0.1 and a median of 0.02. We plot the distribution of the elasticities in Figure 2.[25]

24. Most of the formulas for the post-estimation results can be found in Ellickson, Grieco and Khvastunov (2020). Because we have included random coefficients in our model, we present the elasticity formulas for the RC and RCNL models in Appendix Section B.7.

25. The size of the elasticity matrix is N^2, where N is the number of representative consumer- or cell-to-pharmacy pairs. We plot the distributions for a random sample of 10,000 observations from the elasticity estimates.

Table 3: Demand Model Secondary Results

Utility specification Model	Logit (1)	NL (2)	RC (3)	RCNL (4)
		Pharmacy Characteristics		
β Supermkt Nearby	0.3572 ***	0.0479 ***	0.3680 ***	0.0471 ***
	(0.0517)	(0.0124)	(0.0540)	(0.0130)
β Mall Nearby	0.0407	0.0054	0.0307	0.0039
	(0.0595)	(0.0081)	(0.0618)	(0.0081)
β Health Nearby	0.0125	0.0013	0.0099	0.0012
	(0.0562)	(0.0076)	(0.0605)	(0.0077)
β Transit Nearby	0.0912	0.0125	0.1038	0.0120
	(0.1051)	(0.0146)	(0.1108)	(0.0144)
β Pop. Density	-0.0568 ***	-0.0077 *	-0.0660 ***	-0.0076 *
	(0.0172)	(0.0031)	(0.0180)	(0.0031)
β Jobs Density	-0.0238	-0.0032	-0.0229	-0.0028
	(0.0167)	(0.0023)	(0.0174)	(0.0023)
β Main Pharm.	1.0830 ***	0.1461 ***	1.1670 ***	0.1481 ***
	(0.0636)	(0.0323)	(0.0724)	(0.0354)
β YA Pharm.	1.5276 ***	0.2046 ***	1.5848 ***	0.1991 ***
	(0.1535)	(0.0519)	(0.1645)	(0.0528)
AIC	2410	2402	2403	2393
BIC	989	980	995	985
MSE	5.10e12	5.08e12	5.05e12	5.03e12

Notes: Model statistics: AIC, BIC and MSE. Robust standard errors are presented in parenthesis; * p< 0.1, ** p< 0.05, *** p< 0.01.

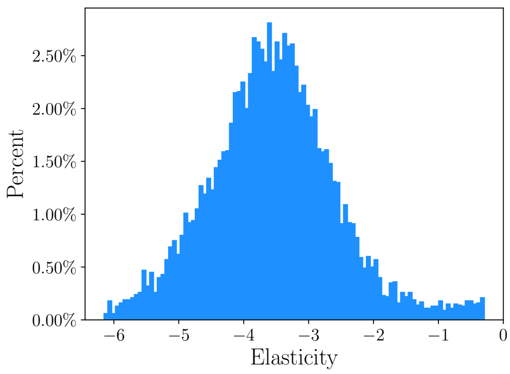
The HHI measures, calculated for each cell in Table 4, indicate that pharmacy markets in Finland are highly concentrated. Most markets exhibit extremely high concentration and limited competition, as reflected by a mean HHI of 4490 and a median of 4086. To further analyze market concentration, we aggregate HHIs from the representative consumer level to the postal code level using population as weights. The spatial variation in HHIs is illustrated in Figure 3. Panel 3a reveals significant spatial variation in the market concentration, with the most competitive markets (lowest HHIs) typically located in and around the largest

Table 4: Post Estimation Results

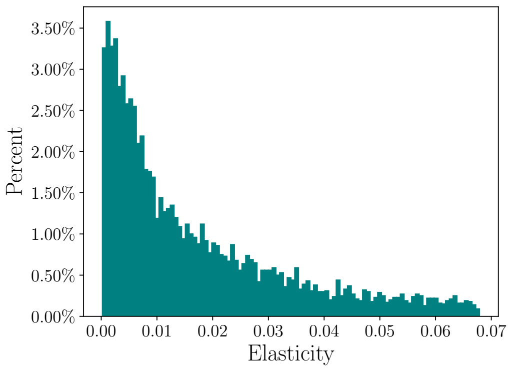
Variable	**Mean**	**Std. Dev.**	**P10**	**P50**	**P90**	**N**
Own Elasticity	-3.55	1.08	-4.82	-3.57	-2.31	6330641
Cross-Elasticity	0.08	0.23	0.00	0.02	0.15	271023390
HHI	4490.62	2546.34	1454.34	4086.45	8356.93	3007

Notes: This table presents post estimation results for our main demand specification. Elasticities are calculated with respect to driving distance in minutes. Own elasticities are computed for every cell × pharmacy pair, while cross-elasticities are computed for every cell × pharmacy × competing pharmacy combination in a choice set. HHIs are population-weighted averages of cell level HHIs aggregated to postal code level.

Figure 2: Elasticity Distributions



(a) Own Elasticities



(b) Cross-Elasticities

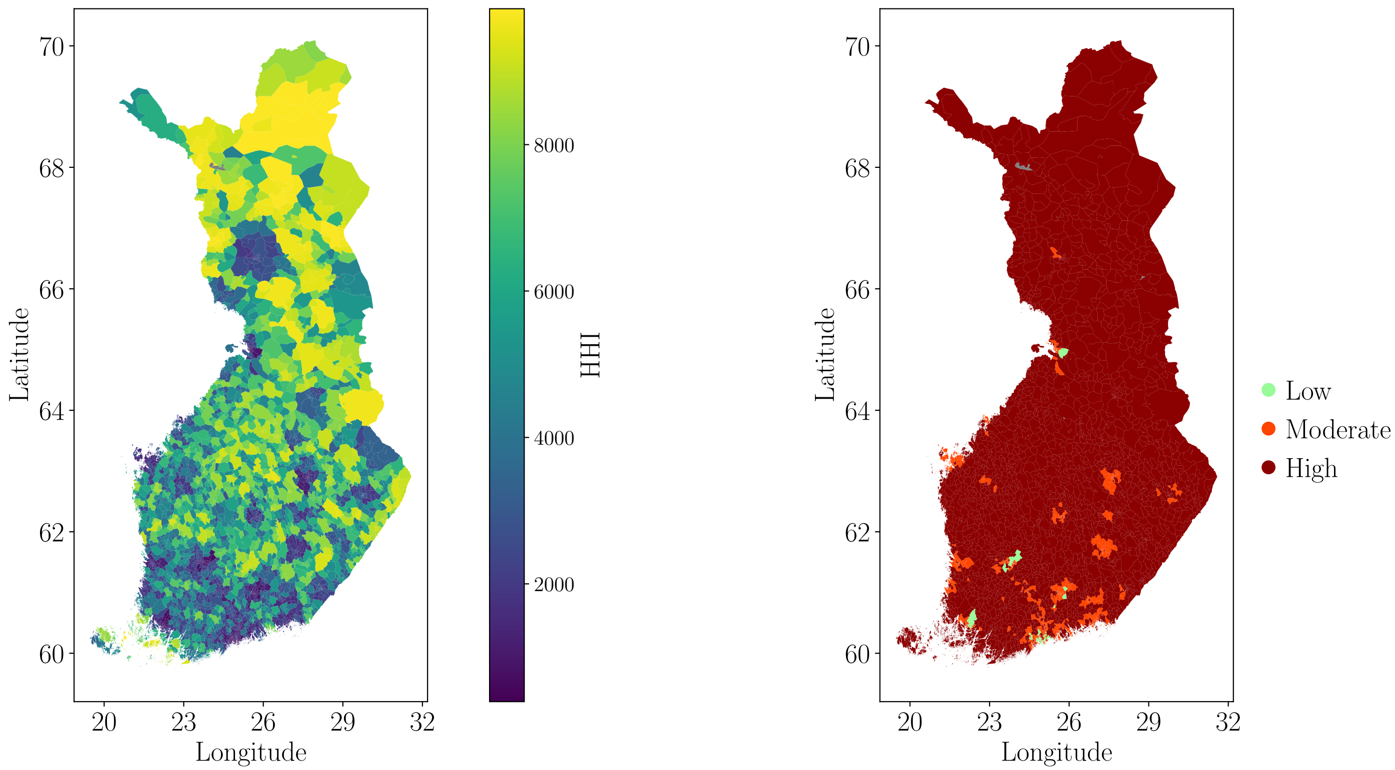
Notes: The figure on the left plots the distribution of cell × pharmacy own-elasticities with respect to distance in minutes. The figure on the right plots the respective cross-elasticities. Both distributions are plotted from a random sample of 10,000 observations from the full population. Extreme tails are excluded from the plots.

population centers.[26] However, as shown in Panel 3b, almost the entire country still falls into the 'High' concentration category, as defined by the EU merger guidelines. This finding points to the direction that the existing market structure, influenced

26. See Figure B.1 for the population distribution of Finland.

by entry restrictions, may be problematic from a competition law perspective, but this interpretation requires that market definition is not too narrow. Secondly, HHI can capture the closeness of competition only when products are not differentiated (Conlon and Mortimer 2021). Finally, an important point related to the use of HHI in a industry with extensive price regulation is that consumer harm arising from rising concentration occurs only through increased travel times.

Figure 3: HHI Maps



(a) Map of HHIs

(b) Map of HHI categories

Notes: The figure on the left shows the aggregated HHIs for postal code areas in Finland. The right figure categorizes them based on EU merger guidelines: 'High' (> 2000), 'Moderate' (1000–2000), and 'Low' (< 1000). Source: Statistics Finland (2021).

5 Supply Model

In this section, we introduce the supply model for pharmacy services. With the supply model, our aim is to identify variable labor and material cost parameters as well as fixed costs. We will use these parameters in the entry game to predict the costs of a pharmacy for a given level of demand. The total costs of a pharmacy consist of four parts: Material costs for the purchase of pharmaceuticals at wholesale prices, labor costs of employees, fixed costs (including capital costs), and taxes. We treat material costs, labor costs, and taxes as variable costs, and the rest as fixed costs. Therefore, fixed costs consist of capital costs but also, and probably mostly, of the opportunity cost of the owner, i.e., the pharmacist.[27]

5.1 Production Function

The regulations governing the Finnish pharmacy market restrict competition in terms of both pricing (of pharmaceuticals) and location choice. Pharmacies are required to order and supply a prescribed pharmaceutical product if it is unavailable. Minimum service quality is ensured by regulations on the education level of the pharmacy staff. There are some dimensions, such as opening hours and staff quality, in which pharmacies could compete quality-wise. However, evidence suggests that staff quality is not a primary issue: The existing literature on occupational licensing does not systematically find that licensing increases the quality of services or goods provided (Kleiner 2006; Angrist and Guryan 2008; Kleiner and Kudrle 2000; Barrios 2022; Farronato, Fradkin, Larsen and Brynjolfsson 2024). The institutional feature supporting our quality assumption is that in Finland there is no shortage of individuals who meet the educational and work experience requirements required for the pharmacy license.[28] It is also likely that such unobserved quality attributes do not have a first-order impact on our main objective: the location choice. Because of these reasons and unavailability of data, we do not include these factors in our

27. The owner's wage (or other reimbursement) is not included in the labor costs. As the owner is required to have a M.Sc. in Pharmacy and to be an experienced professional, they could pursue jobs in the public sector (e.g., the regulator, other health policy related institutions) as well as the private sector (e.g., pharmaceutical companies). Therefore, the opportunity cost is non-negligible.

28. Verboven and Yontcheva (2024) make the same argument related to service quality in their analysis of entry restrictions in the Belgian notary profession.

demand model, nor are they included in our cost estimations. As a result, we consider pharmacies to be cost-minimizers.

We assume that the variable costs of pharmacies consist of the wholesale costs of pharmaceuticals and labor costs. We measure these inputs in expenditure instead of physical quantities due to absence of quantity data. Although there are concerns in the literature about the use of expenditure measures (De Loecker and Syverson 2021), these are unlikely to apply to the Finnish pharmacy sector due to regulated wholesale and retail prices and due to relatively strict labor laws. We assume that the pharmacies' production function is

$$F(L, M) = \min\{\exp(A + \omega_L) \times L^{\kappa}, (B + \omega_M) \times M\} \tag{13}$$

and their objective is

$$\begin{aligned} \min_{L,\,M} \quad & C(L, M) = L + M, \\ \text{s.t.} \quad & F(L, M) \geq R \end{aligned} \tag{14}$$

In equation (13), the pharmacies have two inputs, labor (L) and material costs (M). Productivity is captured by three productivity parameters (A), (B) and (κ), and two productivity shocks (ω_L) and (ω_M). We observe L and M from the accounting data. We consider labor costs to consist of pharmacies' total labor costs (including rental labor) and material costs to consist of the wholesale costs of pharmaceuticals. It is reasonable to assume that pharmacies cannot substitute labor for material costs, or vice versa, and hence the production function form is Leontief.

The parameter A in equation (13) represents labor productivity. It can be thought of as the proportion in which labor is needed to be increased when output increases. Parameter κ represents returns to scale with respect to labor input. The interpretation of the parameter B in equation (13) is straightforward: $1 - B$ represents the mean markup of pharmaceuticals.[29] Note that we do not allow for returns to scale to material inputs due to the fact that material costs consist of

29. See the markups in Appendix Table A.1.

pharmaceutical wholesale costs that do not change as a function of bought quantity. The pharmacy-specific productivity shocks ω_L and ω_M capture differences in input use across pharmacies. These are potentially correlated with unobserved demand shocks and therefore with revenue R. For example, a pharmacy can employ more productive workers who work faster but also provide better service quality for consumers. Alternatively, pharmacy employees can provide better service quality only by being otherwise less efficient. Similarly with material costs, some pharmacies may serve areas that have higher markups than some other observationally similar pharmacies, hence implying correlation between R and ω_M. Equation (5.1) results in the following optimality conditions:

$$R = \exp(A + \omega_L) \times L^{\kappa} = (B + \omega_M) \times M. \tag{15}$$

By taking logarithm of the left side of equation (15) and solving materials M from the right side side of equation (15), this can be further transformed into:

$$\begin{aligned} \ln(L) &= \frac{1}{\kappa}\ln(R) - \frac{1}{\kappa}A - \frac{1}{\kappa}\omega_L \\ M &= \frac{1}{B + \omega_M} \times R. \end{aligned} \tag{16}$$

We use these equations to estimate the parameters A, B, and κ. Because unobserved productivity shocks may be correlated with revenues, the regressions potentially suffer from endogeneity. To deal with this, we use predicted revenues from the demand model as instruments, thereby assuming that the observables on the demand side are orthogonal to unobserved productivity shocks. Predicted revenue is a suitable instrument for dealing with the potential endogeneity problem related to productivity shocks, because the instrument is purely formed from the determinants of the pharmacy service demand. Instruments generated from the demand model are correlated with the observed output, but are uncorrelated with the unobserved productivity shock that is generating the potential endogeneity issue. These are the same identification arguments as in Verboven and Yontcheva (2024).

We present estimation results from equation (17) in Table 5. The cost model is estimated using data on 402 pharmacies, as we cannot separate the accounting

Table 5: Production Function Estimates

Estimator:	OLS		IV	
Model:	(1)	(2)	(3)	(4)
Dependent Variable:	$\ln(L)$	M	$\ln(L)$	M
Variables				
$\ln(R)$ or R	0.88***	0.72***	0.94***	0.72***
	(0.03)	(0.00)	(0.03)	(0.00)
Intercept	-0.35		-1.17***	
	(0.47)		(0.45)	
Observations	402	402	402	402
R^2	0.82	0.99	-	-
F-statistic	-	-	728.45	2857.56
Transformations				
Return to scale (κ)	1.14		1.07	
Productivity (A or B)	0.39	1.39	1.25	1.39

Notes: The point estimates and the standard errors are for the parameters in equation (16), and the transformations give the respective values in the first-order equation (15). The F-statistic represents the weak instrument test from Olea and Pflueger (2013) and Pflueger and Wang (2015) where the critical value for rejecting the null hypothesis with a significance level of 5% is 37.42. Robust standard errors in parentheses; * p< 0.1, ** p< 0.05, *** p< 0.01.

data on costs between main and subsidiary pharmacies operated by the same pharmacist. The production function parameters, which are transformations of the OLS or Two-Stage Least Squares (2SLS) estimates, are presented at the end of the table. First, focusing on labor, the estimates indicate notable returns to scale with respect to labor input. Additionally, the difference in the estimates and the transformed production function parameters demonstrate that failing to account for endogeneity results in biased estimates. The estimated returns to scale (κ) are smaller with 2SLS whereas the productivity (A) is conversely much larger. However, for material costs, the difference between OLS and 2SLS estimates is negligible.[30] Our instruments are strong, as shown by the large F-statistics and weak instruments tests.

30. The difference is not exactly zero. Rather, it is not visible because of rounding.

The endogeneity bias in labor inputs can be explained by the fact that pharmacies with smaller productivity shocks use more of the input in question. This behavior can be explained by the need to comply with industry regulations. Notice that the productivity term, derived from the constant in the estimation, differs significantly in magnitude between the OLS and 2SLS models for labor: the 2SLS estimate of A is more than three times larger than the OLS estimate. On the other hand, we do not observe practically any endogeneity bias in material inputs. This is natural in our setting because material inputs consist of wholesale costs of pharmaceuticals and the wholesale costs have a mechanical relationship with the pharmaceutical revenue due to regulated markups.

Lastly, the predicted (variable) costs for new entrants in our entry model can be obtained as a function of the predicted revenue, as shown in equation (17):

$$C(\hat{R}) = \underbrace{\left(\frac{\hat{R}}{\exp(A)}\right)^{\frac{1}{\kappa}}}_{\substack{\text{Predicted}\\\text{Labor costs}}} + \underbrace{\frac{1}{B} \times \hat{R}}_{\substack{\text{Predicted}\\\text{Material costs}}} . \tag{17}$$

5.2 Modeling Fixed Costs

Our approach to estimating fixed costs is based on Eizenberg (2014). The main idea behind the approach is to use observed entries and exits (or lack thereof) to back out the range of fixed costs that can rationalize these decisions. However, due to the extremely low number of entries and exits in the pharmacy market, we cannot use this information to tighten the bounds.[31] Moreover, due to the regulated nature of the industry, we lack data on the locations locations available for entry where no entrants were willing to enter. Therefore, all the information we have available is the decision of the incumbents to remain in the market. With this information, we can estimate an upper bound for the fixed costs but not a lower bound.

For the fixed cost estimation, we use the same 402 pharmacies that we used for production function estimation. This is because we lack accounting data for the rest of the pharmacies. We first calculate predicted revenues and demand shocks $\hat{\zeta}$

31. We also cannot be sure if the few exits that we observe are for economic reasons.

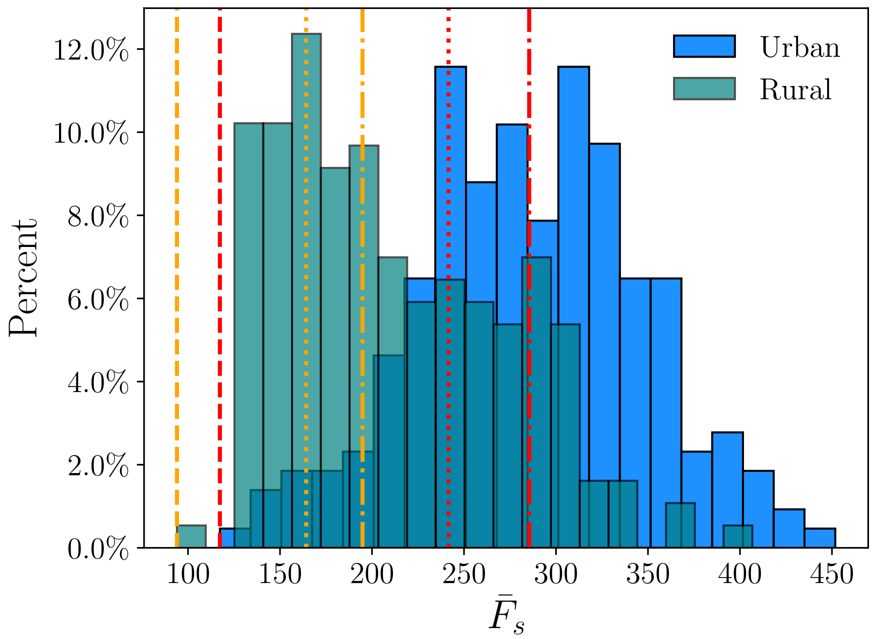
using our RCNL demand model estimates. Next, we use our production function estimates to obtain the productivity shocks $\hat{\omega}_L$ and $\hat{\omega}_M$. We then estimate the empirical joint distribution of these three shocks.

$$\begin{aligned}\Pi = \overbrace{\hat{R} \times \exp(\zeta)}^{\text{Revenue}} - \overbrace{\frac{1}{B + \omega_M} \times \hat{R} \times \exp(\zeta)}^{\text{Material costs}} \\ \underbrace{-\left(\frac{\hat{R} \times \exp(\zeta)}{\exp(A)}\right)^{\frac{1}{\kappa}} \times \exp\left(-\frac{\omega_L}{\kappa}\right)}_{\text{Labor costs}} - \underbrace{T(\hat{R} \times \exp(\zeta))}_{\text{Taxes}}\end{aligned} \tag{18}$$

Equation (18) illustrates pharmacies' gross profits (profits before fixed costs) as a function of predicted revenue ($\hat{R}$) and demand and productivity shocks (ζ, ω_L, ω_M). Following Eizenberg (2014), we take Y draws from the joint distribution of shocks and use these to calculate the gross profits for each pharmacy and each draw. We then average these gross profits over the draws to obtain expected gross profits for each pharmacy. Because these pharmacies choose to remain in the market, these estimates represent the upper bound of the fixed costs that rationalize the pharmacies' decisions. This procedure is detailed in Algorithm 3 in Appendix Subsection A.2.

The procedure above provides estimates for the fixed cost upper bounds for the locations of the 402 pharmacies. Figure 4 illustrates this distribution separately for pharmacies in urban and rural areas. To estimate fixed costs for counterfactual entry locations, we use the minimum of the fixed cost distribution as the fixed cost estimates for entrants. These costs are calculated separately for urban and rural locations, and Figure 4 depicts these estimates with dashed lines. The thresholds are €93,987.95 for rural areas and €117,321.20 for urban areas. The difference in costs between urban and rural locations can be attributed to variations in the opportunity cost of pharmacists (who tend to be older and more experienced in urban pharmacies) and in real estate expenses, with leasing property for a pharmacy being more expensive in urban areas than in rural locations.

Figure 4: Fixed Cost Estimates



Notes: The figure plots the fixed cost estimates for urban and rural pharmacies. Orange lines represent rural pharmacies, and red lines represent urban pharmacies. Dashed lines denote the minimum values (main specification), dotted lines indicate the 25th quantile, and dash-dotted lines indicate the median. Fixed costs $\bar{F}_j^s$ are denoted in thousands of euros.

6 Entry Game

In this Section, we describe how we simulate entry into the Finnish pharmacy market under a counterfactual deregulation of the entry restrictions. In our counterfactual, we keep the existing price regulation in place: New pharmacies can freely enter the market, but price competition between pharmacies remains absent. This allows us to study the effects of entry deregulation in a market with no price competition. Furthermore, this type of deregulation resembles past deregulation policies in Europe, where entry restrictions have been relaxed while price controls have remained in place. Online Appendix Section B.2 and Table B.2 describe the deregulation policies that have been implemented in the EU.

In our counterfactual, pharmacies are making entry decisions based on predicted profits:

$$\hat{\Pi} = \hat{R} - M(\hat{R}) - L(\hat{R}) - T(\hat{R}) - FC. \tag{19}$$

Here, $\hat{R}$ is the predicted revenue from our demand model for the given configuration of pharmacies, material costs (M) and labor costs (L) are obtained from the production function, T represents taxes and it includes the pharmacy tax and VAT, and FC is the fixed cost which is different for urban and rural areas. This profit measure is also our definition for producer surplus (PS) in welfare calculations.

We need to address how we will solve the counterfactual network of pharmacies. The issue is that solving the equilibria of a game of this size is computationally impossible. Instead, we follow the literature and use an algorithmic approach to achieve a configuration of pharmacies that approximates some equilibrium. To be precise, we rely on a SME algorithm, as suggested by Seim and Waldfogel (2013). This algorithm results in a configuration of pharmacies in which no pharmacy wants to enter or exit the market. This deviates from Nash equilibrium since some pharmacies may still want to change their location in the resulting configuration. Furthermore, the SME algorithm assumes that the entrants do not consider the actions of subsequent players and, therefore, are fully myopic. We discuss these features in detail in Subsection 6.1.

In our application, the size of the problem is notably larger than in previous applications that have relied on the SME algorithm.[32] Therefore, in our case, even the SME algorithm is computationally slow. To deal with this, we make two notable alterations. First, we limit potential entry locations to grocery stores. This reduces the number of potential entry locations from 300,000 to approximately 4,000.[33] Second, we introduce an alteration to the SME algorithm that improves computation time. The BSME algorithm is significantly faster, and it produces a

32. Verboven and Yontcheva (2024) analyzed 16,353 notary markets and 2,413 potential entry locations in Belgium, whereas Seim and Waldfogel (2013) used 3,125 census tracts in Pennsylvania. In contrast, our specification includes over 321,000 grid cells and approximately 4,000 potential entry locations.

33. Online Appendix Subsection B.1 provides a detailed explanation of how potential entry locations are defined and the rationale behind our selection. Online Appendix Figure B.2 illustrates potential locations in Finland and in the Helsinki metropolitan area.

configuration that satisfies the same conditions as the SME algorithm. We describe the SME and BSME algorithms below.

As discussed in Section 4, our demand model is estimated using pharmaceutical revenue. Accordingly, our demand model predicts the sales only for pharmaceuticals and not for non-pharmaceutical products, such as hair care products or cosmetics. In reality, pharmacies sell both of these and hence also the non-pharmaceutical products can affect their profitability. In our counterfactual, we exclude these sales altogether. The exclusion of sales such as hair care products or cosmetics is similar to excluding any other type of good that is not pharmaceutical, such as groceries. In a broader multicategory context, different product categories create positive externalities that supermarkets and grocery stores internalize (Thomassen, Smith, Seiler and Schiraldi 2017), which could influence entry patterns. As a consequence of excluding these non-pharmaceutical sales, we may underestimate the amount of entry. However, we do not believe this to be qualitatively important for our results. This is because non-pharmaceutical sales make up only a small fraction of incumbent pharmacies' total sales. In addition, our demand model includes an indicator for the proximity of grocery stores, which captures consumers' preference for one-stop shopping.

Although our entry game may underestimate entry because it does not account for profits from non-pharmaceutical products, there are other reasons why it could overestimate entry. First, entrants in our model are fully myopic, which means they do not anticipate future entrants or try to strategically block competition through their location choices. Second, the model does not account for how new entry affects input costs. Increased demand for labor and retail space could raise wages and rents in input markets, increasing production costs, reducing pharmacy profitability, and deterring further entry. Lastly, our assumption of independent pharmacies may overestimate entry, as individual pharmacies do not consider the business-stealing effects they impose on incumbents. In contrast, if regulations permitted it, horizontal integration through pharmacy chains could internalize these effects. Horizontal integration could also imply decreased fixed costs and economies of scale.

Algorithm 1 Sequential Mopic Entry Algorithm

Initialize a list of potential locations L
Initialize an empty list of store locations S
while there exists a profitable location in L **do**
    For each location $l \in L$, calculate the profit given the existing stores in S
    Find the location $l_{\max}$ with the maximum profit
    if profit at $l_{\max}$ is positive **then**
        Add $l_{\max}$ to S
        For each store $s \in S$, if it is not profitable; remove s from S
    end if
end while
The algorithm terminates when no further profitable locations are found or $\|S\|$ does not change for 10 iterations

6.1 Entry Algorithm

The SME algorithm is shown in Algorithm 1. The algorithm iteratively adds one pharmacy to the market until no new profitable entry locations remain.[34] Each entrant chooses the location with the highest profits at the time of the entry. This is why the algorithm is considered myopic: The entrants do not consider the business-stealing effect caused by and caused to subsequent entrants. If any pharmacies turn unprofitable after new entry, they will exit the market.

In reality, entrants are likely to have some beliefs about future entry. Because entrants do not consider subsequent entry, the algorithm is likely to overestimate the amount of entry. Furthermore, the resulting configuration is not a Nash equilibrium, because some pharmacies might want to change their locations after subsequent entry. In Section 7.2, we test how significant this issue is in our application. Lastly, the existing literature has largely overlooked the algorithm's reliance on fixed costs. In this framework, entry continues until the fixed costs of the last entrant exceed its gross profits. Without fixed costs, other expenses could scale down indefinitely, leading to infinite entry and a lack of convergence. This implies that the choice of fixed costs is crucial in determining the aggregate number of entry. The issue is amplified in our application due to the absence of price competition. However,

34. In our implementation of the algorithm, we also make the algorithm terminate if the aggregate number of pharmacies has not increased in 10 consecutive iterations. This avoids the situation where the algorithm gets stuck in a loop of entries and exits.

even with price competition, fixed costs would still serve as a minimum gross profit requirement for entry. In Appendix Section A.6, we test robustness of our counterfactual results to alternative fixed costs.

For a problem of our size, even the SME algorithm faces computational challenges. To address these, we implement the BSME algorithm shown in Algorithm 2. The BSME algorithm starts with all potential entry locations populated by one pharmacy and then iteratively removes the pharmacy with the largest negative profit until all remaining pharmacies are profitable. This results in a set of locations that can support at least one pharmacy. This is followed by filling these locations with new entrants if some locations can support more than one pharmacy. Because the pharmacies in the entry game are identical apart from their location, we assume that consumers choose randomly between pharmacies in the same location. This assumption means that we do not need to update the choice probabilities during the second stage of the game, as a new entrant does not affect the revenues or profits of neighboring pharmacies. At the end, the resulting configuration of pharmacies may still have locations that are profitable to enter due to consecutive exits in the first stage. To deal with this, we finish the BSME algorithm by running the SME algorithm with the resulting pharmacy allocation. Typically, this last step adds only a handful of new pharmacies before stopping.

The main benefit of the BSME algorithm is that its first step converges to the approximate number of pharmacies in the final configuration much faster than the SME algorithm. This is because the backward step only requires us to check the profits of the existing stores instead of calculating profits for all possible entry locations. This results in a significant reduction in the number of choice probabilities that need to be updated.

In the end, the BSME algorithm produces a configuration that satisfies the same conditions as the SME. However, the configurations that the SME and BSME provide are not necessarily the same. The SME can provide a different configuration depending on the starting configuration, whereas BSME will always provide the same configuration. How the configurations produced by SME or BSME compare to other configurations in the set of all possible configurations is unclear. The BSME is also different from the SME in the sense that it does not produce the order of entry. In some applications where entrants are not identical, the order of

Algorithm 2 Backward Sequential Myopic Entry Algorithm

Initialize a list of potential locations L
Initialize a list of store locations S so that $S = L$
Initialize choice probabilities $\forall s \in S$
while there exists an unprofitable store in S **do**
    Find the store $s_{\min}$ with the minimum profit
    if profit at $s_{\min}$ is negative **then**
        Remove $s_{\min}$ from S
        For each store $s \in S$, update profits
    end if
end while
Initialize a list of stores $S^* = S$
for $s \in S$ **do**
    while s can accommodate a new entrant **do**
        Add a new entrant s to S^*
        For each store $s \in S^*$, if not profitable; remove s from S^*
    end while
end for
Fill the rest of locations with the SME algorithm.

entry can matter. In Section 7.2, we compare the performance of BSME and SME.

In the entry game, we do not draw values for $\zeta, \omega_L, \omega_M$, thereby assuming that potential entrants make their entry and exit decisions based on expected profits. This means that our BSME algorithm and the SME algorithm are fully deterministic: Starting from a given network of pharmacies, the algorithms will always converge to the same configurations. An alternative approach would be to allow pharmacies to have different realizations of shocks and condition entry and/or exit on these. Although studying how these assumptions on shocks might affect entry patterns would be interesting, these approaches would introduce new computational challenges, especially in how they interact with the entry algorithms that we use, so we choose not to pursue these approaches.

7 Counterfactual Results

Entry restrictions are often justified by the assumption that they ensure and protect the availability of pharmacy services nationwide. To evaluate this, we simulate a free entry counterfactual pharmacy network in Subsection 7.1 and compare it with the existing pharmacy network to assess the role of entry regulation in maintaining pharmacy coverage across the country. By keeping the existing price regulation in place, we can isolate and study the specific effects of entry regulation. We analyze the impact of deregulation by calculating changes in consumer welfare, pharmacy revenues, government tax revenue, travel distance to pharmacy, and changes in market concentration measured by HHI. When calculating welfare measures, we convert our travel distance estimates from the (dis)utility of travel time to monetary units following the approach of Einav, Finkelstein and Williams (2016).[35]

In addition to counterfactual results, we also discuss methodological results of the BSME algorithm in Subsection 7.2, and in Appendix Subsection A.6, we show that our counterfactual results presented in Subsection 7.1 are robust to variation in the fixed costs used in the counterfactual.

7.1 Free Entry Counterfactual

Our counterfactual simulation has five main results. First, entry regulation substantially increases the number of pharmacies (1459 pharmacies, 178%). In this configuration, only a tiny fraction (1.4%, see Subsection 7.2) of pharmacies would want to change their location. This suggests that our modeling framework provides a good representation of the pharmacy network in Finland after entry deregulation.

Second, deregulation decreases total welfare (CS+PS+taxes) by €76.5 million (-7%), although most consumers benefit from deregulation. The increase in CS (€67.9 million, 14%) is relatively modest compared to the costs associated with deregulation. Meanwhile, each new pharmacy incurs additional fixed costs, resulting in a significant increase in aggregate industry fixed costs (€162.07 million, 188%) whereas market expansion remains limited (€197.55 million, 8%).

Third, deregulation causes a substantial redistribution of surplus among consumers, pharmacies, and government tax revenue. The government incurs the largest losses due to a sharp reduction in tax revenue (€102.5 million, -24%), but pharmacies also experience a significant decrease in profits (€41.8 million, -28%). The increase in CS is not sufficient to offset these losses.

35. We explain further details of our welfare calculations in Appendix Section A.3.

Table 6: Counterfactual Results

Variable	**Absolute**	**Relative**
	Panel A: Consumers	
Δ Consumer surplus (CS)	67.94	14%
Sum of negative Δ CS	-1.79	-29%
Average Δ weigh. distance	-0.48	-3%
	Panel B: Pharmacies	
Δ Number of pharmacies	1459	178%
Δ Revenue	197.55	8%
Δ Labor costs	57.54	20%
Δ Fixed costs	162.07	188%
Δ Gross profits	120.25	51%
Δ Net profits	-41.73	-28%
	Panel C: Government and Total Surplus	
Δ Pharmacy tax	-122.38	-71%
Δ Value-added tax	19.76	8%
Δ Total surplus	-76.41	-7%

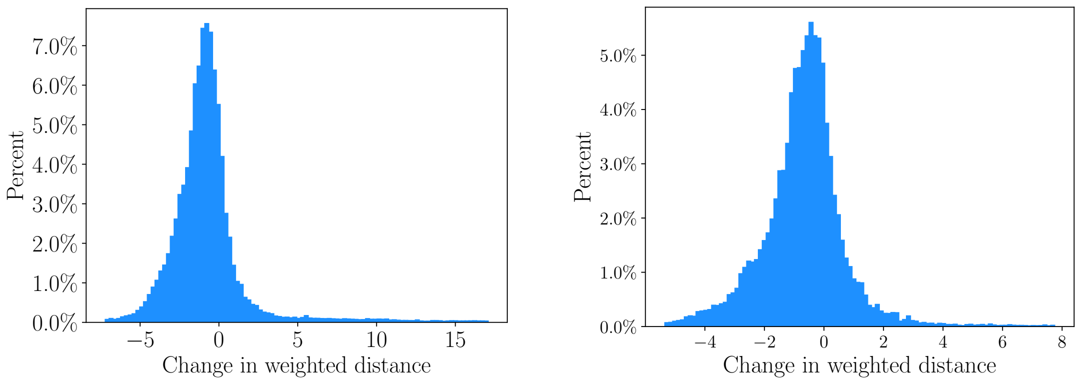
Notes: This table shows aggregate changes in the market under free entry counterfactual relative to the current pharmacy network. All monetary values are in thousands of euros. Gross profits are calculated as revenue minus material costs, labor cost and taxes. Net profits are calculated as gross profits minus fixed costs.

Fourth, counterfactual pharmacies are smaller in size and this makes pharmacy service production less efficient due to the loss of economies of scale.

Finally, although almost all consumers benefit from deregulation, the benefits are unevenly distributed across different consumer groups and geographical areas, with young consumers and urban areas gaining the most. Table 6 Panel A shows how entry deregulation affects consumers. The increase in CS (€67.9 million, 14%) is driven by reduced travel times for consumers who already purchase the inside good and the shift of consumers from the outside good to the inside good. However, focusing only on aggregate CS changes could hide adverse distributional effects of the deregulation policy.[36] With this in mind, the sum of negative CS changes is

36. Appendix Subsection A.5 presents more detailed heterogeneity analyzes on how different consumer groups were affected by the deregulation policy.

Figure 5: $\Delta E[Distance]$



(a) Cells

(b) Population

Notes: The figure on the left plots the distribution of the cell-level changes in expected distance to a pharmacy. The figure on right plots the same changes at the population level. Both figures show the 1–99 percentile range.

only around €1.8 million. Moreover, less than 1.5% of the population experience a negative CS change (Appendix Figure A.4). It should therefore be feasible to find not-too-costly remedies to compensate the small fraction of customers who are left worse off. Figure 5 illustrates how the choice probability-weighted distance to pharmacies changes at the cell and consumer level. The core finding is that a large proportion of expected distance changes are in the range of [-6min, 6min].

Table 6 panel B displays how free entry influences pharmacies. Under free entry, we see 1459 more pharmacies than in the regulated system (an increase of 178%). Simultaneously, the sizes of pharmacies decrease due to pharmacies mainly attracting demand from their competitors.[37] We find that aggregate pharmacy revenue increase by €198 million (8%), labor costs by €57.5 million (20%), fixed costs by €162 million (188%), gross profits by €120 million (51%), and net profits or PS decrease by €41.8 million (28%). The 8% increase in aggregate revenue is non-trivial market expansion considering that our RCNL model showed limited substitution between inside and outside goods. Despite this, the revenue increase

37. Pharmacy-level characteristics are shown in Appendix A.4.

is still relatively small compared to the large increase in fixed costs and labor costs. The former is driven by the increase in the number of pharmacies, and the latter is caused by both market expansion and the decrease in average revenue per pharmacy, which leads to a loss of economies of scale. Together, the increase in fixed costs and labor costs leads to a decrease in aggregate industry profits.

An important consideration related to our market expansion result is that standard welfare calculations cannot account for the health effects of increased pharmaceutical spending. On one hand, this spending could be directed towards less effective or redundant treatments. On the other hand, increased spending could result from, for example, distance-sensitive individuals, such as elderly or low-income households, gaining access to nearby pharmacy services. In such cases, the health effects are likely to be positive.

The increase in labor costs stems from two factors: The demand generated by market expansion and the demand driven by reduced labor productivity. To evaluate the loss of labor productivity, we compare ratio of revenues to labor costs between the current regime and the counterfactual. In the current regime, the ratio of predicted revenues to labor costs was 8.5, whereas after deregulation, this ratio drops to 7.7. This reflects a 9.8% decrease in revenue per labor cost. This implies that for every euro of sales, the pharmacy sector spends nearly ten percent more on labor costs after deregulation.

The increased labor costs suggest that pharmacy deregulation leads to significant increase in labor demand for pharmacy professionals. This raises the question whether the supply of labor is sufficient to meet this demand. We argue that the additional workforce required by the pharmacy market is not unrealistically large compared to the existing workforce in the Finnish pharmaceutical industry. Assuming an average salary of €39,000 and a 30% overhead, the increase in labor costs corresponds to an increase of more than 1,100 pharmacists (B.Sc. in Pharmacy). As of 2021, Finland had 10,606 licensed pharmacists (B.Sc. in Pharmacy) under the age of 65, alongside 3,139 licensed pharmacists (M.Sc. in Pharmacy) (National Supervisory Authority for Welfare and Health of Finland 2024). With approximately 4,500 pharmacy professionals currently employed in the pharmacy sector (Kokko, Hyvärinen and Reinikainen 2024), it appears that the labor supply is sufficient to meet the additional demand created by deregulation.[38] However, these calculations do not account for potential wage adjustments caused by increased labor demand. It is likely that wages would rise, suggesting that deregulation could shift income from pharmacy owners to employees through higher labor market earnings. This also suggests that our free entry counterfactual likely overestimates entry, as it does not account for the impact of new entrants on prevailing market wages and, consequently, labor costs.

In addition to labor costs, our model does not account for the effects of free entry on the real estate market. Property owners, such as shopping malls, might have incentives to restrict the entry of competing pharmacies to protect or enhance their rental income. Furthermore, the increased demand for retail space could lead to general equilibrium effects, raising costs not only for pharmacies but also for other retailers.

Entry deregulation has the ability to influence government tax revenue through pharmacy tax and VAT. In the free entry counterfactual we keep the existing tax system in place and Table 6 Panel C shows that that aggregate tax revenue collected from the pharmacy industry decreased by around €103 million (-24%). The substantial decrease in tax revenue is explained by the fact that the pharmacy tax is a progressive tax (Appendix Table A.2) based on pharmacies' revenue, and the increase in VAT revenue from market expansion is not enough to balance the decrease from pharmacy tax. Free entry resulted in a decrease in the average size of the pharmacies, which also implied a lower tax burden on pharmacies. A comparison between Table 1 Panel C and Table A.3 Panel C shows that counterfactual pharmacies have, on average, lower per pharmacy revenue than existing pharmacies. The structure of the Finnish tax system explains why aggregate gross profits increased despite the decrease in labor productivity. It also shows that it is the government that is carrying the largest monetary loss from the deregulation policy. In the Finnish context, this suggests that the government should consider reforming the pharmacy tax system alongside policies that deregulate entry to the pharmacy market.

38. Figure B.6 in the Online Appendix shows the number of trained pharmacy professionals across the years.

7.2 Methodological Results

Our contribution to the methodological literature on entry algorithms is our BSME algorithm, which converges quickly to a configuration where, at least in our empirical application, almost no one wants to deviate from. Depending on the size of the problem and the fixed costs, we estimate that our algorithm is at least an order of magnitude faster than the SME algorithm used in the previous literature. For example, in our main specification, the BSME algorithm is more than 40 times faster, taking approximately 90 minutes compared to 3900 minutes for the SME algorithm.[39] The BSME Algorithm, like similar algorithms used in the previous literature, does not necessarily converge to a Nash equilibrium (Seim and Waldfogel 2013; Verboven and Yontcheva 2024). To assess this, we check how many pharmacies would prefer to switch locations given the locations of other entrants. Reassuringly, only 1.4% of pharmacies find it more profitable to relocate (assuming costless relocation). The median distance to their preferred alternative was around 4.4 kilometers. Some pharmacies wanted to move significant distances, but all of them are located in sparsely populated municipalities. To our knowledge, no previous study has evaluated how much the algorithm outcome deviates from Nash equilibrium.[40] Based on this robustness check, we argue that our counterfactual simulation provides a good ballpark estimate of the number and location of pharmacies in the market under entry deregulation.

8 Conclusions

We study the effects of entry deregulation in the Finnish pharmacy market by i) estimating a spatial model for pharmacy choice, ii) estimating a production function to model variable labor and material costs of operating a pharmacy, and by iii) backing out the upper bound of fixed entry costs from the location choices of existing pharmacies. Free entry results in a significant increase in the number of pharmacies, primarily concentrated in densely populated urban areas. Free

39. These simulations were conducted on a server equipped with 128 GB of RAM and an Intel Xeon Gold 6342 processor running at 2.8 GHz

40. Due to computational challenges and a server migration, the Nash equilibrium results were obtained from a different simulation than the main results presented in this article.

entry increases CS for 98% of the population, although the benefits are unevenly distributed. About 2% of consumers experience a decline in welfare due to loss of local services and the need to travel further for pharmacy services. Our results confirm that deregulating a heavily regulated market can be a mixed bag: some consumers gain, but others may be left worse off (Joskow 2005).

Consumers benefit from a larger variety of pharmacies and shorter travel times, but these benefits are outweighed by a significant decrease in industry profits and government tax revenue. The entry of approximately 1400 new pharmacies suggests excessive entry from a welfare perspective, even with more conservative fixed cost estimates. Additionally, the proliferation of smaller pharmacies post-deregulation leads to reduced labor productivity due to foregone economies of scale. In conclusion, we find that the free entry of pharmacies, at least in the absence of other reforms, can lead to a decrease in total welfare compared to the current highly restrictive entry and location regime. Although our results suggest that the current pharmacy regulation can work reasonably well from a total welfare perspective, it has potentially undesirable distributional consequences, as it leads to high pharmacy profits and lower CS than the free entry regime. If distributional effects were a concern, a possible remedy could be adjustments to pharmacies' taxation and/or markups.

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A Appendix

This primary appendix contains supplementary materials and is structured as follows. Section A.1 provides further details on the institutional background of the Finnish pharmacy market. Section A.2 outlines our fixed cost estimation strategy. Section A.3 describes the formulas used to calculate CS. Section A.4 presents additional results from our free-entry counterfactual. Section A.5 examines how entry patterns in our main specification vary across different demographic groups. Finally, Section A.6 presents simulation results using alternative fixed cost estimates.

A.1 Institutional Background

Fimea determines the number and locations of pharmacies according to need and pharmaceutical availability. To establish or manage a pharmacy, a pharmacist must be granted a personal pharmacy license by Fimea. A pharmacy license requires a master's degree in pharmacology, the ability to manage a pharmacy, and that the pharmacist has not have been declared bankrupt, appointed a conservator, or convicted of a crime relevant to the operation of a pharmacy. A pharmacist can only hold one license for one main pharmacy at a time but can own up to three additional subsidiary pharmacies that are established at the initiative of Fimea, the pharmacist, or the municipality if Fimea considers it necessary to ensure pharmaceutical availability. As an exception, the University of Helsinki is allowed to own and operate a main pharmacy and up to 16 subsidiary pharmacy branches. Furthermore, the University of Eastern Finland is allowed to operate one pharmacy. Beyond usual pharmacy activities, these pharmacies have a responsibility to carry out activities related to pharmaceutical education and medical research. The manager of a branch pharmacy must be appointed by the pharmacist of the main pharmacy and have a pharmacy degree.[41]

Only pharmacists (with a degree in pharmacology) are allowed to dispense prescription drugs. Wholesalers are required to sell medicines at the same price to

41. For further information on pharmacy license rules, see the Finnish Medicines Act 395/1987 43 b §. The pharmacy privileges for universities are detailed in 42 §, and the subsidiary regulations are in 52 §.

Table A.1: Retail prices for RX and OTC drugs in Finland

Wholesale price (WP)	Retail price (2003)	Retail price (2014)	Retail price (2023)
0–9.25	1.5 × WP + 0.50 €	1.45 × WP	1.42 × WP
9.26–46.25	1.4 × WP + 1.43 €	1.35 × WP + 0.92 €	1.35 × WP + 0.52 €
46.26–100.91	1.3 × WP + 6.05 €	1.25 × WP + 5.54 €	1.24 × WP + 4.92 €
100.92–420.47	1.2 × WP + 16.15 €	1.15 × WP + 15.63 €	1.15 × WP + 13.92 €
over 420.47	1.125 × WP + 47.68 €	1.1 × WP + 36.65 €	1.10 × WP + 33.92 €
over 1 500			1 × WP + 183.92 €

Notes: This table presents the markup regulation for RX and OTC pharmaceuticals in Finland. The second column the retail price formulas applied to RX products between 2003–2013 and for OTC products between 2003–April 2022, after which they apply as maximum pharmacy markups. The third column gives the RX formulas for 2014–2022 and the fourth column presents the current markup formula for RX drugs.

all pharmacies.[42] Retail prices for prescription drugs are determined by a formula based on nationwide wholesale prices, plus a dispensing fee and the VAT. Since 2021, the pricing of OTC drugs is regulated separately from prescription drugs, with a formula based on wholesale price determining the maximum retail price.[43] Reimbursable medicines are reimbursed based on the reference price at a rate of 40%, 65% or 100% depending on the product. The reimbursement system includes an annual minimum copayment of 50 euros and the maximum copayment is capped at roughly 610 euros (for 2024). In generic markets within the reimbursement system, The Pharmaceutical Pricing Board (Hila) establishes reference price groups based on substitutable drugs.[44] In 2021, Kela reimbursed medicines amounting to 1.7 billion euros, representing 47% of total pharmaceutical expenditure and 62% of retail market expenditure for that year (Finnish Medicines Agency and Finnish Social Insurance Institution 2022).

The core principles of the Medicines Act have remained largely unchanged since its introduction in 1987. However, significant modifications have occurred, especially in the areas of generic substitution and pricing. Finland transitioned

42. For the dispensing rules, see Fimea order 2/2016 Sectio 4.2. Price discrimination at the wholesale-level is forbidden by the Finnish Medicines Act 37 a §.

43. Pharmacy prices are governed by the Finnish Medicines Act 58 §, whereas the markups are set by a government degree. The markups during our data sample are given in Degree 713/2013, while the OTC rules were changed in Degree 193/2022.

44. The reimbursement rates are set in Section 5 of the Finnish Health Insurance Act 1224/2004. The reference price system has been in place since April 1st, 2009. It is governed by Section 6 18–24 §.

Table A.2: Pharmacy Tax Rates

Revenue Range (€)	Base Tax at Lower Bound (€)	Tax Percentage for Excess Revenue (%)
871,393–1,016,139	0	6.10
1,016,139–1,306,607	8,830	7.15
1,306,607–1,596,749	29,598	8.15
1,596,749–2,033,572	53,245	9.20
2,033,572–2,613,212	93,432	9.70
2,613,212–3,194,464	149,657	10.20
3,194,464–3,775,394	208,945	10.45
3,775,394–4,792,503	269,652	10.70
4,792,503–6,243,857	378,483	10.95
Over 6,243,857	537,406	11.20

Notes: This table presents the pharmacy tax rates in Finland. The tax rates are based on the pharmacy revenues.

from voluntary to mandatory general substitution, which requires pharmacy staff to dispense the cheapest available substitute, in 2003 in an effort to reduce pharmaceutical expenditure. The sale of nicotine products in places other than pharmacies has been allowed since 2006.[45] Until 2010, a pharmacist had to be a citizen of a country in the European Economic Area (EEA) to own a pharmacy in Finland. The same amendment introduced regulation of online pharmacies, allowing licensed pharmacists to open an online pharmacy after notifying Fimea.[46] In 2016 the pharmacy fee was replaced by the pharmacy tax, which also transferred responsibility for the payment from Fimea to the Finnish tax authority.[47] We present the pharmacy tax rates in Table A.2. The pharmacy tax in Finland is based on pharmacist's total revenue from all locations (the main pharmacy and its subsidiaries). Although the highest tax brackets in Table A.2 exceed the current markups in Table A.1, the revenues from pharmaceutical sales exceeding the €1,683.92 retail price level are not included in the revenues included in the calculation of the pharmacy tax.

45. Generic substitution was adopted in an amendment to the Finnish Medicines Act 80/2003 57 b §. The sale of nicotine products was liberalized in 22/2006 54 a–54 e §.

46. See Finnish Medicines Act 1112/2010 43 § and 52 b §.

47. Although the tax rates have been adjusted to benefit small and branch pharmacies, the current rates have remained constant since 2013. For further reference, see Amendment 977/2013 2 a §.

The current tax system is revenue-based, unlike standard business taxes that are based on gross profits. We maintain the same tax system in place in our counterfactual simulation. Consider a median pharmacy with a taxable revenue of €3,480,000 and a profit net of materials and labor of €490,000. According to the tax table, this revenue falls in the range of €3,194,464 to €3,775,394. The base tax at the lower bound of this range is €208,945, and the tax percentage for the excess revenue over the lower bound is 10.45%. To calculate the total tax, first determine the excess revenue over the lower bound: Excess Revenue = €3,480,000 - €3,194,464 = €285,536. Then, calculate Tax on Excess Revenue = €285,536 × 0.1045 = €29,838.51. Finally, add the base tax at the lower bound: Total Tax = €208,945 + €29,838.51 = €238,783.51. For comparison, the standard corporate tax of 20% would result in a tax of €94,722.40.

A.2 Fixed Cost Algorithm

We present our fixed cost estimation algorithm in Algorithm 3. This algorithm is based on Eizenberg (2014) and proceeds in three phases steps. In the first phase (Algorithm 3 step 1), joint probability distribution of demand, labor and material costs shocks is estimated. This requires that prior this step the demand system and production function have been estimated. In the second phase (Algorithm 3 steps 2-6), demand and cost shocks are drawn from the joint distribution and for each draw gross profits are calculated. This allows to compute the upper bound fixed cost for each draw of the shocks. In the last phase (Algorithm 3 step 6), the fixed cost upper bound estimate is obtained by averaging the gross profits over the Y draws.

Algorithm 3 Fixed Cost Estimation Algorithm

Use realized demand, labor and material shocks $\hat{\zeta}$, $\hat{\omega_L}$, and $\hat{\omega_M}$ to estimate joint probability distribution of the shocks $f_{\zeta,\omega_L,\omega_M}$

Take Y draws from the joint distribution $(\zeta_y, \omega_{Ly}, \omega_{My}) \sim f_{\zeta,\omega_L,\omega_M}$

for each pharmacy s and each draw y **do**

  Calculate gross profits:

$$\Pi_{sy} = \overbrace{\hat{R}_s \times \exp(\zeta_y)}^{\text{Revenue}} - \overbrace{\frac{1}{B + \omega_{My}} \times \hat{R}_s \times \exp(\zeta_y)}^{\text{Material costs}}$$

$$\underbrace{-\left(\frac{\hat{R}_s \times \exp(\zeta_y)}{\exp(A)}\right)^{\frac{1}{\kappa}} \times \exp\left(-\frac{\omega_{Ly}}{\kappa}\right)}_{\text{Labor costs}} - \underbrace{T(\hat{R}_s \times \exp(\zeta_y))}_{\text{Taxes}}$$

  Compute the upper bound fixed cost:

$$\bar{F}_{sy} = \Pi_{sy}$$

end for

Estimate the fixed cost upper bound by taking the average over Y draws:

$$\bar{F}_s = \frac{1}{Y}\sum_{y=1}^{Y} \bar{F}_{sy}$$

A.3 Welfare Calculations

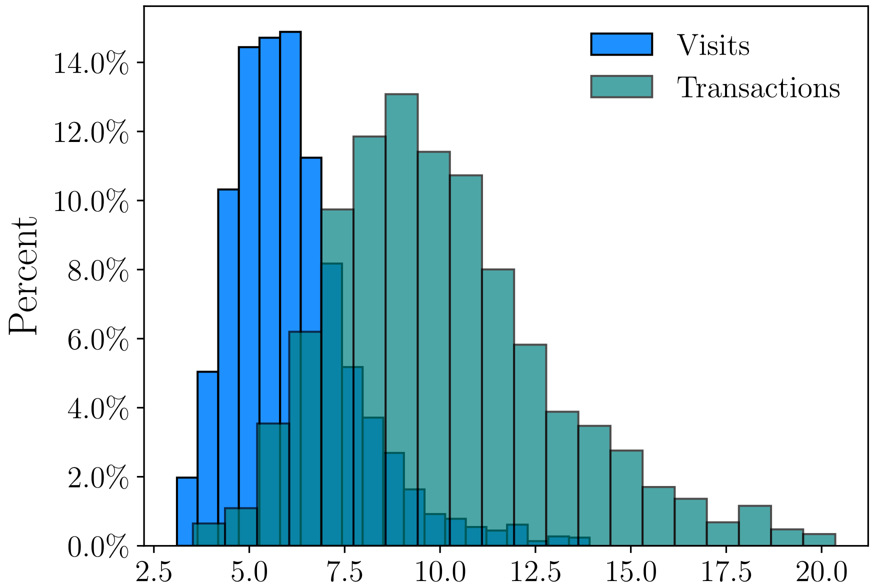
Our welfare analyses help us to understand how different counterfactual scenarios influence the Finnish pharmacy market. The main interest is in what happens to consumer welfare when the surrounding pharmacy network changes. However, a challenge to surplus calculations is that due to uniform pricing in the Finnish pharmacy sector, our pharmacy choice model does not include prices that we could use to calculate consumer surpluses in monetary terms. We overcome this by focusing on the changes in consumers' travel distance and converting these to monetary terms with an outside estimate of travel cost t_{dt}. In addition, we assume that the marginal utility of the distance traveled is independent of the income of the consumer. This assumption means that our welfare analyses do not consider income effects. The rationale for the assumption is the regulatory and reimbursement system that makes consumer choices less dependent on income. A change in CS for post code t can be calculated using the following formula:

$$\Delta E\left(\mathrm{CS}_t\right) = \int \frac{t_{dt}}{\beta_i^{dist}} \left[I_i^1 - I_i^0\right] d\beta_i, \tag{20}$$

where β_{dist} represents the estimated distance parameter from the demand model and the I terms represent the log-sum from equation (8) with the superscript 0 denoting the baseline model and superscript 1 the counterfactual scenario (Train 2009). The term $\Delta E(CS_t)$ should be interpreted as the average consumer surplus for sub-population who have the same utility as individual i. This idea can be used to calculate surplus changes for consumers living in a certain geographic area (Hackmann 2019) or with respect to certain consumer demographics (Bento, Goulder, Jacobsen and Von Haefen 2009; Conlon and Rao 2023). The total surplus in the general population is then calculated as the weighted sum of equation (20) where the weights represent the number of consumers who share the same representative utility (Train 2009).

In equation (20) we add term t_{dt} to the numerator before the square brackets, because this allows us to monetize consumer utility in a scenario where demand specification does not include a price coefficient (Verboven and Yontcheva 2024). Previous literature contains two alternative approaches for obtaining the parameter t_{dt} in equation (20). The first method, as used by Verboven and Yontcheva (2024),

Figure A.1: Pharmacy Visits and Transactions



Notes: The figure plots the distributions of pharmacy visits and transactions accross postal code areas.

involves using travel cost estimates from previous studies.[48] The second way to obtain a travel cost estimate is to calculate the income a consumer loses if they need to travel to a pharmacy instead of using that travel time for work. This approach, described by Einav, Finkelstein and Williams (2016), is simple because it only requires information on the travel time to the pharmacy and the consumer's income.[49] It is also our method for calculating travel costs. We calculate travel cost (t_{dt}) using the following formula:

$$t_{dt} = 2 \times \text{average hourly wage} \times N_{trips} \tag{21}$$

Equation (21) provides travel cost estimate for each cell t. We base our travel costs calculations on using auxiliary data sources, as we are not aware of any

48. Ramjerdi and Lindqvist Dillén (2007) and Gowrisankaran, Nevo and Town (2015, 2015) provide direct estimates that we could use in our application.

49. Einav, Finkelstein and Williams (2016) calculate travel costs for radiology services as average wage $\times$ trips to radiology facility $\times$ 2

studies that estimate health service travel costs in Finland. We parametrize equation (21) by using the average hourly wage in Finland and the average number of pharmacy visits by each postal code area. Equation (21) contains multiplication with number two as the consumer needs to drive home from the pharmacy. We plot the distribution of pharmacy visits in Figure A.1 together with the transactions. The figures demonstrates that consumers typically make several purchases per visit.

A.4 Additional Counterfactual Simulation Results

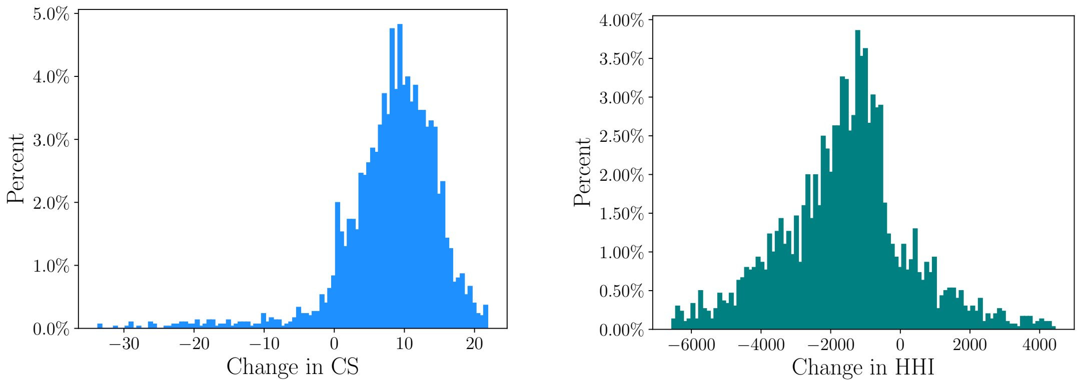
In this Subsection we provide additional results on how free entry affects market concentration and CS changes at the cell and at the population level. These analyses are presented in Figure A.2 and Figure A.3 displays the pharmacy network configuration under regulated and free entry.

Figure A.2 plots the cell-level distribution for changes in CS (Figure A.2a) and HHI (Figure A.2b). There are two important insights. First, CS is positive for almost all cells, but the distribution's left tail is very long, and this indicates that the policy benefits are very unequally distributed. Another observation is that market concentration increases for a substantial share of cells (around 13%), but these cells have low population density—Appendix Figure A.4 shows that only around 1.5% of the Finnish population face an increase in market concentration. At the same time Figure A.4 shows that for 1% of the population, welfare decreases despite a reduction in market concentration.[50] This interesting pattern occurs when consumers lose access to local services and must travel to more distant areas with higher competition. Our findings demonstrate that, in some edge cases, improvements in market concentration metrics can counterintuitively lead to welfare losses. In Subsection A.5 we use descriptive regressions to show how CS, HHI, and negative CS changes are associated with consumer demographics and geographical areas.

Finally, Figures A.3a and A.3b show the counterfactual and the existing pharmacy network side by side. When comparing these figures, we see that urban areas tend to get more pharmacies under deregulation, but this increased entry to urban

50. Appendix Figure A.4 cross tabulates CS and HHI changes on the basis of the CS and HHI sign changes. The majority of CS increases coincide with HHI decreases, and vice versa (96% of consumers).

Figure A.2: Δ CS and Δ HHI Distributions



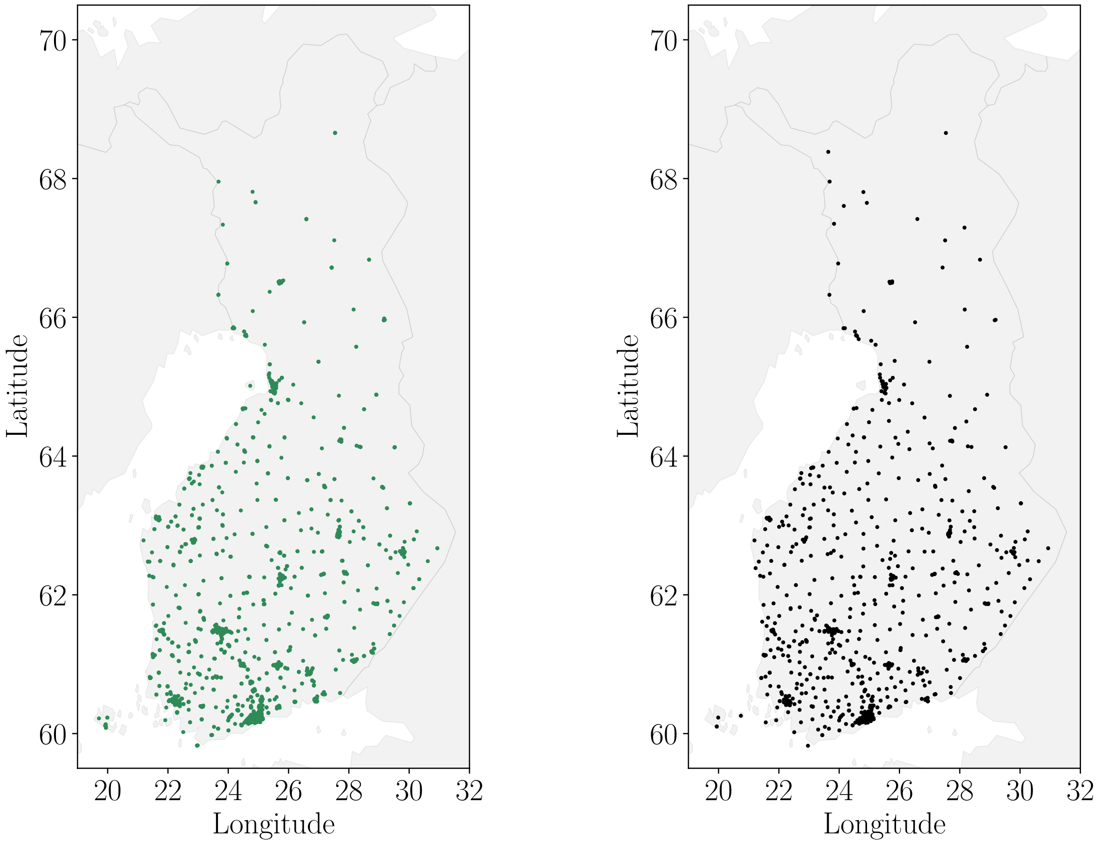
(a) Δ CS (b) Δ HHI

Notes: The figure on the left plots the distribution of the cell-level changes in CS per capita. The figure on the right plots the changes in HHI. Both figures show the 1–99 percentile range.

areas does not remove rural pharmacies from the network. The most significant change in the pharmacy network occurs in Northern Finland, where the upper part of the country is left without pharmacies. Online Appendix Figure B.5b displays the counterfactual pharmacy network for the Helsinki capital region.

Table A.3 presents the descriptive statistics for the free entry counterfactual scenario. In Panel A, we show the statistics at the representative consumer (cell) level for changes in HHI concentration, CS and two different distance measures and Panel B represents the same statistics for the actual population that lives in these cells. The first distance measure is the weighted distance, where we weight the distance to pharmacies with their consumer-level choice probabilities. The minimum distance simply gives the minimum distance in the choice set. Most importantly, the results in Table A.3 Panel A show that, on average, consumer welfare increases through increased competition, which is denoted by the substantial average decrease in HHI. Importantly, in most areas, consumer welfare increases as shown by the positive 10th percentile threshold. Comparisons between CS distribution 10th, 50th and 90th percentile in Table A.3 Panels A and B show that consumer surplus increases are mainly positive, but unevenly distributed in the

Figure A.3: Counterfactual Pharmacy Network



(a) Counterfactual Network

(b) Existing Pharmacy Network

Notes: The figure on the left plots the post entry game pharmacy network. The figure on the right shows old pharmacy network.

population. We present the empirical distributions of the cell-level HHI and CS changes in main text Figure A.2.

Table A.3 Panel C displays descriptive statistics for pharmacies that enter the Finnish market in our counterfactual. Due to free entry, the number of pharmacies increases substantially from the regulated baseline scenario. Counterfactual pharmacies are on average smaller and less profitable than pharmacies in the regulated scenario (compare Table 1 Panel C and Table A.3 Panel C). This change is an expected result, because business stealing between pharmacies significantly decreases

Table A.3: Entry Descriptive Statistics

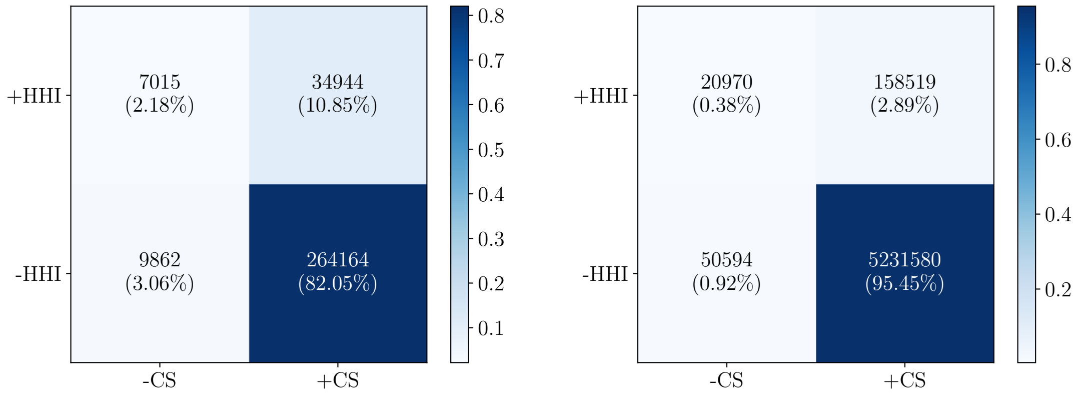
Variable	Mean	Std. Dev.	P10	P50	P90	N
			Panel A: Cell characteristics			
Δ HHI	-1914.91	2186.36	-4656.22	-1774.99	442.45	315985
Δ CS	211.04	840.80	3.62	27.59	388.43	321950
Weigh. distance	16.04	12.78	6.56	14.45	25.93	315980
Min distance	12.99	13.94	3.12	10.86	24.40	315985
			Panel B: Consumer characteristics			
Δ HHI	-1814.04	1594.27	-4079.24	-1414.29	-465.57	5461663
Δ CS	12.40	6.50	7.57	13.04	17.46	5480966
Weigh. distance	9.70	6.53	4.45	8.88	15.42	5461654
Min distance	4.97	6.92	1.11	3.16	11.22	5461663
			Panel C: Pharmacy characteristics			
Revenue	1183.56	208.68	945.13	1150.51	1479.06	2276
Labor costs	154.23	20.26	137.28	146.12	184.84	2276
Pharmacy tax	21.48	15.51	4.50	18.44	43.65	2276
Net profit	46.03	23.61	11.85	47.34	76.55	2276

Notes: This table presents descriptive statistics of the free entry counterfactual. The first panel consists of cell-level measures, second panel of consumer-level measures, and third panel of pharmacies. The 2276 pharmacies in the market are located in 2191 unique locations. All variables are in absolute values.

the revenue per pharmacy whereas the market expansion effects are modest. At the same time the average labor input decreases. Labor costs do not vary between counterfactual pharmacies as much as costs vary in the regulated scenario.

Figure A.4 tabulates cell and population specific CS and HHI changes. This tabulation clearly shows that, after the removal of entry restrictions, most cells and a majority of the Finnish population experience an improvement in consumer CS. Figure A.4a shows that 82% of cells are such that market concentration decreases and consumer surplus increases and only around 2% of the cells are such that market concentration increases and consumer surplus decreases. Welfare decreases only for 5% of the cells in comparison to the regulated scenario. The results are

Figure A.4: HHI and CS combinations



(a) Cells (b) Population

Notes: The figure on the left plots the combinations for HHI and CS pairs between cells. The figure on the right scales these by population. The population counts differ slightly from Table A.5 because of missing HHI values due to loss of service.

qualitative the same when the effects of the deregulation policy on the whole population are studied in Figure A.4b. Now it is important to observe that the magnitude of adverse effects shrinks, because in reality many people can live in the same cell. If cells facing adverse effects are small in comparison to cells that benefit from the policy, then this should reduce the number of people who do not gain from the policy. Only around 1.5% of the Finnish population lose in terms of consumer welfare. It is worthwhile to mention that almost 95.5% consumers face increases in consumer surplus and a reduction in market concentration.

A.5 Heterogeneity Analysis

Results included in the main text showed that allowing free entry into the Finnish pharmacy market leads to a large majority of consumers experiencing an increase in welfare, with a modest average increase in aggregate CS. In this subsection, we examine how the benefits of free entry are distributed across different demographic groups and geographical areas. Specifically, we investigate the incidence of reform benefits to determine whether certain demographic groups or geographical locations systematically gained more from the policy, or if the gains from the deregulation were evenly distributed across consumers and regions. We aggregate our data to the postal code level because most of the demographic information is censored at the cell-level. We quantify the changes by estimating a linear regression model presented in equation (22):

$$\Delta \bar{y}_p = \bar{X}_p \beta + \bar{Z}_p \gamma + \bar{\varepsilon}_z. \tag{22}$$

We have three outcome variables ($\Delta \bar{y}_p$) for the distributional impact of the reform: Percentage change in CS, percentage change in HHI, and an indicator for a negative change in CS. We regress these outcome measures on mean demographics $\bar{X}$ and regional characteristics $\bar{Z}$. The vector of demographic characteristics ($\bar{X}$) contains log average income, log average age, share of pensioners, share of unemployed, and the share of population with only comprehensive education. For the geographic characteristic ($\bar{Z}$) we include a degree of urbanization that is divided into "Urban", "Suburban", and "Rural". Our base group are rural areas, and the two dummies distinguish between cities ("Urban") and neighborhoods surrounding cities ("Suburban").

The first column of Table A.4 shows the results for the change in CS, the second column for the change in HHI, and the last column for characteristics associated with a decrease in CS. The results in the first column (change in CS) are consistent with our earlier observation that rural areas with an older population and more pensioners tend to benefit less from free entry. Regions characterized by higher unemployment, lower educational attainment, and suburban locations exhibit a more pronounced increase in CS as a result of deregulation. However, only age and the degree of urbanization yield statistically significant coefficients.

Column 2 in Table A.4 presents the regression results for changes in the aggregated HHI index. Higher average income, the share of pensioners and unemployed, and the suburbia indicator are all associated with a decrease in the HHI. In contrast, areas with older and less educated populations, as well as suburban areas, see an increase in HHI. Statistically significant coefficients are found for income, age, the share of pensioners, education, and the suburban dummy. The results for market concentration closely mirror the results for the change in CS, as the changes in

Table A.4: Heterogeneity Analysis

Dependent Variable: Model:	% Δ CS (1)	% Δ HHI (2)	Δ CS < 0 (3)
Dependent Variable Mean	.1125	-.4101	.0758
	(.0036)	(.0077)	(.0048)
Independent Variables			
Log Average income	.0404	-.245***	-.0286
	(.0327)	(.0657)	(.0458)
Log Average age	-.0032*	.0256***	.007***
	(.0017)	(.0035)	(.0024)
% pensioners	-.073	-.3383	.0594
	(.1037)	(.2089)	(.1455)
% unemployed	.0445	-1.244***	-.355
	(.1803)	(.3647)	(.2528)
% comprehensive education only	.0832	.3333**	.2391**
	(.0796)	(.1601)	(.1116)
Suburban	.0278***	-.0253	-.0163
	(.0095)	(.019)	(.0133)
Rural	-.0253***	.143***	.0186
	(.0087)	(.0175)	(.0122)
Constant	-.1388	.911	-.0182
	(.3326)	(.6688)	(.4665)
Observations	2910	2897	2910
R^2	.0347	.2235	.0639

Notes: Municipality groups follow Statistics Finland definitions: Urban: Cities, Suburban: Densily populated municipalities, Rural: Rural municipalities. Clustered standards errors in parentheses; * p< 0.1, ** p< 0.05, *** p< 0.01.

market structure is the main driver behind the change in CS.

Our analysis suggests that changes in CS and HHI vary with demographic and geographic characteristics. In Table A.4, Column 3, we further examine how these characteristics are associated with a decrease in CS. For this, we use an indicator to denote whether the postal code area faced a decrease in CS or not. The results show that the age of the population, the share of pensioners, the share of consumers with only comprehensive education, and suburban areas face a decrease in CS relatively more often. The opposite applies to areas with higher average income, higher unemployment, and areas that are considered urban.

Although most coefficients in Table A.4 are not statistically significant, the results suggest that rural areas and areas with higher proportions of pensioners benefit less from entry deregulation than consumers living in urban areas.

A.6 Free Entry Counterfactual with Alternative Fixed Costs

This analysis revisits our free entry counterfactual by changing the fixed costs used in the analysis. Analyses with increased fixed costs intuitively mean that we artificially raise the minimum profit requirement for operating a pharmacy both in rural and urban areas. We use this analysis to understand how robust our headline results are to changes in the fixed costs. We adjust our counterfactuals with fixed costs set to the 25th quantile and the median of the distribution of estimated fixed cost upper bounds and we calculate separate costs for urban and rural regions.

Table A.5 presents the main results for different fixed costs specifications. The first column presents the main results discussed in section 7 as a benchmark, whereas the second and third columns present results for the alternative fixed costs. Even with unrealistically high fixed cost, the change in total surplus (TS) remains negative, but the negative surplus change is much smaller than in the main results (Table A.5 column 1). Changes in TS are mainly explained by decreased aggregate fixed and labor costs in addition to increased pharmacy tax revenue.

Increasing fixed costs decreases aggregate CS in comparison to the main results, but the aggregate CS does not decrease linearly. With fixed costs set in the 25th Quantile, the change in aggregate CS is 6 pp. smaller than in the main results, but with median fixed costs, the change in CS is only 9 pp. smaller. It is worthwhile to note that even with Quantile 50 fixed costs (Table A.5 column 3) the number of pharmacies increase by 136 pharmacies (17%). The sum of negative CS changes increases in absolute value. The sum of negative CS either doubles (Quantile 25) or almost quadruples (Quantile 50). This means that even with unrealistically high fixed costs, the negative CS changes are in per capita terms quite modest and it should be relatively easy to find ways to compensate individuals who are hurt by the reform.

Table A.5: Counterfactual Results With Different Fixed Costs

Variable	**Fixed Costs Quantile 0**	**Fixed Costs Quantile 25**	**Fixed Costs Quantile 50**
	Panel A: Consumers		
Δ Consumer surplus (CS)	67.94	39.23	25.45
	(14%)	(8%)	(5%)
Sum of negative Δ CS	-1.79	-3.72	-7.01
	(-29%)	(-25%)	(-19%)
Average Δ weigh. distance	-0.48	-0.06	0.49
	(-3%)	(-0%)	(3%)
	Panel B: Pharmacies		
Δ Number of pharmacies	1459	429	136
	(178%)	(52%)	(17%)
Δ Revenue	197.55	92.59	35.24
	(8%)	(4%)	(1%)
Δ Labor costs	57.54	22.34	10.48
	(20%)	(8%)	(4%)
Δ Fixed costs	162.07	90.26	35.92
	(188%)	(55%)	(18%)
Δ Gross profits	120.25	50.61	21.74
	(51%)	(22%)	(9%)
Δ Net profits	-41.73	-39.49	-13.99
	(-28%)	(-56%)	(-35%)
	Panel C: Government and Total Surplus		
Δ Pharmacy tax	-122.38	-46.98	-22.34
	(-71%)	(-27%)	(-13%)
Δ Value-added tax	19.76	9.26	3.52
	(8%)	(4%)	(1%)
Δ Total surplus	-76.41	-37.98	-7.35
	(-7%)	(-4%)	(-1%)

Notes: This table shows aggregate changes in the market under free entry counterfactual relative to the current pharmacy network. The columns represent different specifications for fixed costs. All monetary values are in thousands of euros. Gross profits are calculated as revenue minus material costs, labor cost and taxes. Net profits are calculated as gross profits minus fixed costs.

Table A.5 Panel B displays changes in pharmacy revenue, labor costs, fixed costs, and gross and net profits for the different fixed cost specifications. With Quantile 25 fixed costs, pharmacy revenue is 4 pp. smaller than in baseline results, but for median fixed costs, the difference is only 1 pp. . At the same time, labor costs are 12 pp. (Quantile 25) or 16 pp. (Quantile 50) smaller than in the baseline scenario. At the same time net pharmacy profits remain smaller than in the regulated scenario but net profits are larger than in the free entry counterfactual. Sum of net profits changes non-linearly between different columns in Table A.5 because same fixed costs are applied to the status quo situation and to the counterfactual scenario.

The change in pharmacy and value added taxes is reported in Table A.5 Panel C. Tax revenue from pharmacy taxes is smaller than it was under entry regulation because tax is revenue based, but with Quantile 25 or Quantile 50 fixed costs tax revenue from pharmacy tax increases in comparison to free entry counterfactual (Table A.5 column 1 vs columns 2 and 3). The opposite happens with value added tax, because aggregate pharmacy market sligthly expands in counterfactual scenario. Market expansion mechanically leads to value added tax revenue increasing in comparison to regulated scenario.

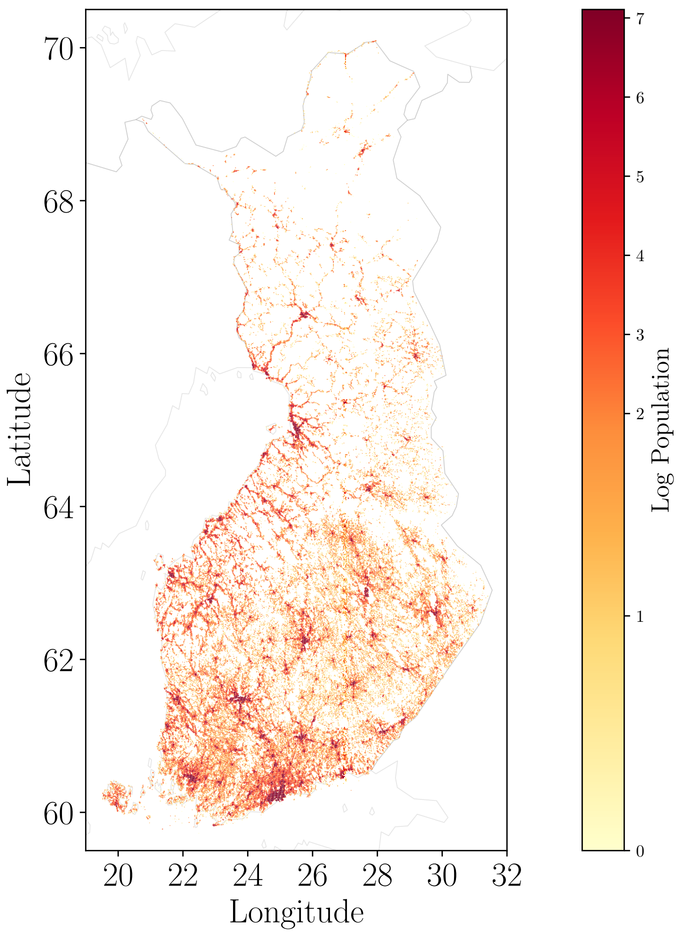
B Online Appendix

This secondary appendix contains supplementary materials and is structured as follows. Section B.1 provides several maps of descriptive statistics and counterfactual simulation results. Section B.2 offers an overview of EU regulatory frameworks across member states. Section B.3 describes the datasets used in the analysis and their sources. Section B.4 explains the methodology for calculating travel times between locations. Section B.5 presents time series of the labor supply of relevant pharmacy professionals. Section B.6 outlines the derivations for the analytical gradients used in the optimization procedure. Finally, Sections B.7 and B.8 include the mathematical expressions and results for computing elasticities and diversion ratios from the demand model.

B.1 Additional Maps

Descriptive Statistics. We present the map of Finland with log population densities in Figure B.1. Finland's population is highly unevenly distributed, with the majority concentrated in the southern and southwestern regions. In contrast, much of Finland's northern and eastern regions are sparsely populated.

Figure B.1: Finland Population Map

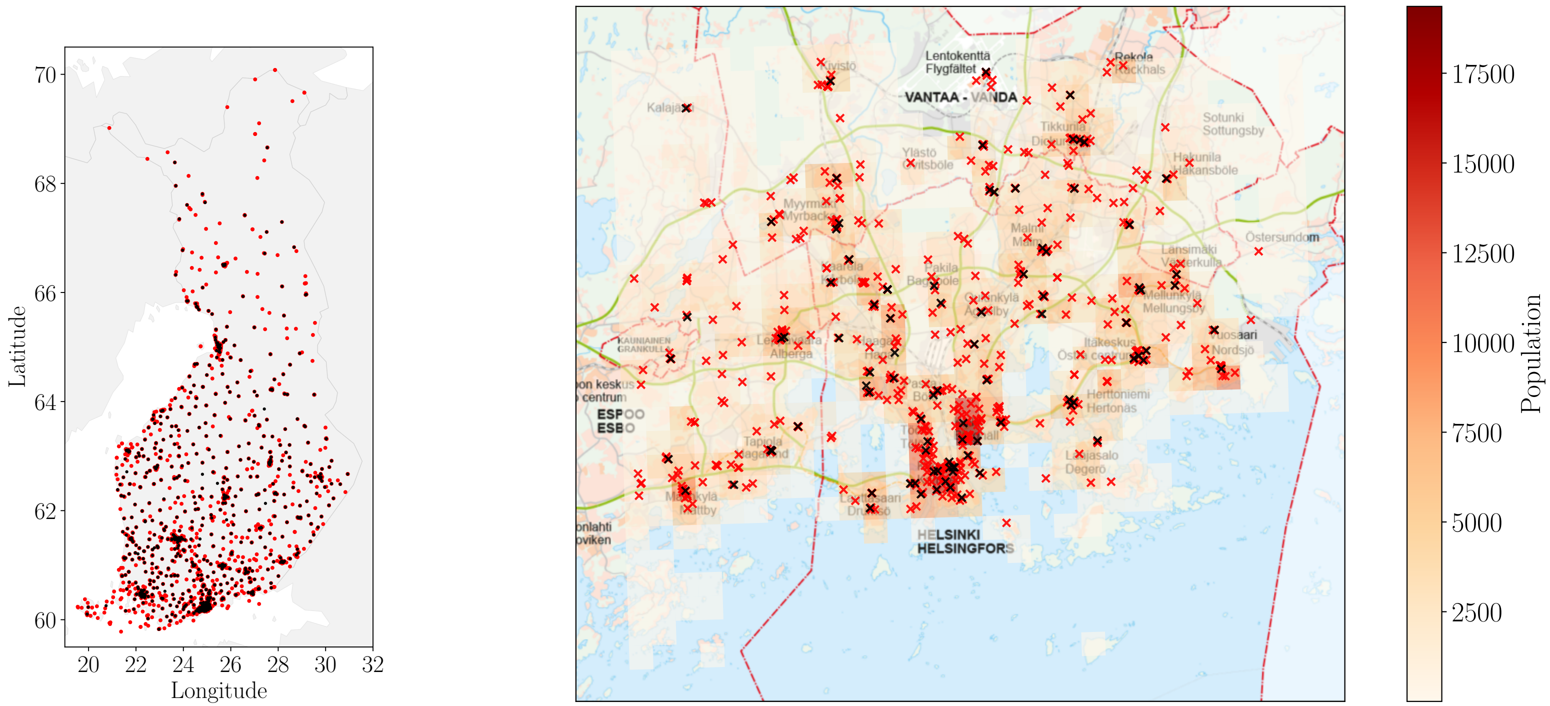


Potential Entry Locations. The computationally most challenging part in the SME and BSME algorithms is related to the size of the set of potential entry locations L. With our 250m$\times$250m sized map, the number of potential entry locations is in the hundreds of thousands, so iterating over the entire set is slow. Faced with similar problems, Verboven and Yontcheva (2024) restrict L to locations close to post offices. We take a similar approach and restrict entry to all locations next to a grocery store in Finland, which yields roughly 4000 potential entry locations. The choice to use grocery stores, supermarkets and key retail centers as potential entry location comes from the Finnish policy discussion where significant policy interest is on should groceries be allowed to sell pharmaceuticals as pharmacies do. We plot the possible entry locations in Figure B.2.

For several reasons, we argue that this is a rather conservative approach. First, we allow the entry of multiple pharmacies in the same location, which means that the number of entrants can exceed the number of locations. Second, the deregulation of the pharmacy markets in Norway and Sweden gives us a good benchmark for the number of pharmacies in equilibrium. In Norway, the number of pharmacies increased from 395 pharmacies in 2000 to 1045 pharmacies in 2023 (Rudholm 2008; Norwegian Pharmacy Association 2024). In Sweden, the number of pharmacies increased from 929 to 1407 between the years 2010–2022 following entry deregulation in 2009 (Swedish Pharmacy Association 2023). Furthermore, OECD (2023) reports an average of 28 pharmacies per 100,000 inhabitants in OECD member countries in 2021. For Finland, below the mean with 15 pharmacies per 100,000 inhabitants per pharmacy, an average rate or a maximum rate of 47 would correspond to 1600–2600 pharmacies.[51] Thus, we expect that our restriction on L has limited influence on our results, but it significantly reduces computational time.

51. In 2021, Spain had approximately 47 pharmacies per 100,000 people. Greece had the highest rate of 97, more than double that of Spain.

Figure B.2: Potential Entry Locations



(a) Whole Finland

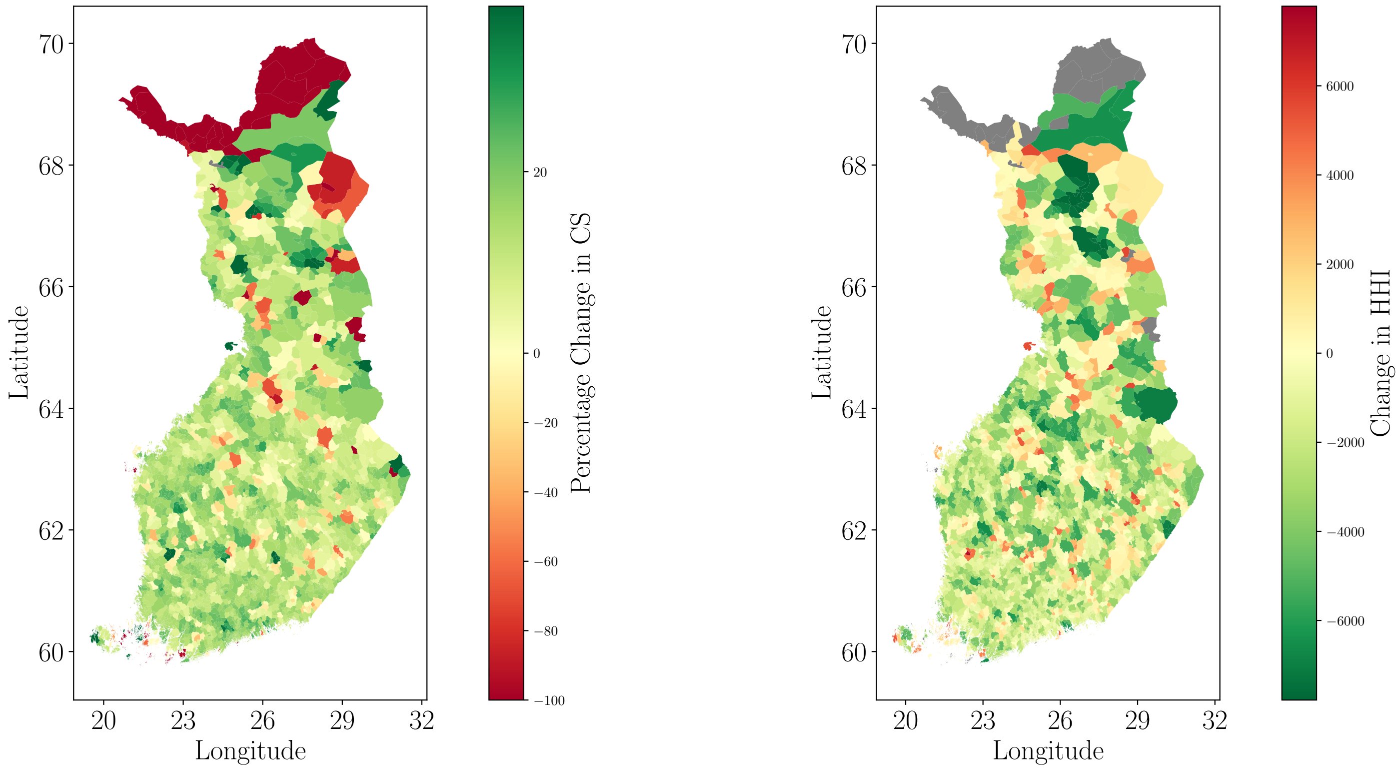
(b) Helsinki

Notes: The figure on the left plots the entry locations and pharmacy locations. The figure on the right shows the same locations in Helsinki. Sources for the maps: Fimea (2021), Nominatim and OpenStreetMap contributors (2024), Statistics Finland (2023), Helsinki City Survey Services, Cities of Espoo, Vantaa, and Kauniainen (2022) and EuroGeographics (2024).

Free Entry Counterfactual Results in Spatial Form. We present the changes in CS and HHI below, along with the HHI classifications. Finally, we provide the map of our counterfactual simulation (main specification).

In Figure B.3, we aggregate our cell-level results to the postal code level and plot maps showing how CS and HHI illustrate changes in postal code-specific consumer welfare and HHI across Finland. These maps show that adverse CS effects mainly come from Northern and Northeast Finland, and because these areas are sparsely populated, the direct population impact remains modest. The increases in market concentration are distributed more evenly across Finland than decreases in CS.

Figure B.3: Postal Code-level Changes in CS and HHI



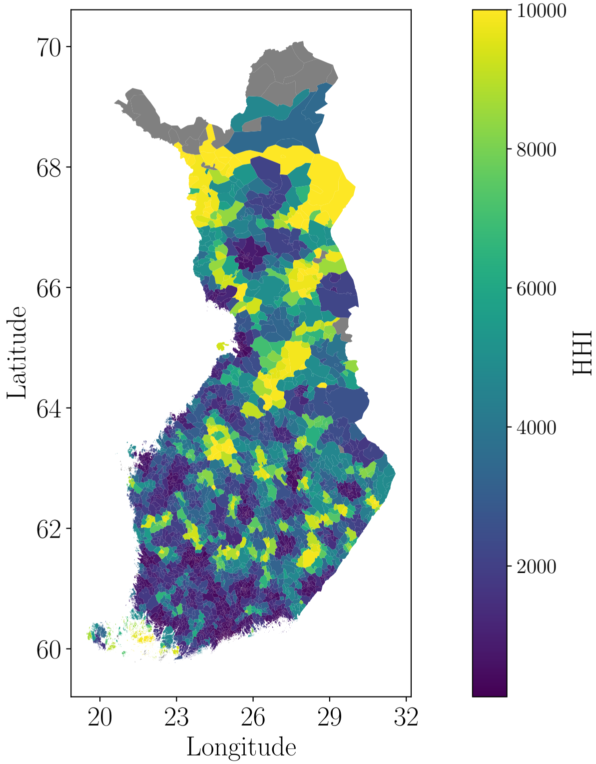
(a) Change in CS

(b) Change in HHI

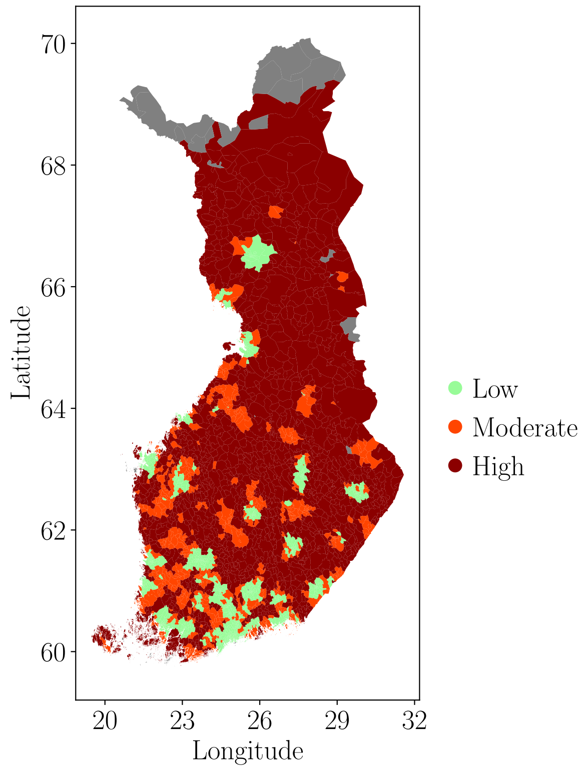
Notes: The figure on the left shows the change in CS for all postal code areas in Finland. The figure on the right shows the change in HHI. Gray areas denote loss of pharmacy access. Source: Statistics Finland (2021).

Figure B.4 illustrates the market concentration in the counterfactual scenario. Figure B.4a displays post code-level HHI and Figure B.4b displays HHI split into categories Low (green), Moderate (orange) and High (Red). Two important facts can be seen from HHI figures. Most of the heavily concentrated (HHI close to 10,000) postal code areas are located in Northern Finland which is inline with the CS changes presented in Figure B.3a. Secondly, the use of HHI thresholds reveals that in the counterfactual scenario only large cities and densely populated areas are the locations where market concentration measured in HHI is low. The usual caveats and challenges related to HHI use must be taken into consideration when Figure B.4 is interpreted through the lens of market concentration.

Figure B.4: HHI Entry Game Maps



(a) Post Entry Game Map of HHIs

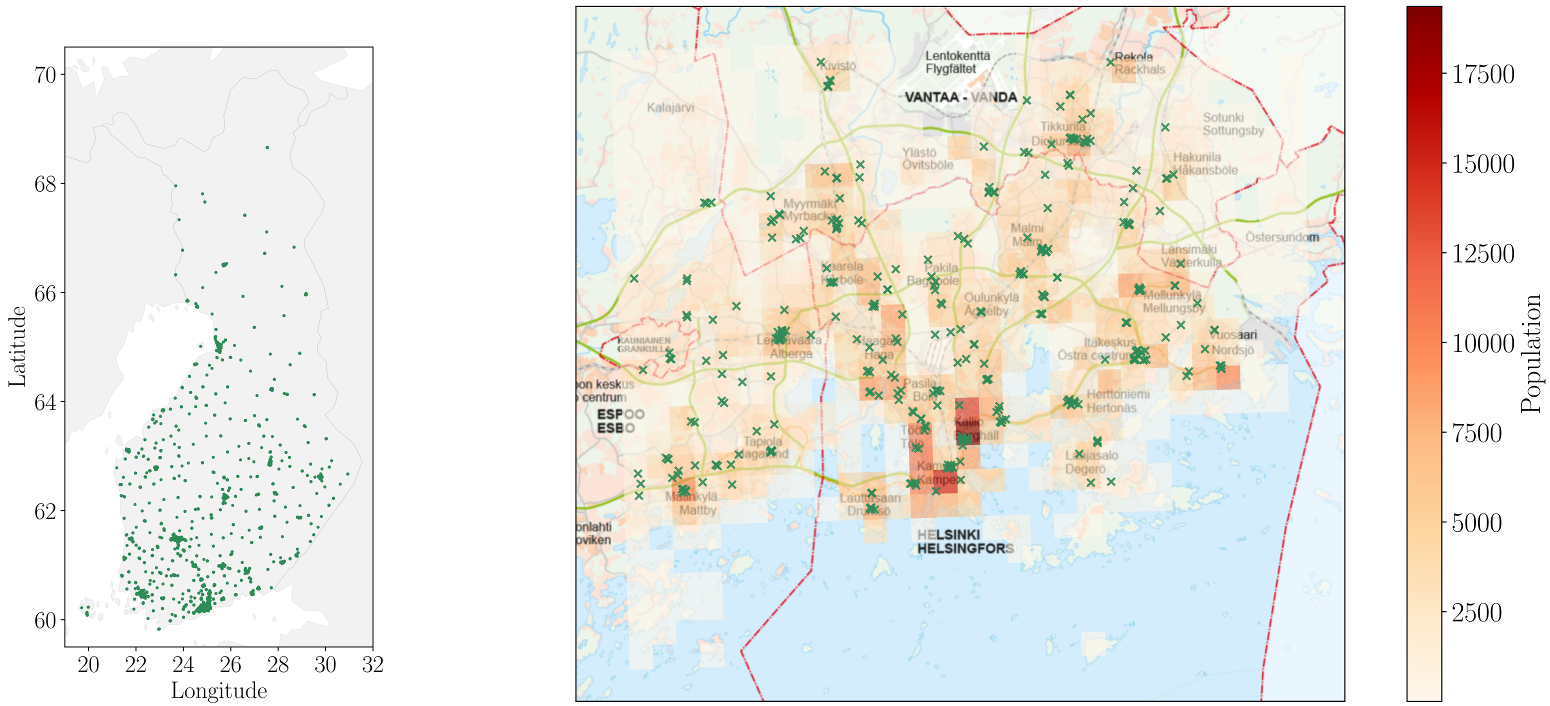


(b) Post Entry Game Map of HHI categories

Notes: The figure on the left shows the aggregated HHIs for all postal code areas in Finland. Gray areas denote loss of pharmacy access. Source: Statistics Finland (2021).

Figure B.5 displays the free entry counterfactual pharmacy network for whole Finland (Figure B.5a) and the Helsinki Capital Region (Figure B.5b). The main text Figure A.3a displays the map of Finland. In free entry counterfactual we see that most pharmacies enter locations that are on the fringes of densely populated locations. When a pharmacy is located outside a densely populated area, demand for its services comes from both the population center and the surrounding areas. This explains why only a few pharmacies are located in the centroids of the most populated areas (dark red in Figure B.5b), because then a large part of the demand would come from the highly populated area.

Figure B.5: Post-Entry Pharmacy Network



(a) Whole Finland

(b) Helsinki Capital Region

Notes: The figure on the left plots the post entry game pharmacy network in Finland. The figure on the right shows the same locations in Helsinki. Sources for the maps: Fimea (2021), Nominatim and OpenStreetMap contributors (2024), Statistics Finland (2023), Helsinki City Survey Services, Cities of Espoo, Vantaa, and Kauniainen (2022) and EuroGeographics (2024).

B.2 Pharmacy Regulation in the EU

Table B.1 shows an overview of pharmacy regulation in EU countries. Most countries impose restrictions on the number of pharmacy licenses issued, which are often based on the number of inhabitants per pharmacy. In most EU countries, pharmacy ownership is not restricted to pharmacists. However, in those countries where ownership is restricted to pharmacists, only Estonia, Hungary, and Poland allow a pharmacist to own multiple pharmacies. The amount of higher education required for pharmacy technicians or assistants ranges from none to four years with an average of 2.5 years. The degree of horizontal integration regulation varies between countries, with most countries allowing pharmacy chains. Bulgaria, Estonia, Hungary, Poland, and Portugal limit the chains to four pharmacies. Branch pharmacies and minority stakes are not included in horizontal integration. Most EU countries allow pharmacies to be owned by pharmaceutical wholesalers, making vertical integration possible. In particular, the regulation of horizontal and vertical integration is highly correlated, and in many countries, wholesalers also own pharmacy chains.

Table B.2 presents past pharmacy regulation policies focused on price setting, specifically in countries that do not regulate the number or location of pharmacies. The key takeaway is that even when a country allows more flexibility regarding pharmacy quantities or locations, some form of price regulation remains in place, and pharmacy pricing is rarely unregulated. The only exceptions are Sweden and Germany, where pharmacies have some discretion in pricing over-the-counter (OTC) drugs. This suggests that our free-entry counterfactual scenario with regulated pharmacy pricing closely mirrors an institutional framework with partial liberalization.

Table B.1: Pharmacy Regulation in the European Union (EU)

Country	Pharmacy Quantity	Pharmacy Location	Ownership Limits	Tech Educ.	Integration Horz.	Integration Vert.
Austria	Yes	Yes	Yes	2–3 y	No	No
Belgium	Yes	Yes	No	3 y	Yes	Yes
Bulgaria	No	No	No	3 y	Yes*	Yes
Croatia	Yes	Yes	No	4 y	Yes	Yes
Cyprus	No	Yes	Yes	None	No	No
Czechia	No	No	No	3 y	Yes	Yes
Denmark	Yes	Yes	Yes	3 y	No	No
Estonia	Yes	Yes	Yes	3 y	Yes*	No
Finland	Yes	Yes	Yes	3 y	No	No
France	Yes	Yes	Yes	2 y	No	No
Germany	No	No	Yes	2.5 y	No	No
Greece	Yes	Yes	No	2 y	Yes	Yes
Hungary	Yes	Yes	Yes	None	Yes*	No
Ireland	No	No	No	2 y	Yes	Yes
Italy	Yes	Yes	No	-	Yes	Yes
Latvia	Yes	Yes	No	2.5 y	Yes	Yes
Lithuania	No	Yes	No	3 y	Yes	Yes
Luxembourg	Yes	Yes	-	-	-	-
Malta	Yes	Yes	No	2 y	Yes*	Yes
Netherlands	No	No	No	2 y	Yes	Yes
Poland	Yes	Yes	Yes	2 y	Yes*	No
Portugal	Yes	Yes	No	4 y	Yes*	Yes
Romania	Yes	Yes	No	3 y	Yes	Yes
Slovakia	-	Yes	No	-	No	-
Slovenia	Yes	Yes	No	4 y	No	No
Spain	Yes	Yes	Yes	2 y	No	No
Sweden	No	Yes	No	<2 y	Yes	Yes

Notes: Overview of pharmacy regulation in the EU. "Pharmacy Quantity" refers to restrictions on the number of pharmacies that can operate. "Pharmacy Location" indicates restrictions on pharmacy locations. "Ownership Limits" describes whether ownership is limited to pharmacists. "Tech Educ." refers to the education requirements for pharmacy technicians in years. "Integration (Horz. & Vert.)" reflects the allowance of horizontal and vertical integration within the pharmacy sector. *Limited to four pharmacies, or one per town for Malta. Source: World Health Organization (2019).

Table B.2: Pharmacy Market Deregulation and Pricing in the EU

Country	Price Regulation	Free Pricing
Bulgaria	Yes	No
Cyprus	Yes	No
Czechia	Yes	No
Germany	Yes	No (RX), Yes (Non-RX)
Ireland	Yes	No
Lithuania	Yes	No
Netherlands	Yes	No
Slovakia	Yes	No
Sweden	Yes	No, Yes (OTC)

Notes: This table provides price regulation information for countries listed in Appendix Table B.1 that have implemented some form of entry deregulation. "Price Regulation" refers to existence of price regulation policies when some part of the pharmacy market entry regulation is lifted. "Free Pricing" refers whether pharmacies can set prices freely or not. Sources; Bulgaria: (Rohova, Dimova, Mutafova, Atanasova, Koeva, Ginneken et al. 2013; Dimova, Rohova, Atanasova, Kawalec and Czok 2017; Medicines for Europe 2022, 2023; Vogler, Arts and Habl 2006) Cyprus: (Zimmermann and Haasis 2021; Medicines for Europe 2023; Kanavos and Wouters 2014) Czechia: (Skoupá 2017; Medicines for Europe 2022, 2023) Germany: (Reese and Kemmner 2023; Medicines for Europe 2022, 2023) Ireland: (Medicines for Europe 2022, 2023; Doyle-Rossi and Gallagher 2023; Vogler, Arts and Habl 2006) Lithuania: (Enterprises 2021; Medicines for Europe 2022, 2023) Netherlands: (Zuidberg, Vogler and Mantel 2010; Medicines for Europe 2022, 2023) Slovakia:(Smatana, Pažitný, Kandilaki, Laktišová, sdláková, Palušková, Ginneken and Spranger 2016; Medicines for Europe 2022, 2023) Sweden: (Medicines for Europe 2022, 2023; Panteli, Arickx, Cleemput, Dedet, Eckhardt, Fogarty, Gerkens, Henschke, Hislop, Jommi et al. 2016)

Table B.3: Data Sources

Data	Source	Open source	Usage
Pharmacy accounting data	Fimea	No	Analysis
Grid Database	Statistics Finland	No	Analysis
Zip-code RX expenditure	Kela	No	Analysis
Zip-code pharmacy visits	Kela	No	Analysis
Community structure data	SYKE	Yes	Analysis
Urban/Rural classifications	SYKE	Yes	Analysis
Pharmacy register	Fimea	Yes	Analysis, Maps
Country boundaries	EuroGeographics	Yes	Maps
Population Grid Data 1 km $\times$ 1 km	Statistics Finland	Yes	Maps
Paavo postal code area data	Statistics Finland	Yes	Analysis, Maps
Helsinki Metropolitan Area map	Helsinki	Yes	Maps
Pharmacy addresses, local amenities and travel distances	OpenStreetMap contributors	Yes	Analysis, Maps

Notes: This table lists our data sources. The first three sources are proprietary and used in the empirical estimations. We use publicly available data to calculate distances and travel times, to characterize population at the post code-level and as well as for plotting maps.

B.3 Data Sources

We list our data sources in Table B.3. The first three data sources are proprietary data from Fimea, Statistics Finland, and Kela. The grid database is a commercial product available for purchase. In addition to this data, we use publicly available data from several institutions and open source projects. Data from SYKE cover several classifications for the urban and rural characterization of the cells. For further information, see Finnish Environment Institute (2021a, 2021b).

Most importantly, we use several data sources and software from various OpenStreetMap contributors and projects. We use Nominatim and OpenStreetMap contributors (2024) data and software to map our pharmacy addresses to geolocations. We use OverPy and OpenStreetMap contributors (2024) data and software to locate nearby amenities for all pharmacies and our entry game locations. Finally, we use Geofabrik and OpenStreetMap contributors (2024) data to compute the travel time distances between the cells and pharmacies or the cells and the entry locations. We describe the computation of these distances in the next subsection.

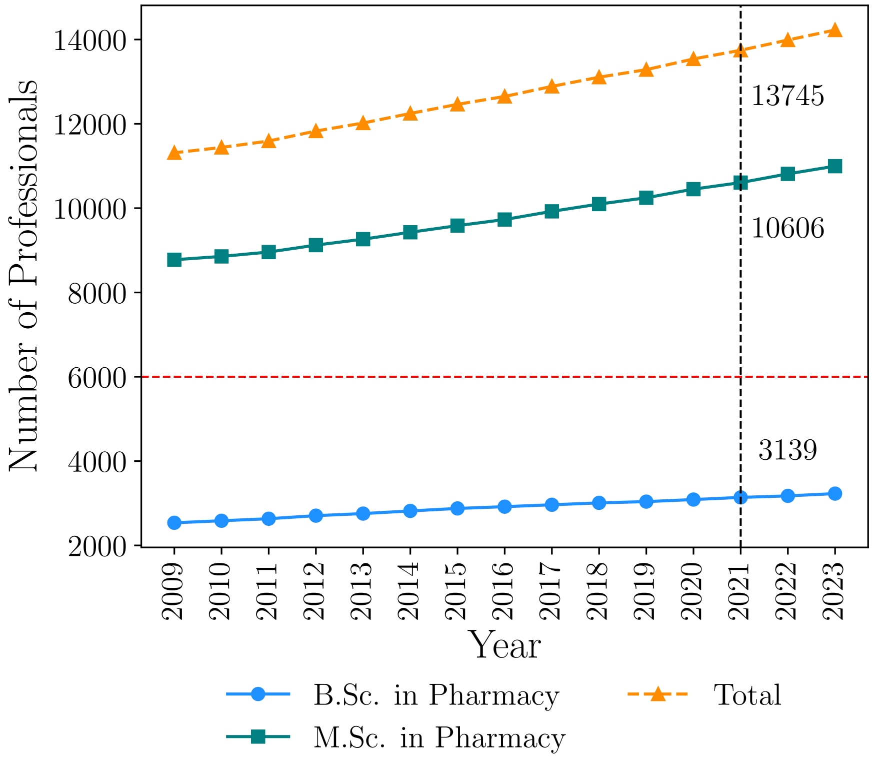
B.4 Travel Time Distances

We use the open source route planner OpenRouteService (2024) to calculate the travel distances between the pharmacy and the cells in its catchment area. We also repeat this for all the possible entry locations and their catchment areas. Due to the large number of cells and destinations (more than fifty million distances), we do not use the publicly available API. Instead, we run the OpenRouteService (2024) as a local instance from their pre-build Docker image. The travel distances are computed for car travel for all cells within 80 kilometer Euclidean distance from every pharmacy and entry location. We use the default options of the OpenRouteService (2024) image and do not use elevation data.

B.5 Number of Pharmacists

We present the number of pharmacists in Figure B.6. The figure shows a steady increase in the number of individuals with a university degree in Pharmacy in Finland. It also indicates some slack in the labor market, as the supply of university-educated professionals appears sufficient. Therefore, we do not anticipate significant concerns about a shortage of pharmacists under a free-entry market structure. However, it is important to note that our approximation does not account for potential wage increases driven by higher labor demand.

Figure B.6: Number of Pharmacists, B.Sc. and M.Sc. in Pharmacy



Notes: The figure shows the number of pharmacists under the age of 65 in Finland, categorized by their education level, from 2009 to 2023. The red dashed line indicates the approximate number of pharmacists needed under our free entry market structure, whereas the black dashed line marks the year for which data is available. Source: National Supervisory Authority for Welfare and Health of Finland (2024).

B.6 Analytical Gradients

In this section, we present the derivations for the analytical gradients we employ in our estimation procedure. Our objective function is:

$$\log\left(\hat{R}_s(\theta,\alpha)\right) - \log(R_s) \tag{23}$$

with $\theta = (\beta, \sigma)$. We omit the squared part of the log difference from equation (12) because `scipy.optimize.least_squares` requires the objective fuction and gradients in this form. Take derivative with respect to θ:

$$\frac{1}{\hat{R}} \times \frac{\partial \hat{R}_s(\theta,\alpha)}{\partial\theta} = \frac{1}{\hat{R}} \times \frac{\partial \sum_t R_{st}(\theta,\alpha)}{\partial\theta} \tag{24}$$

$$= \frac{1}{\hat{R}} \times \frac{\partial \sum_t \alpha \times N_t \times p_{st}(\theta)}{\partial\theta} \tag{25}$$

$$= \frac{1}{\hat{R}} \times \alpha \times \sum_t N_t \frac{\partial p_{st}(\theta)}{\partial\theta}. \tag{26}$$

For the linear terms $\beta \in \theta$ we have the following expression for the partial derivative $\frac{\partial p_{st}(\theta)}{\partial\theta}$:

$$\frac{\partial p_{st}}{\partial\beta} = \int \frac{\frac{\partial \exp(u_{ist}(\theta))}{\partial\beta} \times \sum_k \exp(u_{ikt}(\theta)) - \exp(u_{ist}(\theta)) \times \frac{\partial \sum_k \exp(u_{ikt}(\theta))}{\partial\beta}}{\left[\sum_k \exp(u_{ikt}(\theta))\right]^2} d\nu \tag{27}$$

$$= \int \frac{\exp(u_{ist}(\theta)) \times x_{st} \times \sum_k \exp(u_{ikt}(\theta)) - \exp(u_{ist}(\theta)) \times \sum_k x_{kt}\exp(u_{ikt}(\theta))}{\left[\sum_k \exp(u_{ikt}(\theta))\right]^2} d\nu \tag{28}$$

$$= \int \frac{\exp(u_{ist}(\theta)) \times (x_{st}\sum_k \exp(u_{ikt}) - \sum_k x_{kt}\exp(u_{ikt}))}{\left[\sum_k \exp(u_{ikt}(\theta))\right]^2} d\nu. \tag{29}$$

$$= \int p_{ist}(\theta) \times \left(x_{st} - \frac{\sum_k x_{kt}\exp(u_{ikt})}{\sum_k \exp(u_{ikt})}\right) d\nu. \tag{30}$$

For the non-linear terms $\sigma \in \theta$ we simply replace x_{st} with $x_{ist} = x_{st} \times \nu_i$ to obtain the partial derivative $\frac{\partial p_{st}}{\partial \theta}$.

The analytical gradients for the RCNL model are more complicated:

$$\frac{\partial p_{st}}{\partial \beta} = \int \frac{\partial p^h}{\partial \beta} \times p^n + p^h \times \frac{\partial p^n}{\partial \beta} d\nu. \tag{31}$$

where (with abusing our notation) p^h denotes the within-nest probability and p^n the nest choice probability from equation (6). The derivative for the first term is

$$\begin{aligned}\frac{\partial p^h}{\partial \beta} = &\frac{\exp\left(u_{ist}/\left(1-\rho\right)\right) \times \frac{x_{st}}{1-\rho} \times \sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)}{\left[\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)\right]^2} \\ &- \frac{\exp\left(u_{ist}/\left(1-\rho\right)\right) \times \sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right) \times \frac{x_{kt}}{1-\rho}}{\left[\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)\right]^2},\end{aligned} \tag{32}$$

which simplifies to

$$= p^h \times \left(\frac{x_{st}}{1-\rho} - \frac{1}{1-\rho} \times \frac{\sum_k x_{kt} \exp\left(u_{ikt}/\left(1-\rho\right)\right)}{\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)}\right). \tag{33}$$

The derivative for the second term is

$$\begin{aligned}\frac{\partial p^n}{\partial \beta} = &\frac{\left(1-\rho\right)\left(\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)\right)^{-\rho} \sum_k \frac{x_{kt}}{1-\rho} \exp\left(u_{ikt}/\left(1-\rho\right)\right) \exp\left(I_i\right)}{\left[\exp\left(I_i\right)\right]^2} \\ &- \frac{\exp\left(I_{ih(s)}\right)\left(1-\rho\right)\left(\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)\right)^{-\rho} \sum_k \frac{x_{kt}}{1-\rho} \exp\left(u_{ikt}/\left(1-\rho\right)\right)}{\left[\exp\left(I_i\right)\right]^2},\end{aligned} \tag{34}$$

which simplifies to

$$= p^n \times \left(1-p^n\right) \times \frac{\sum_k x_{kt} \exp\left(u_{ikt}/\left(1-\rho\right)\right)}{\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)}. \tag{35}$$

Using equations (33) and (35), equation (31) becomes

$$\frac{\partial p_{st}}{\partial \beta} = \int p^h p^n \left(\frac{x_{st}}{1-\rho} - \frac{\sum_k x_{kt} \exp\left(u_{ikt}/\left(1-\rho\right)\right)}{\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)} \left(\frac{1}{1-\rho} + \left(1-p_n\right)\right)\right) d\nu. \tag{36}$$

The partial derivative with respect to ρ is

$$\frac{\partial p_{st}}{\partial \rho} = \int \frac{\partial p^h}{\partial \rho} \times p^n + p^h \times \frac{\partial p^n}{\partial \rho} d\nu. \tag{37}$$

The derivative for the first term is

$$\begin{aligned} \frac{\partial p^h}{\partial \rho} = & \frac{u_{ist}}{(1-\rho)^2} \frac{\exp\left(u_{ist}/\left(1-\rho\right)\right) \sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)}{\left(\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)\right)^2} \\ & - \frac{\exp\left(u_{ist}/\left(1-\rho\right)\right)}{(1-\rho)^2} \frac{\sum_k u_{ikt} \exp\left(u_{ikt}/\left(1-\rho\right)\right)}{\left(\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)\right)^2}, \end{aligned} \tag{38}$$

which simplifies to

$$= \frac{p^h}{(1-\rho)^2} \left(u_{ist} - \frac{\sum_k u_{ikt} \exp\left(u_{ikt}/\left(1-\rho\right)\right)}{\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)} \right). \tag{39}$$

The derivative for the second term is

$$\frac{\partial p^n}{\partial \rho} = \frac{\frac{\partial I_{ih(s)}}{\partial \rho} \times \exp(I_{ih(s)}) \times \exp(I_i) - \frac{\partial I_i}{\partial \rho} \times \exp(I_i) \times \exp(I_{ih(s)})}{\exp(I_i)^2}, \tag{40}$$

where

$$\frac{\partial I_{ih(s)}}{\partial \rho} = -\ln \sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right) + \frac{1}{1-\rho} \frac{\sum_k u_{ikt} \exp\left(u_{ikt}/\left(1-\rho\right)\right)}{\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)} \tag{41}$$

and

$$\frac{\partial I_i}{\partial \rho} = p_n \times \frac{\partial I_{ih(s)}}{\partial \rho} \tag{42}$$

resulting in

$$\begin{aligned} \frac{\partial p^n}{\partial \rho} = p^n \left(1-p^n\right) \Bigg(& -\ln \sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right) \\ & + \frac{1}{1-\rho} \frac{\sum_k \exp u_{ikt} \left(u_{ikt}/\left(1-\rho\right)\right)}{\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)} \Bigg) \end{aligned} \tag{43}$$

Using equations (39) and (43), equation (37) becomes

$$\frac{\partial p_{st}}{\partial \rho} = \int p^h p^n \Bigg(\frac{u_{ist}}{(1-\rho)^2} - (1-p^n) \ln \sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right) + \frac{1}{1-\rho} \times \frac{\sum_k \exp u_{ikt}\left(u_{ikt}/\left(1-\rho\right)\right)}{\sum_k \exp\left(u_{ikt}/\left(1-\rho\right)\right)} \times \left((1-p^n) - \frac{1}{1-\rho} \right) \Bigg) d\nu. \tag{44}$$

B.7 Elasticity Formulas

In this section, we present the elasticity formulations for the random coefficients model. Let η^x_{srt} be the revenue elasticity of pharmacy s with respect to the characteristic x for pharmacy r in cell t. From equation (9) we obtain:

$$\eta^x_{srt} = \frac{\partial \hat{R}_{st}}{\partial x_{rt}} \times \frac{x_{rt}}{\hat{R}_{st}} \tag{45}$$

$$= \alpha \times N_t \times \frac{\partial p_{st}}{\partial x_{rt}} \times \frac{x_{rt}}{\hat{R}_{st}} \tag{46}$$

where $\frac{\partial p_{ist}(\theta)}{\partial x_{irt}}$ is the partial derivative of the choice probability of pharmacy s with respect to the characteristic x for pharmacy r. By the chain rule and the Leibniz integration rule:

$$
\begin{aligned}
\frac{\partial p_{st}(\theta)}{\partial x_{rt}} &= \int \frac{\partial p_{ist}(\theta)}{\partial u_{irt}(\theta)} \times \frac{\partial u_{irt}(\theta)}{\partial x_{irt}} d\nu \\
&= \int \frac{\mathbb{1}\left[s=r\right] \times \exp(u_{ist}(\theta)) \times \sum_k \exp(u_{ikt}(\theta)) - \exp(u_{ist}(\theta)) \times \exp(u_{irt}(\theta))}{\left[\sum_k \exp(u_{ikt}(\theta))\right]^2} \\
&\times \frac{\partial u_{irt}(\theta)}{\partial x_{irt}} d\nu \\
&= \int \frac{\exp(u_{ist}(\theta)) \times \left[\mathbb{1}\left[s=r\right] \times \sum_k \exp(u_{ikt}(\theta)) - \exp(u_{irt}(\theta))\right]}{\left[\sum_k \exp(u_{ikt}(\theta))\right]^2} \times \frac{\partial u_{irt}(\theta)}{\partial x_{irt}} d\nu \\
&= \int p_{ist}(\theta) \left(\mathbb{1}\left[s=r\right] - p_{irt}(\theta)\right) \times \frac{\partial u_{irt}(\theta)}{\partial x_{irt}} d\nu \\
&= p_{st}(\theta) \left(\mathbb{1}\left[s=r\right] - p_{rt}(\theta)\right) \times \left(\sum \theta^x\right)
\end{aligned} \tag{47}
$$

where $\sum \theta^x$ represents all the terms associated with x (the main terms and the interactions). We can then present the elasticity as

$$
\eta^x_{srt} = \alpha \times N_t \times p_{st}(\theta) \left(\mathbb{1}\left[s=r\right] - p_{rt}(\theta)\right) \times \left(\sum \theta^x\right) \times \frac{x_{rt}}{\hat{R}_{st}} \tag{48}
$$

From equation (9) we had $\hat{R}_{st} = \alpha \times N_t \times p_{st}(\theta)$ so that equation (48) simplifies to

$$
= \left(\mathbb{1}\left[s=r\right] - p_{rt}(\theta)\right) \times \left(\sum \theta^x\right) \times x_{rt}. \tag{49}
$$

To obtain the elasticity formulations for the RCNL model, we begin with

$$
\frac{\partial p_{st}(\theta)}{\partial x_{rt}} = \int \frac{\partial p^h_{ist}(\theta)}{\partial u_{irt}(\theta)} \times \frac{\partial u_{irt}(\theta)}{\partial x_{irt}} p^n + p^h_{ist} \frac{\partial p_n(\theta)}{\partial u_{irt}(\theta)} \times \frac{\partial u_{irt}(\theta)}{\partial x_{irt}} d\nu. \tag{50}
$$

Because

$$\begin{aligned}\frac{\partial p^h_{ist}(\theta)}{\partial u_{irt}(\theta)} &= \frac{\mathbb{1}\left[s=r\right]\times\exp\left(u_{ist}/\left(1-\rho\right)\right)\times\sum_k\exp\left(u_{ikt}/\left(1-\rho\right)\right)}{\left(1-\rho\right)\times\left[\sum_k\exp(u_{ikt}(\theta)/(1-\rho))\right]^2}\\ &-\frac{\exp\left(u_{ist}/\left(1-\rho\right)\right))\times\left(\exp\left(u_{irt}/\left(1-\rho\right)\right)\right)}{\left(1-\rho\right)\times\left[\sum_k\exp(u_{ikt}(\theta)/(1-\rho))\right]^2}\\ &=\frac{p^h_{ist}}{\left(1-\rho\right)}\times\left(\mathbb{1}\left[s=r\right]-p^h_{irt}\right)\end{aligned} \tag{51}$$

and

$$\begin{aligned}\frac{\partial p^n(\theta)}{\partial u_{irt}(\theta)} &= \frac{\exp\left(u_{irt}/\left(1-\rho\right)\right)\left(\sum_k\exp\left(u_{ikt}/\left(1-\rho\right)\right)\right)^{-\rho}\exp\left(I_i\right)}{\left[\exp\left(I_i\right)\right]^2}\\ &-\frac{\exp\left(I_{ih(s)}\right)\exp\left(u_{irt}/\left(1-\rho\right)\right)\left(\sum_k\exp\left(u_{ikt}/\left(1-\rho\right)\right)\right)^{-\rho}}{\left[\exp\left(I_i\right)\right]^2}.\end{aligned} \tag{52}$$

Using the definition for p^n and adding a term $1/\sum_k\exp\left(u_{ikt}/\left(1-\rho\right)\right)\times\sum_k\exp\left(u_{ikt}/\left(1-\rho\right)\right)$ we obtain

$$\begin{aligned}&=\left(1-p^n\right)\times\frac{1}{\sum_k\exp\left(u_{ikt}/\left(1-\rho\right)\right)}\times\sum_k\exp\left(u_{ikt}/\left(1-\rho\right)\right)\\ &\times\frac{\exp\left(u_{irt}/\left(1-\rho\right)\right)}{\exp\left(I_i\right)\left(\sum_k\exp\left(u_{ikt}/\left(1-\rho\right)\right)\right)^{\rho}}\end{aligned} \tag{53}$$

and

$$=\left(1-p^n\right)\times p^h_{irt}\times p^n \tag{54}$$

equation (50) becomes

$$\begin{aligned}\frac{\partial p_{st}(\theta)}{\partial x_{rt}} &= \int p^h_{ist}\times p^n\left[\frac{\mathbb{1}\left[s=r\right]}{1-\rho}+p^h_{irt}\left(1-\frac{1}{1-\rho}\right)-p^h_{irt}\times p^n\right]\frac{\partial u_{irt}(\theta)}{\partial x_{irt}}d\nu\\ &=p_{st}(\theta)\left[\frac{\mathbb{1}\left[s=r\right]}{1-\rho}+p^h_{rt}\left(1-\frac{1}{1-\rho}\right)-p_{rt}(\theta)\right]\times\left(\sum\theta^x\right),\end{aligned} \tag{55}$$

where $\sum\theta^x$ represents all the terms associated with x (the main terms and the interactions). Substituting equations (55) and (9) into the elasticity formula (46), we obtain

$$\eta_{srt}^{x} = \left[\frac{\mathbb{1}\left[s=r\right]}{1-\rho} + p_{rt}^{h}\left(1-\frac{1}{1-\rho}\right) - p_{rt}(\theta)\right] \times \left(\sum \theta^{x}\right) \times x_{rt}. \tag{56}$$

B.8 Diversion Ratios

In this section, we present the diversion ratios beginning with the random coefficients model. Using $\partial p_{ist}(\theta)/\partial u_{irt}(\theta)$ in Equation (47), the semielasticity of store s's revenue with respect to the utility of store $r \neq s$ is

$$\sigma_{s,r} = \frac{1}{\hat{R}_s}\sum_{t\in L_S} \alpha \times N_t \times \frac{\partial p_{st}}{\partial u_{rt}} \quad = -\frac{1}{\hat{R}_s}\sum_{t\in L_S} \alpha \times N_t \times \int p_{ist}(\theta) p_{irt}(\theta) d\nu \tag{57}$$

and its own semielasticity is

$$\sigma_{s,s} = \frac{1}{\hat{R}_s}\sum_{t\in L_S} \alpha \times N_t \times \frac{\partial p_{st}}{\partial u_{st}} \quad = \frac{1}{\hat{R}_s}\sum_{t\in L_S} \alpha \times N_t \times \int p_{ist}(\theta)\left(1-p_{ist}(\theta)\right) d\nu. \tag{58}$$

As a result, we can define the store-level diversion ratios for each store as the proportion of decreased revenue from an improvement in the utility offered by store r that is diverted from store s (or, by symmetry, vice versa),

$$D_{s,r} = \frac{\sigma_{s,r}}{\sigma_{s,s}} = -\frac{\sum_{t\in L_S} N_t \times \int p_{ist}(\theta) p_{irt}(\theta) d\nu}{\sum_{t\in L_S} N_t \times \int p_{ist}(\theta)\left(1-p_{ist}(\theta)\right) d\nu}. \tag{59}$$

To obtain the diversion ratios for the RCNL model, we use $\partial p_{ist}(\theta)/\partial u_{irt}(\theta)$ in Equation (55), and the semielasticity of store s's revenue with respect to the utility of store $r \neq s$ is

$$\begin{aligned} \sigma_{s,r} &= \frac{1}{\hat{R}_s}\sum_{t\in L_S} \alpha \times N_t \times \frac{\partial p_{st}}{\partial u_{rt}} \\ &= -\frac{1}{\hat{R}_s}\sum_{t\in L_S} \alpha \times N_t \times \int p_{ist}^{h} \times p^{n}\left[p_{irt}^{h}\left(\frac{\rho}{1-\rho}\right) + p_{irt}^{h} \times p^{n}\right] d\nu \end{aligned} \tag{60}$$

and its own semielasticity is

$$\begin{aligned}\sigma_{s,s} &= \frac{1}{\hat{R}_s} \sum_{t \in L_S} \alpha \times N_t \times \frac{\partial p_{st}}{\partial u_{st}} \\ &= \frac{1}{\hat{R}_s} \sum_{t \in L_S} \alpha \times N_t \times \int p^h_{ist} \times p^n \left[\frac{1}{1-\rho} + p^h_{irt} \left(1 - \frac{1}{1-\rho} \right) - p^h_{irt} \times p^n \right] d\nu. \end{aligned} \tag{61}$$

As a result, we can define the store-level diversion ratios for each store as the proportion of decreased revenue from an improvement in the utility offered by store r that is diverted from store s (or, by symmetry, vice versa),

$$D_{s,r} = \frac{\sigma_{s,r}}{\sigma_{s,s}} = -\frac{\sum_{t \in L_S} N_t \times \int p^h_{ist} \times p^n \left[p^h_{irt} \left(\frac{\rho}{1-\rho} \right) + p^h_{irt} \times p^n \right] d\nu}{\sum_{t \in L_S} N_t \times \int p^h_{ist} \times p^n \left[\frac{1}{1-\rho} + p^h_{irt} \left(1 - \frac{1}{1-\rho} \right) - p^h_{irt} \times p^n \right] d\nu}. \tag{62}$$

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