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Spatial Effects of Price Regulations and Competition. A Dynamic Approach to the German Retail Pharmacy Market.

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work in progress

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Abstract

This paper examines the effect of price competition on the location choices of retail pharmacies in large cities. I exploit a regulatory change in 2004 that introduced price competition for non-prescription drugs to estimate the parameters of a dynamic spatial entry model, using a comprehensive panel dataset of retail pharmacy locations. The dynamic model is estimated by means of a nested fixed point approach, because the asymmetric nature of the entry game renders conventional two-step estimators inapplicable. The computational burden of this approach is alleviated by tailoring the concept of oblivious equilibrium, developed by Weintraub et al. (2008), to the spatial nature of the game. I find that the regulatory change lead to more intense local competition and lower entry costs. The estimated structural model is then used to decompose the effects of the regulatory change on market structure and consumers' travel distances. I find that one third of the total decline in the number of pharmacies between 2004 and 2016 is attributable to increased local interaction, whereas it caused the consumers' distance to the nearest pharmacy to increase only marginally. This suggests that price competition is beneficial for consumers not only because it lowers retail prices, but also because it leads to a more efficient spatial distribution of retail pharmacies.

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1 Introduction

Modern developed economies spend about a tenth of their national incomes on health care, and pharmaceuticals contribute a sizeable portion of this spending block. Figure 1 shows that the expenditure share of pharmaceuticals alone is close to two percent in major industrial nations. And while online pharmacies are pushing into this large market, the majority of prescription drugs is still sold in retail pharmacies:[1] their emblem is ubiquitous in many cities. This is also true in Germany, the world's fourth largest market for pharmaceuticals: In 2004, one fifth of all pharmacies were located closer than 110 metres apart from their nearest competitor.[2] But to the consumer (or patient) in need of a prescription drug, two adjacent pharmacies are in no way better than just one single pharmacy, because prescription drugs are subject to quality and price regulations. Therefore, a more dispersed spatial allocation that reduces travel costs would be preferable from a consumers' perspective. In this paper, I develop a spatial entry model to show that such a pattern has gradually emerged in Germany as a result of a regulatory change in 2004 which introduced price competition for non-prescription drugs. The topic is of current interest because the European Commission and the European Court of Justice have recently challenged the German system of fixed prices for prescription drugs. My contribution is twofold: First, I document a case where the introduction of price competition had a profound impact on the spatial market structure. Second, I develop a feasible method to estimate a dynamic spatial entry model with a large number of asymmetric agents and a very flexible notion of "space". I motivate my research with an illustrative theoretical model of space-then-price competition.

I illustrate the mechanism through which price competition affects location choices by means of a simple variant of the classical Hotelling model. In this model, retail firms typically face the trade-off between choosing a central location to attract high demand ("market share effect") and differentiating themselves from their competitors to increase their local market power ("market power effect"). The market share effect should lead to spatial clustering, while the market power effect should lead to spatial dispersion. If competition is mitigated due to price regulation, the market power effect should therefore become more dominant and lead to more clustering, and vice versa. As a result, the inter-firm distances should increase, while the consumers' average travel distances should decrease. This hypothesis will be examined for the retail pharmacy sector in Germany. Of course, the process of gradual re-locations that is at the heart of the Hotelling model cannot be observed empirically. It should rather be considered as an approximation to the dynamic process of entry and exit which forms the aggregate market patterns.

Until 2003, the German market was characterized by three distinctive institutional features:

[1]The German statistical office puts the share of revenue from e-commerce in this large retail sector below 1. (destatis, 2019, table 45341-0001)

[2]Source: Deutscher Apotheker Verlag (2016), own calculations

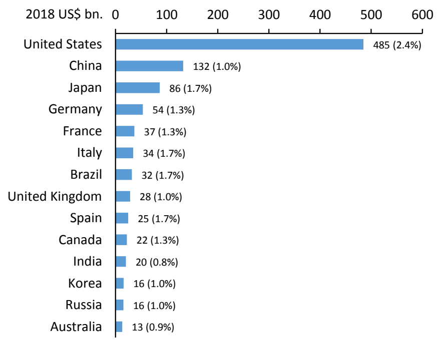


Figure 1: Spending on pharmaceutical products in 2018, by country. Share of national GDP in parentheses. Source: author's representation based on IQVIA (2019).

retail prices for prescription and non-prescription drugs alike were fixed, pharmacies were only allowed to operate as a single-store business, and no minimum distance regulations were imposed. A major health reform in 2004 changed the first two aspects: it introduced price competition for non-prescription drugs and allowed local pharmacy "chains" of up to four branches. I document that, following this reform, the number of pharmacies declined by about six percent, while the average consumer's distance to the nearest pharmacy only increased by a small amount, which suggests that the decline in the number of pharmacies was largely due to intensified competition between, and exit of, nearby or adjacent stores. In order to isolate and quantify the effect that the introduction of price competition had on pharmacies' location choices, I develop a dynamic structural model of spatial entry and fit it to the data on pharmacy locations. Using this model, I find that the period following the reform can be characterized by lower entry costs, lower period returns, and more intense competition among nearby competitors. I interpret the latter as a direct consequence of introducing price competition for non-prescription drugs and use simulations to isolate its effect on aggregate outcomes and consumer travel distances. The simulation results show that the price competition effect alone can explain one third of the observed decline in the number of pharmacies, but only one fifth of the observed increase in consumer travel distances. Therefore, the introduction of price competition contributed to a very consumer-friendly change in the spatial distribution of stores, with lower overall fixed costs and only marginally higher travel costs.

One particularly illustrative example is shown in figure 2. That figure shows the location of five pharmacies in the small town "Hagenow" with about twelve thousand inhabitants. What is striking about the picture – apart from the fact that such a small town can sustain five pharmacies – is the observation that they are all situated very close to what one may call the "city centre", an archetypical outcome of the classical Hotelling model: competitors exhibit an "undue tendency [...] to imitate each other in quality of goods, in location, and in other essential ways" (Hotelling, 1929). I show that such inefficient market outcomes have become less prevalent due the health care reform of 2003.

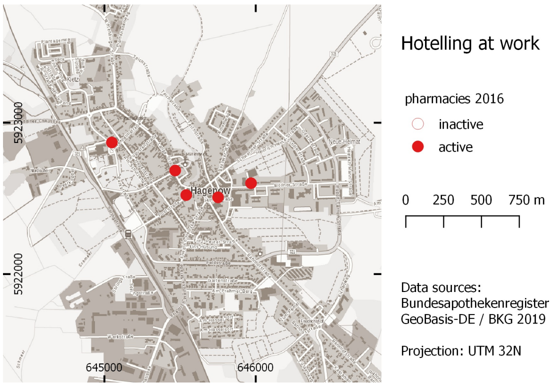


Figure 2: Hotelling at work: agglomeration of pharmacies in a small town. Source: author's own representation.

I have structured this chapter as follows. Following a description of the institutional background, the relevant literature on spatial competition and location choice is reviewed in depth, and related to my approach. Section four develops a very stylized model of space-then-price competition to motivate the research question. Section five sets up a dynamic spatial entry model, section six describes my data and section seven applies the model to the data and estimates its structural parameters. The last section concludes.

2 Institutional background

This section briefly describes the German pharmacy market and then outlines the most relevant legislations. More detailed accounts of the pharmacy market in Germany can be found in Horvath (2010) or Coenen et al. (2011).

2.1 Business structure

In order to obtain a brief overview on the market under consideration, some key figures from two years, 2005 (the earliest year for which these data are available) and 2015, are compiled in table 1. The table shows that the industry has undergone some important changes from 2005 to 2015. First, the number of stores has declined by approximately six percent. After having reached a peak of 22 thousand stores in 2005, there are currently around 20 thousand pharmacies in Germany which amounts to 25 stores per 100,000 inhabitants. More importantly, the net profit margin – that is, the overall profitability of a store relative to its generated revenues – has halved from twelve to six percent. That figure is roughly comparable to the profitability of bakery shops in that period (Destatis, 2017). The table further shows that retail pharmacies are rather small, with revenues that average around 2m Euros in 2015 and roughly ten employees per store. Pharmacies sell medicine to patients that can be classified into prescription (Rx) and non-prescription,

	2005	2015
Stores	21,968	20,639
Employees ('000)	157	210
Revenues per store ('000)	1,392	2,110
% prescriptions drugs	–	83
% from e-commerce	0.3	1.0
Number of packages sold (bn.)	–	1405
% prescriptions drugs	–	53
Gross earnings on sales per store† ('000)	402	509
% margin on revenues	29	24
Operating profits per store§ ('000)	159	125
% margin on revenues	12	6

Sources: Destatis (2017), ABDA (2016)
† revenues less wholesale cost
§ Earnings after costs, wages, taxes, rents

Table 1: Business indicators of retail pharmacies.

or over-the-counter (OTC) drugs. The table shows that prescription drugs account for the bulk of aggregate revenues, but make up only slightly more than half of the packages that were sold. The share of revenues generated online is still very small in this retail sector. However, online resellers from abroad, who are not subject to price regulation on prescription drugs[3] are pushing into the market meaning this market segment could become more important in the future.[4]

2.2 Regulatory framework

The retail pharmacy market is subject to a large body of regulations that sets standards for the operation of pharmacies. This regulatory framework consists of several separate laws which, taken together, determine who may operate a pharmacy, set standards for the establishment of one and govern the compensation schemes. The relevant regulations are summarized below.

First and foremost, the German pharmacies act (*Apothekengesetz, ApoG*) lays out the general conditions under which a pharmacy may be operated. It states that pharmacies are responsible to guarantee the "proper supply" of medication to the population. A pharmacy may only be operated by a certified pharmacist who has obtained a licence from the authorities. This licence expires if the business ceases to exist or if the operator dies. While a pharmacy may be operated jointly by more than one pharmacist (each of whom requires a licence), partnerships which make the compensation of one partner, indirectly or directly, contingent on profits or revenues, are in general not allowed. Neither may a pharmacy commit to exclusively sell the products of certain manufacturers, or strike

[3]Ruling of the European Court of Justice, Case C-148/15, retrieved from http://curia.europa.eu on 5 June 2020.

[4]On July 08, 2017, the Swiss company "Zur Rose Group AG" has collected CHF 200m with its IPO and declared that it would use the proceedings to expand its German online business. (BZ, 2017)

special deals with physicians to prescribe a certain range of products. All pharmacies are obliged to participate in a scheme which guarantees the provision of emergency services during night times or on public holidays. It is admissible for pharmacies to distribute products by post, although the numbers from Destatis (2017) suggest that this is a niche market. Since 2004, a licenced pharmacist may obtain permission to operate up to three subsidiary branches that must be in the same district as the main branch, or in an adjacent one. Each subsidiary branch must be operated by a licenced pharmacist, and fulfil all the requirements of a regular pharmacy with the exception that it need not have an own laboratory. Most importantly, the pharmacist is free to choose the location of his or her pharmacy, subject of course to residential zoning regulations but independent of the locations of other competitors.[5]

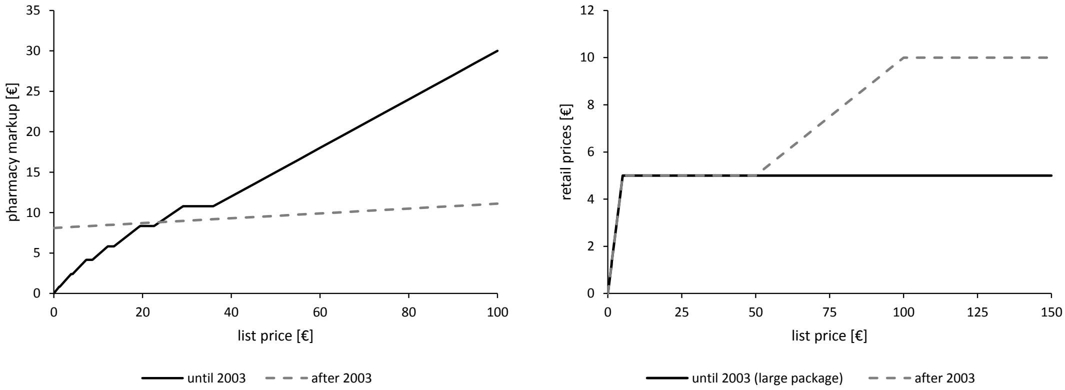
Further legislation is delegated to the ordnance on the operation of pharmacies (*Apotheken-betriebsordnung, ApoBetrO*) issued by the federal health ministry: first, the pharmacist who operates a pharmacy must do so in person, *i.e.* they cannot hire a manager to run the store. Every pharmacy must have a floorspace of at least 110 sq.m. and a laboratory that is fully equipped to produce custom medications, unless it is a subsidiary branch of another store in which case a laboratory is not mandatory. Stocks must be sufficient to cover the needs of the population for at least one "average" week, notwithstanding the obligation to always maintain further stocks of medications and vaccines for emergency purposes.[6]

In most European health insurance systems, patients pay some share of the costs of their prescribed medication out of their own funds (Panteli et al., 2016) and this is also the case in Germany. In what follows, the price that the patient sees under this cost-sharing rule will be referred to as the retail price. Usually, this retail price is a function of the list price, and it is in general the same for all members of a public health insurance. Unlike in most other retail markets, the pharmacy's variable profit per unit of prescription drug sold is not the difference between retail prices and list prices. Instead, markups are regulated directly, again as a function of the list price.[7] Figures 3a and 3b show how the implied markups and consumer retail prices as a function of list prices changed due to the reform in late 2003. The figure implies that prior to the reform, pharmacies had a strong incentive to sell expensive drugs, while consumers had no or little incentive to ask for cheap generics. The reform partially reversed this, as pharmacies now have a very small incentive to sell expensive drugs, while patients now have a stronger incentive to ask for a cheaper generic product. Until 2003, retail prices of OTC and Rx drugs were both regulated. The health care reform in late 2003 changed this: the price regulation scheme for non-prescription drugs was abandoned so that today, roughly half of all packages accounting for 15% of

[5] §§1, 3, 8, 9, 10, 11, , 11a, 14, and 18 Apothekengesetz (ApoG), retrieved from gesetze-im-internet.de/apog on 28 June 2017

[6] §§2, 4 and 15, Apothekenbetriebsordnung (ApoBetrO), retrieved from gesetze-im-internet.de/apobetro_1987 on 28 June 2017

[7] *cf.* §3 Arzneimittelpreisverordnung (AmPreisV) as of 1 January 2002 and 11 May 2019; and §§31,61 SGB V as of 1 January 2003 and 1 January 2005. Retrieved from research.wolterskluwer-online.de on 24 July 2019.



(a) Regulated markups for prescription drugs **(b)** Retail prices of prescription drugs

Figure 3: Price regulation for prescription drugs, until and after 2003. Source: own representation based on the relevant legislative texts.

total revenues are sold competitively (see table 1). On the other hand, retail prices and markups of prescription drugs remain subject to regulation.[8]

The European Commission (EC) has repeatedly called on its member states to liberalize their pharmacy markets, and was often supported in its view by the European Court of Justice (ECJ).[9] While the EC sees pharmacies as part of the retail sector and applies the rules of the common market to it, the prevailing view in some member states, manifested in their regulatory frameworks, regards pharmacies as part of the health care system where price competition should not play a role. Therefore, it is possible that the near future will see significant changes of the regulatory regimes in Europe.

To summarize, the health care reform of 2003 has changed the pharmacies' compensation scheme in Germany, it has likely changed the entry costs by permitting up to three subsidiary branches, and it has presumably increased competition among adjacent pharmacies by introducing price competition for non-prescription drugs. These considerations will guide my empirical approach.

[8] See Art. 1 (39,92,94) and 24 (1,3), GKV Modernisierungsgesetz. *Bundesgesetzblatt I*, 2003(55):2190–2258

[9] For example, the European Commission (EC) has urged members to take action in the following areas: legislation restriction the freedom of establishment in Italy, Spain and Austria (EC press release IP/06/858, ECJ ruling C-367/12); legislation restricting the number of pharmacies that may be owned in Italy (EC press release IP/06/1789); and legislation concerning the delivery of pharmaceuticals (EC press release IP/09/438). In 2016, the ECJ ruled that online pharmacies that are located in a member state of the European Union outside Germany are not obliged to comply with the German price regulation scheme for prescription drugs if they ship to Germany (ECJ ruling C 148/15). In July 2019, the EC reiterated its request for Germany to abandon its price regulation scheme (EC press release MEMO-18-3446). In response, the German cabinet has drafted a law that makes adherence to the German price regulation scheme a precondition for medical expenses to be accounted for with the German public health insurers ("Gesetz zur Stärkung der Vor-Ort-Apotheken", currently under parliamentary revision, document no. 373/19, retrieved from bundestag.de on 5 June 2020).

3 Related Literature

3.1 Theoretical literature

For a long time, economists and social scientists have discussed the question of where and how economic agents locate. Nearly two centuries ago, Johann Heinrich von Thünen provided an economic explanation for different agricultural structures around cities. Weber and Pick (1909) discussed where production facilities should optimally be located, taking into account the locations and transport costs of different inputs and keeping market conditions constant. Next Christaller (1933) developed theories on the ideal spatial constellation of cities (or "central places"), and Lösch (1940) adopted a more general equilibrium approach which predicts that economic agents will be positioned such that each unit serves a hexagonal market area giving rise to a "honeycomb pattern" of market areas. Neither of these authors has considered the problem of price competition. A review of these classical approaches can be found in Kulke (2013) and Fischer (2011). An interesting extension to the works of Lösch and Christaller is Rushton (1972) who computes optimal market structures under non-uniform consumer distributions using a numerical approach. This leads to skewed point patterns, while the original hexagonal structure is still visible.

Taking into account that firms choose their locations strategically, and also compete on attributes other than their location complicates the analysis. Hotelling (1929) was the first to point out that profit maximizing competitive firms may choose to agglomerate, thus inflicting inefficiently high travel costs on the consumer side. He applies his finding to the political economy sphere:

> The competition for votes between the Republican and Democratic parties does not lead to a clear drawing of issues, an adoption of two strongly contrasted positions between which the voter may choose. Instead, each party strives to make its platform as much like the other's as possible. (Hotelling, 1929, p. 54)

Of course, there is no price competition in politics so what may be true for political parties must not necessarily hold for competitive firms. This was already apparent to Hotelling who noted that "Bertrand's objection applies" as soon as both competitors are in the same place (p. 52). An early extension of his work is Smithies (1941) who introduced elastic aggregate demand, thus disposing of the zero-sum nature of the original set up. Smithies finds that minimal differentiation is not a necessary outcome under this assumption. This finding has been confirmed by d'Aspremont et al. (1979) who even show that Hotelling's model with linear transport costs does not have an equilibrium at all, and, by assuming quadratic transport costs, derives a contrary outcome: that firms will optimally tend to locate at both extremes of the market. From there onwards, quadratic transportation costs have become a standard in the theoretical literature. For instance, Bester et al. (1996) is an in-depths game theoretic analysis of the location-then-prices model with quadratic transportation costs and deterministic consumers and Anderson et al. (1997) derive conditions for general, non-uniform population distributions under which an equilibrium exists.

The difficulties with establishing an equilibrium outcome are closely linked to firms' incentive to undercut each others' prices when both firms are located at the same point and perfect competition causes consumers to purchase the cheapest product (adjusted for travel costs) in a deterministic way. Thus, as soon as consumers are assumed to posses preferences over attributes other than the delivery price, price competition is softened and this problem can be expected to be alleviated. The first to note this were de Palma et al. (1985) who modelled consumer demand for two spatially differentiated firms by using the discrete choice framework that has now become standard in the literature on empirical industrial organization. Consumers care about travel costs and prices, but also posses idiosyncratic preference shocks over visiting different stores, and firms are assumed to sell their products at a given price. As a consequence, consumers may now purchase from a store that offers a higher travel cost adjusted retail price because this store appeals to the consumer in some other, unknown dimension. It will now be worthwhile for both firms to locate at the centre, because consumer heterogeneity "eliminates discontinuities in the profit function" (p. 771) so that any deviation from the market centre leads to lower demand. A similar conclusion is reached by Ben-Akiva et al. (1989) who introduce price competition and a second dimension along which products are differentiated, but which the firms do not choose strategically. This set up achieves the same effect in that it eliminates the incentive to undercut and thus makes the agglomeration a feasible equilibrium. Finally, (Anderson et al., 1992, p.343–392) combine logit demand, price competition and location choices along the real line. They show analytically that the location-then-prices game has a centralized equilibrium if consumers are sufficiently heterogeneous. They also solved their game numerically with two firms and locations on the real line, yielding both symmetric non-central equilibria and agglomeration as the outcome. They do not derive de-centralized equilibrium locations analytically.

The literature in the previous paragraph modelled space as a unidimensional line for the sake of analytic simplicity. Yet, most spatial patterns observed in the real world are two-dimensional. Eaton and Lipsey (1975) were the first to take spatial competition to the two-dimensional space, by simulating the movements of up to seventeen firms that sequentially re-locate so as to maximize their market shares *while keeping prices fixed.* They find that the honeycomb pattern of Lösch quickly breaks up and thus the authors "strongly suspect, but as yet cannot prove, the non-existence of any equilibrium configurations in the disc beyond $n = 2$" (Eaton and Lipsey, 1975, p. 44). Irmen and Thisse (1998) consider the case with quadratic transport costs and deterministic consumers who care about multiple product characteristics. Their finding is that firms will, in equilibrium, choose maximum differentiation in the dimension which consumers care about most, and minimum differentiation in the other dimensions. A similar result appears to have been simultaneously derived by Ansari et al. (1998) for the case of three product attributes. A more recent attempt to characterize equilibrium locations in a competitive environment is worked out by the four computer scientists Ottino-Loffler et al. (2017) who follow the approach of Eaton and Lipsey (1975) and find stable spatial patterns with up to seven firms, using deterministic consumers who care about travel costs. Yet, their pricing stage is not modelled explicitly and they employ a rather coarse grid such that their results should be considered with some caution. In a theoretical paper, Vogel (2008) studies location-then-price equilibria on the unit circle and finds that more productive firms locate in more isolated areas. Yet, his main contribution is a mathematical trick that establishes equilibrium existence in such a game despite using linear transportation costs. In a more recent paper, Allen and Arkolakis (2014) derive the existence of spatial equilibria in a general equilibrium setting. A continuum of consumers (who are also workers) equipped with CES preferences is distributed across a compact two-dimensional space. Each consumer also produces exactly one unit of the output good, and bilateral trade is then governed by a gravity equation. A spatial equilibrium is a distribution of consumers/workers such that their incomes equal their expenditures, and there are no profitable relocations. Finally, a recent review article by Biscaia and Mota (2013) reiterates that research on location-then-price competition in the two-dimensional plane is still not so abundant.

Specifically concerned with price regulation in the health care sector are theoretical papers by Brekke et al. (2011, 2006). Both add a quality dimension to firms' decision space letting firms effectively compete on locations and on quality. The theoretical paper (Brekke et al., 2006) is cast in a Hotelling duopoly environment with a linear choice of location and quality-specific investment. Representative consumers have a linear utility function and care about the price, quadratic transportation costs and quality of the service. The basic insight of their model is that, while price regulation leads to an agglomeration of firms, quality competition counteracts this force, leading to more spatial differentiation. A regulator who cares for social welfare would attempt to choose a price so as to maximize welfare, taking into account the subsequent quality and location decisions of firms. If location decisions are exogenous, the optimal quality level can be attained whereas if both location and quality choices are exogenous, the second best outcome would either entail too much spatial differentiation and too low quality or vice versa. In Brekke et al. (2011), the relation between quality choice and competition is examined theoretically, but the total number of hospitals and their location is taken as given.

3.2 Empirical literature

For the empirical analysis of spatial competition, it is necessary to model both consumers' spatial demand, and firms' location choices. Modelling spatial demand empirically does not pose substantial challenges. The standard ARUM model of consumer utility over spatially differentiated alternatives with random coefficients and logit choice probabilities can be found in papers such as Davis (2006), Ho and Ishii (2011), Crawford (2012) and the references therein and Aguirregabiria and Vicentini (2016). Most of the insights from Berry (1994) can be readily applied to the spatial context, using a distance function that enters a consumer's utility function. Further works who use this framework are Chisholm and Norman (2012) and Davis (2006) who examine the market for cinemas and Ho and Ishii (2011) who study retail banking.

It is far more difficult to model location choice in a tractable, yet plausible and flexible way. Some implications of the theoretical literature on multi-attribute competition in a spatial context have been tested empirically by Netz and Taylor (2002) who find evidence that gasoline stations respond to tougher competition with more spatial differentiation. Further, Thomadsen (2007) uses a structural pricing model to derive demand parameters and builds on (Anderson et al., 1992, p.343-392) to examine the optimal location decisions under different cost structures. Yet, his counter-factual simulations are restricted to spatial competition along one dimension. Contrary to the theoretical literature, empirical models of the supply side often assume that firms choose to enter in a discrete set of locations and derive equilibria under incomplete information. This approach was pioneered by Seim (2006) who uses relatively few locations and a reduced form profit function.

A few studies exist that are dedicated to competition in the retail pharmacy market. Horvath (2010) analyses the nexus of price regulation and quality and spatial competition on the German pharmacy market. However, he reviews models of quality and circular spatial competition and free entry which are less suited to study location choices because firms will usually locate at equidistant locations around the circle. His empirical results are based on rather coarse county-level data. Hence, an important extension of this work is to model spatial entry in a more detailed fashion, and to link it more tightly to detailed data sources. A related study published by Coenen et al. (2011) also features a very detailed institutional description of the pharmacy market in Germany. In a scenario-based approach, they compare different reform options with regard to their cost saving potential. The competitive reactions of firms in the market are not endogenously determined in their approach. In both aforementioned studies, the focus seems to be more on the equilibrium number of pharmacies rather than on their location choices. Similarly, Schaumans and Verboven (2008) set up a model of joint entry by physicians and pharmacies in small local markets but again, the focus is on entry and exit as opposed to the small-scale geographical distribution of economic units.

3.3 Dynamic empirical literature

The empirical approach that this paper presents relies on a dynamic entry game with a large number of players. These players interact with each other the more intensely, the closer they are together, but in principle, every agent interacts with every other agent. In solving dynamic discrete games with many players such as the one described below, a direct solution of the game becomes infeasible even for moderately-sized problems. The crucial point here is that the size of the state space grows exponentially in the number of players, which poses computational problems for two principal reasons: first, the large amount of computer storage required to store the entire value function, and second, the computational burden associated with computing an expectation over the future state space. The state space of the game presented above is of magnitude 2^N and so will be usually too large to estimate the full model using conventional methods – a typical city in Germany has around eighty pharmacies, and it is often not desirable to delineate ad hoc market boundaries.[10] The literature on dynamic discrete games has put forward a few approaches to modify the problem in such a way to be able to solve it, or at least to be able to estimate its key parameters. These approaches will be discussed in turn.

A first branch of the literature has evolved around the so-called two-step estimators that were initially proposed by Hotz and Miller (1993) and later refined by Aguirregabiria and Mira (2002) for single agent decision processes. Two-step (or k-step) estimators rely on obtaining non-parametric estimates of either the policy function, or the continuation values in a first stage, which are then used to compute the players' best responses and a likelihood function in a second stage. These ideas have been applied to games with many players by Aguirregabiria and Mira (2007) who use estimates of the conditional choice probabilities, and by Pakes et al. (2007) who estimate continuation values in a first step. Bajari et al. (2007) extend these methods to allow for continuous choice variables. A recent addition to this literature is proposed by Aguirregabiria and Magesan (2019) who study dynamic entry when players' beliefs are not in equilibrium. Their approach also relies on obtaining non-parametric choice probabilities in a first stage. But while being computationally efficient and elegant, two-step estimators are unfortunately not applicable to my setting, for the following reasons. First, the size of the state space which is much larger than the number of observed decisions obviously prevents a direct application of the concept. Second, the nature of spatial competition is not symmetric: in a certain state of the world, one firm may face a lot more local competition than another firm and so their policy choices, or their strategies, would be very different. And even if one conditions on the local environment of each firm, certain configurations of their nearest competitors mean very different things to different firms due to differences in their relative spatial constellation to each other. Thus, in a spatial entry game, the asymmetry of players' strategies prevents a direct application of these two-step estimators.

The asymmetry of the problem at hand instead calls for a nested fixed point estimator where each firm solves a distinct dynamic problem and therefore has its own policy function. To alleviate the computational burden associated with solving such a dynamic discrete model, several approaches have been put forward that will be reviewed first, followed by a

[10] To get an idea of the magnitudes, $2^{80} \approx 10^{24}$ so even storing the value function infeasible.

description of the approach followed in this paper.

First, Doraszelski and Judd (2012) set up a dynamic model in continuous time which significantly reduces the computational burden of calculating the expected future state. The expectation is easier to compute because it becomes increasingly unlikely that more than one player makes a move, as the time periods become shorter and eventually approach a continuum. Therefore, at each point in time there are only as many possible future states as there are players in the game. However, an empirical application of this setting requires that the precise timing of all entry and exit decisions be known, which is not the case in the data at hand.

Pakes and McGuire (2001) propose a stochastic algorithm to compute an approximation to the MPE. The algorithm relies on the fact that in many cases, the Markov chains that are induced by dynamic discrete games have a very large state space, but eventually wander into a smaller set of states that is known as the recurrent class. Their algorithm draws a new state in every iteration according to the current policy function, and updates the current state's continuation value with the new state's value. It reduces the number of states that are visited, and the computational burden associated with computing the expectation over future states, but adds a simulation error to the problem so that more iterations are necessary for the problem to converge. Their ideas cannot readily be applied to the setting at hand, mainly because the sampling procedure is not guaranteed to sample uniformly from the recurrent class of the game. The recurrent class of many dynamic discrete games encompasses the entire state space because the transition cost shock has, by assumption, full support, so that "anything goes" (albeit it may do so with very low probability). However, even if the MPE is unique, the transition dynamics in some games are likely to imply that the recurrent class is partitioned into a number of sub-classes which are almost recurrent in themselves. Once the Markov Chain that is induced by equilibrium play has wandered into one of these subclasses it is likely to remain there (although it is not certain that it does so). To make this point clearer, consider a dynamic entry model in which an even number of firms is located on a circle, and let the parameters be such that having two active direct nearest neighbours leads to negative (or very small) period returns, while the presence of an active indirect neighbour does not affect profits. If the market entry costs are chosen sufficiently large, it becomes equally likely that only firms with even numbers are active, or only firms with odd numbers. Small permutations of these configurations may arise, but it will be very unlikely to see a complete reversal of fortunes. Therefore, an unguided sampling procedure similar to the one described by Pakes and McGuire (2001) is likely to miss a large part of the state space that may be equally likely to occur as the one that was sampled, and so the procedure is not well suited for the empirical application at hand.

A different approach is taken by Weintraub et al. (2008, 2010) who develop an equilibrium concept in an entry game with quality investment that they call *oblivious equilibrium*, wherein individual firms condition their actions only on their own state and on the long-run average aggregate industry state. This aggregate industry state can be assumed to remain approximately constant over time if the number of firms and potential entrants is large so that individual decisions are averaged out. A requirement for being able to condition the decision process is that the period returns of each firm depend only on its own state, and on an aggregate state because all competitors are the same. Thus, the oblivious equilibrium is easier to compute because it greatly reduces the dimensionality of the problem. But in a spatial context, not all competitors are the same and it is difficult to reduce the spatial distribution of firms to an aggregate statistic with low dimensionality so that the concept of oblivious equilibrium is not readily applicable. Furthermore, the separation of the state space into an aggregate industry state that remains constant, and an individual state, effectively restricts the permissible state space very strongly. In my empirical spatial entry model, I will adapt and extend the oblivious equilibrium concept of Weintraub et al. to the spatial domain in order to address the aforementioned concerns. This extension of the oblivious equilibrium concept constitutes the main methodological contribution of this paper.

3.4 Contribution

This paper extends the literature on empirical dynamic entry models to incorporate a large number of heterogeneous, spatially interacting players without having to resort to simplifying symmetry considerations. I extend the ideas put forward in the concept of an oblivious equilibrium to develop a heuristic approach that reduces the dimensionality of the problem, and yet maintains the spatial and dynamic features of the model. As an empirical contribution, this paper presents evidence that the introduction of price competition in a retail market has profound effects on the spatial equilibrium distribution of retail firms' locations.

4 A stylized model

To illustrate the characteristic mechanisms and trade-offs of the market under consideration, and to motivate my research, I first set up a very simple modified Hotelling model of space-then-price competition on the real line. The analysis is related to the work of Brekke et al. (2006) who consider quality competition and location choices of hospitals.

Consider the case of two pharmacies competing on prices and locations: first, both pharmacies choose their location and next, taking location choices as given, they compete on prices. Denote the location of both stores by x_a and x_b and assume that admissible locations are restricted to the unit interval $[0, 1]$, and that $x_a \leq x_b$. Pharmacies sell prescription drugs (Rx) at a regulated price $\bar{r} = 0$ and non-prescription drugs (OTC) at price p_j, $j \in \{a, b\}$. To reflect the institutional characteristics of the retail pharmacy market, I assume that both pharmacies earn a regulated margin on each sold unit of a prescription drug. For simplicity, the regulated margin on prescription drugs is assumed to be equal to one. The marginal costs of non-prescription drugs are assumed to be zero, so that the margin on each unit of non-prescription drugs that is sold is equal to its retail price p_j. Hence, pharmacies' profits are given by

$$\pi_j = Q_j^{Rx} + p_j Q_j^{OTC}$$

where Q_j^{Rx} and Q_j^{OTC} are the demands for prescription and non-prescription drugs, respectively. A unit mass of consumers is distributed uniformly on this unit interval and indexed by their location $i \in [0, 1]$. Consumers incur quadratic travel costs and there is no outside option so that one consumer certainly purchases a product from one of the competitors. Each consumer purchases either a prescription drug or a non-prescription drug, but not both, from one of the stores. With probability α, the consumer purchases a prescription drug at the regulated price $\bar{r} = 0$. Her (normalized) utility from obtaining the drug at store j is

$$\nu_{ij} = -(i - x_j)^2$$

Therefore, consumers will always obtain their prescription drugs from the nearest pharmacy. On the other hand, a consumer purchases a non-prescription drug with probability $1 - \alpha$. Her utility when purchasing it from pharmacy j is given by

$$u_{ij} = -p_j - \tau(i - x_j)^2$$

I assume that $0 < \tau < 1$, as consumers purchase a prescription drug because they are seriously ill so they should have higher travel costs than those who are not. Since d'Aspremont et al. (1979) have shown that quadratic travel costs are sufficient to guarantee equilibrium existence, this has become a standard in the literature, and I abide by it.

4.1 Equilibrium

As a benchmark, consider first the trivial case were prices of non-prescription drugs are also regulated, so that $p_a = p_b = \bar{p}$, but firms choose their locations freely. This is the classical Hotelling model in which both firms tend to locate at the market centre so as to maximize their market shares, that is $x_a = x_b = 1/2$.

Next, I investigate whether the introduction of price competition for non-prescription drugs can lead to a market outcome that is preferable from a consumer's perspective. I focus on symmetric equilibria. The following proposition characterizes a symmetric space-then-price equilibrium of the model:

Proposition 1. *A symmetric space-then-price equilibrium of the model is given by location* *choices* $x_a = x^*$ *and* $x_b = 1 - x^*$ *with*

$$x^* = \begin{cases} 0 & \text{if } \alpha \leq \frac{\tau}{3+\tau}, \\ -\frac{1}{4} + \frac{3}{4}\frac{\alpha}{\tau(1-\alpha)} & \text{if } \frac{\tau}{3+\tau} < \alpha < \frac{\tau}{1+\tau}, \\ \frac{1}{2} & \text{if } \alpha \geq \frac{\tau}{1+\tau}, \end{cases} \tag{1}$$

and prices $p_a = p_b = p^*$ *with*

$$p^* = \begin{cases} \tau & \text{if } \alpha \leq \frac{\tau}{3+\tau}, \\ \frac{3}{2}\left(\tau - \frac{\alpha}{1-\alpha}\right) & \text{if } \frac{\tau}{3+\tau} < \alpha < \frac{\tau}{1+\tau}, \\ 0 & \text{if } \alpha \geq \frac{\tau}{1+\tau}. \end{cases} \tag{2}$$

The proof is standard, and it is given in appendix A for completeness. This result encompasses two interesting polar cases: first, when the share of consumers purchasing price regulated prescription drugs, α, is equal to one, the locational equilibrium sees both firms located at the market centre – this is Hotelling's minimal differentiation result. Second, if pharmacies sell only non-prescription drugs ($\alpha = 0$), the market power effect dominates and both firms are located at the market boundaries. This corresponds to the principle of maximum differentiation of d'Aspremont et al. (1979). This result is interesting because it shows that the introduction of price competition for non-prescription drugs does not necessarily lead to an increase in spatial differentiation, as the centralized equilibrium may prevail for a large range of parameters. Whether this happens or not will depend crucially on local market circumstances that affect consumers' relative and absolute travel costs, and on the share of either consumer type.

4.2 Welfare analysis

Next, I compute consumer welfare and producer surplus in the competitive market, and compare these to the outcomes under complete price regulation, and to the social optimum. Throughout, I will assume that pharmacies can freely choose their location. Note first that the consumers' aggregate travel costs in any given symmetric locational equilibrium $x \in [0, 1/2]$, with $x_a = x$ and $x_b = 1 - x$, are given by $\tau T(x)$, where

$$T(x) = 2\int_0^{\frac{1}{2}} (i - x)^2 \mathrm{d}i = \frac{1}{12} - \frac{1}{2}x + x^2$$

Then, consumer welfare with retail prices of non-prescription drugs p and regulated prescription prices $\bar{r} = 0$ is

$$W(x, p) = -(1 - \alpha)p - (\alpha + (1 - \alpha)\tau)T(x)$$

and equilibrium profits are always given by $\pi^* = \frac{1}{2}(\alpha + (1-\alpha)p^*)$.

Price regulation Consider first the case where both prescription and non-prescription drugs are regulated at prices $\bar{r} = 0$ and $\bar{p} \geq 0$, respectively, but firms can choose their locations freely. This case will be denoted as the regulatory benchmark in the discussion that follows. As was discussed above, the absence of price competition induces firms to locate at the market centre, and consumer welfare in this setting is given by

$$W\left(\tfrac{1}{2}, \bar{p}\right) = (1-\alpha)\bar{p} - \frac{(\alpha + (1-\alpha)\tau)}{12}$$

As is well known, the tendency of the two firms to bunch together at the market centre inflicts an inefficiently large amount of travel costs on consumers. The welfare maximizing location pattern would be the one that minimizes travel costs, with $x_a = \frac{1}{4}$ and $x_b = \frac{3}{4}$. Aggregate profits remain the same, but consumer welfare would increase to

$$W\left(\tfrac{1}{4}, \bar{p}\right) = -(1-\alpha)\bar{p} - \frac{(\alpha + (1-\alpha)\tau)}{48}$$

In fact, it is easy to see that any symmetric location pattern with $x_a \in (0, \frac{1}{2})$ and $x_b = 1 - x_a$ improves welfare compared to the laissez-faire case. Hence, a social planner could improve welfare by imposing a minimum distance regulation, but of course such a regulation could induce adverse effects that are not captured by this simple model: by effectively creating local monopolies, pharmacies have less incentives to invest in quality, or to expand opening hours – Brekke et al. (2006) discuss such aspects of quality competition in the context of hospital regulation in much greater detail.

Price competition Next, consider the case where pharmacies choose their locations first and then compete on prices for non-prescription drugs. For any given symmetric locational equilibrium $x^* \in [0, \frac{1}{2}]$ retail prices are given by $p^* = \tau(1 - 2x^*)$ where x^* is itself a function of α and τ. I am interested in conditions on α, τ, and $\bar{p}$ under which consumers' welfare in the location-then-prices equilibrium is larger than in the regulatory benchmark, *i.e.* when $W(x^*, p^*) \geq W(\frac{1}{2}, \bar{p})$. The change in welfare in the competitive equilibrium relative to the regulatory benchmark is given by

$$\Delta W(\bar{p}) = W(x^*, p^*) - W(\tfrac{1}{2}, \bar{p}) \tag{3}$$

where both x^* and p^* depend on parameters α, τ, and $\bar{p}$.

Welfare comparison To compare consumer welfare in both scenarios, I first consider the case where the non-prescription price in the regulatory benchmark is set to marginal costs (which are zero), $\bar{p} = 0$, so that prices must weakly *increase* under competition relative to the regulatory benchmark. Under this condition, I show that consumer welfare in the competitive equilibrium is weakly *smaller* than under the regulatory regime. Then I consider the case where the non-prescription price in the regulatory benchmark is initially larger than marginal costs. I argue that this opens up the possibility that consumer welfare is larger in the competitive equilibrium with free location choices.

The following proposition shows that consumer welfare in the competitive equilibrium is weakly smaller than in the regulatory benchmark if prices are initially regulated at marginal costs, which are zero:

Proposition 2. *Suppose that the regulated price of non-prescription drugs, $\bar{p}$, was initially zero. Then:*

1. *if α and τ are such that $x^* = \frac{1}{2}$, consumer welfare is the same in the competitive equilibrium as in the regulatory benchmark ($\Delta W(0) = 0$);*
2. *if α and τ are such that $x^* < \frac{1}{2}$, (a) the difference of consumer welfare in the competitive equilibrium relative to the regulatory benchmark increases strictly in the share of prescription consumers ($\frac{\mathrm{d}}{\mathrm{d}\alpha}\Delta W(0) > 0$), and it decreases strictly in the travel costs of non-prescription consumers ($\frac{\mathrm{d}}{\mathrm{d}\tau}\Delta W(0) < 0$); and (b) consumer welfare is smaller in the competitive equilibrium ($\Delta W(0) < 0$).*

The proof is delegated to appendix A. Now consider the case where the initial regulated price of the non-prescription drug, $\bar{p}$, was larger than zero. This leads to the possibility that consumer welfare in the competitive equilibrium is strictly larger than under the regulatory benchmark for a range of parameter values. To see this, note that price competition in the competitive location-then-prices equilibrium will drive down the price of the non-prescription drug to zero in such parameter constellations where firms choose to locate at the market centre. Under those parameter constellations, consumer welfare will therefore be larger in the competitive equilibrium than under the regulatory benchmark, as travel costs are the same, but non-prescription prices are lower. Now note that the difference between consumer welfare under the competitive equilibrium and consumer welfare under the regulatory benchmark at a non-prescription regulated price $\bar{p}$ is $\Delta W(\bar{p}) = \Delta W(0) + (1-\alpha)\bar{p}$. By the above proposition, there are parameter constellations for which x^* is smaller than, but sufficiently close to $\frac{1}{2}$ so that $\Delta W(0)$ is large enough to obtain $\Delta W(\bar{p}) > 0$. This result is illustrated in figure 4 which shows the sets of α and τ, at which consumer welfare in the competitive location-then-prices equilibrium is equal to consumer welfare with regulated prices and free location choice, for different values of the regulated price $\bar{p}$. That figure confirms that welfare is strictly larger in the competitive equilibrium for a large range of parameter values if the regulated non-prescription price $\bar{p}$ is larger than zero. This insight is summarized in the following corollary:

Corollary. *If the regulated price of prescription drugs was initially larger than zero, and the share of prescription consumers α is less than one, consumer welfare in the competitive*

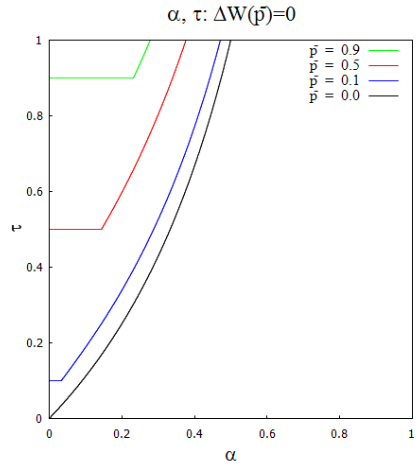


Figure 4: Sets of α and τ, at which consumer welfare in the competitive location-then-prices equilibrium is equal to consumer welfare with regulated prices and free location choice, for different values of the regulated price $\bar{p}$. Consumer welfare in the competitive equilibrium is (weakly) larger than under the regulatory benchmark to the south east of the curves.

equilibrium is strictly larger than in the regulatory benchmark, provided that the share of prescription consumers is sufficiently large, and the travel costs of non prescription consumers are sufficiently small.

The theoretical analysis in this section is very stylized because it abstracts from entry and exit, assumes firm locations along a univariate line, and leaves the question open how the economy will transition from the regulatory to the competitive equilibrium. Still, this simple model serves to illustrate the fact that the introduction of price competition, apart from its impact on prices, can induce firms to enter in different locations so as to better serve the consumer. The model also illustrates that this re-location is not guaranteed to be beneficial for consumers: firms differentiate themselves in space because it increases their local market power, so they can raise their prices. Thus, in order to generate consumer welfare gains, the prices of non-prescription drugs must have been rather high initially, so that competitive prices decrease relative to the regulatory benchmark.

5 Empirical Model

This section develops a spatial dynamic entry model of pharmacy competition that will be fitted to data on retail pharmacy locations. It is designed to describe the process of entry and exit by which the spatial distribution of retail locations gradually responds to a regulatory change that introduced price competition for non-prescription drugs. I first outline a general framework of dynamic spatial entry that suffers from the curse of dimensionality. Then, I develop a new, computationally tractable approach to model the spatial entry dynamics in a large market. Finally, I describe how the model's structural parameters can be estimated. Importantly, I do not rely on symmetry or anonymity to ease the computational burden of the model.

The focus of this paper is on the spatial structure of the German pharmacy market, and how it reacts to regulatory changes, so one may ask why a dynamic model component is needed. The answer is twofold: first, the data on pharmacy locations spans a large time period of sixteen years, which makes it necessary to include a notion of time in the analysis. But more importantly, what is observed in these data are entry and exit decisions and such decisions are invariably dynamic in nature. Any decision maker who decides whether to set up a pharmacy, or whether to close it, will necessarily try to make some educated guess about the future, and most importantly, about the decisions of his current or future competitors. The interplay of these considerations is what drives the spatial industry structure over time. Therefore, a model needs to include both a spatial and a dynamic aspect. A more detailed argument is given in section 5.4.1.

5.1 Dynamic entry decisions

The economy consists of N firms (or potential entrants) indexed by j, which are located at a fixed location x_j. In each discrete time period t, each of these firms can either be active or inactive, indicated by $a_{jt} \in \{0, 1\}$. Let $\mathbf{a}_t = (a_{jt})_{j \in N}$ be called the state of the economy at time t, and denote the entire state space as $A = \{0, 1\}^N$. The usual notation is adopted where $\mathbf{a}_{-jt} = (a_{it})_{i \neq j}$ denotes the states of all firms but firm j. Sometimes, the tuple $(a_{jt}, \mathbf{a}_{-jt})$ is used as an alternative way of writing the aggregate state $\mathbf{a}_{jt}$. Each firm earns a period return $\pi_j(\mathbf{a}_t)$ when the aggregate state of the economy is $\mathbf{a}_t$, and it is assumed that $\pi_j(\mathbf{a}_t) = 0$ if $a_{jt} = 0$. The timing is as follows: at the beginning of every period t, every firm earns its period return $\pi_j(\mathbf{a}_t)$, and all firms learn the realization of a private information idiosyncratic random variable ξ_{jt} that follows a distribution function F with full support over $\mathbb{R}$. Upon learning this value, each potential entrant decides whether it should enter the market in period $t + 1$ and incur an entry cost of $\theta^x + \xi_{jt}$. Similarly, every incumbent decides whether it should stay in the market, or leave the market in which case it receives a sell-off value $\theta^e + \xi_{jt}$. The introduction of privately known transition costs ξ_{jt} is a common assumption in the literature on dynamic discrete games because it guarantees equilibrium existence, see e.g. Seim (2006), Doraszelski and Satterthwaite (2010), or Aguirregabiria and Magesan (2019). I do allow for re-entry because it is observed in the data. In the empirical application, it will be assumed that there are M independent large markets indexed by $m = 1, \ldots, M$, and T observed periods indexed by t, but the market subscripts will often be omitted for convenience.

The solution concept employed here is a Markov Perfect Equilibrium (MPE) where all players base their decisions solely on the current state of the economy (including their own activity status) and on a privately known disturbance to their transition costs. Let the strategy of firm j be denoted by

$$\sigma_j : (a_{jt}, \mathbf{a}_{-jt}, \xi_{jt}) \mapsto a_{jt+1} \in \{0,1\} \tag{4}$$

and collect all strategies into $\sigma = (\sigma_j)_{j=1}^N$. Note that the behaviour of firm j is deterministic conditional on its latent variable ξ_{jt}, but stochastic from the point of view of its competitors.[11] From the perspective of another firm k, and of the econometrician, the probability that firm j chooses to be active in period $t+1$ is given by $q_j(\mathbf{a}_t) = \int \sigma_j(a_{jt}, \mathbf{a}_{-jt}, \xi)\mathrm{d}F(\xi)$. Taking the strategies of their competitors and the realization of the transition cost shock as given, each firm j decides whether to be active or not in the next period. Let the value function $V_j^\sigma(a_{jt}, \mathbf{a}_{-jt}, \xi_{jt})$ denote the expected discounted future profits of firm j when the state is $(a_{jt}, \mathbf{a}_{-jt})$ and the transition cost shock is ξ_{jt}. The value function is given by

$$\begin{aligned} V_j^\sigma(a_{jt}, \mathbf{a}_{-jt}, \xi_{jt}) = \pi_j(\mathbf{a}_t) + \max \Big\{ & a_{jt}\left(\theta^x + \xi_{jt}\right) + \beta\mathbb{E}[V_j^\sigma(0, \mathbf{a}_{-jt+1}, \xi_{jt+1})|\mathbf{a}_t], \\ & -\left(1 - a_{jt}\right)\left(\theta^e + \xi_{jt}\right) + \beta\mathbb{E}[V_j^\sigma(1, \mathbf{a}_{-jt+1}, \xi_{jt+1})|\mathbf{a}_t] \Big\} \end{aligned} \tag{5}$$

The expectation operator integrates over the distribution of all future states that is induced by σ, and over the future idiosyncratic shocks ξ. Since there is a one-to-one mapping from players' actions to states (unlike in many dynamic investment games, where idiosyncratic and market-specific shocks affect the success of an investment), this amounts to integrating over all conceivable actions of firm j's competitors, taking their strategies as given. The σ-superscript was added to clarify this dependence on the other firms' strategies.

To write this problem in a more compact form, I will follow Aguirregabiria and Vicentini (2016) and integrate out the idiosyncratic error term ξ_{jt}: first, let

$$\overline{V}_j^\sigma(a_{jt}, \mathbf{a}_{-jt}) = \int V_j^\sigma(a_{jt}, \mathbf{a}_{-jt}, x)\mathrm{d}F(x) \tag{6}$$

be the integrated value function of firm j. Sometimes I will write $\overline{V}_j^\sigma(\mathbf{a}_t)$ as a shorthand. Further, let the choice-specific integrated value function

$$v_j^\sigma(1, \mathbf{a}_t) = \pi_j(\mathbf{a}_t) - (1 - a_{jt})\theta^e + \beta\mathbb{E}^\sigma\left[\overline{V}_j^\sigma(1, \mathbf{a}_{-jt+1})|\mathbf{a}_t\right] \tag{7}$$

denote the expected value of choosing to be active in the next period, and let

$$v_j^\sigma(0, \mathbf{a}_t) = \pi_j(\mathbf{a}_t) + a_{jt}\theta^x + \beta\mathbb{E}^\sigma\left[\overline{V}_j^\sigma(0, \mathbf{a}_{-jt+1})|\mathbf{a}_t\right] \tag{8}$$

denote the expected value of choosing to be inactive in the next period, where the current

[11] Or, as Doraszelski and Satterthwaite (2010, p.216) put it: "Although a firm formally follows a pure strategy in making its entry/exit decision, the dependence of its entry/exit decision on its randomly drawn, privately known setup cost/scrap value implies that its rivals perceive the firm as though it were following a mixed strategy."

activity status $a_{jt} \in \{0,1\}$ governs whether the firm incurs any transition costs or period returns.[12] Then, the value function can be written more compactly as

$$V_j^\sigma(a_{jt}, \mathbf{a}_{-jt}, \xi_{jt}) = \max\left\{a_{jt}\xi_{jt} + v_j^\sigma(0, \mathbf{a}_t), -(1-a_{jt})\xi_{jt} + v_j^\sigma(1, \mathbf{a}_t)\right\} \tag{9}$$

and the integrated value function is

$$\overline{V}_j^\sigma(a_{jt}, \mathbf{a}_{-jt}) = \int \max\left\{a_{jt}x + v_j^\sigma(0, \mathbf{a}_t), -(1-a_{jt})x + v_j^\sigma(1, \mathbf{a}_t)\right\} \mathrm{d}F(x) \tag{10}$$

Given strategies σ and conditional on its own transition cost shock ξ_{jt}, firm j decides to be active in the next period if the second part of the above equation (9) is greater than the first, i.e. if

$$\begin{aligned} -(1-a_{jt})\xi_{jt} + v_j^\sigma(1, \mathbf{a}_t) &\geq a_{jt}\xi_{jt} + v_j^\sigma(0, \mathbf{a}_t) \\ &\Leftrightarrow \xi_{jt} \leq v_j^\sigma(1, \mathbf{a}_t) - v_j^\sigma(0, \mathbf{a}_t) \end{aligned}$$

The above equation implicitly defines cutoff values which govern each firm's behaviour conditional on its observed private information shocks. The probability of being active next period can then conveniently be expressed as

$$\Pr(a_{jt+1} = 1|\mathbf{a}_t) = F\left(v_j^\sigma(1, \mathbf{a}_t) - v_j^\sigma(0, \mathbf{a}_t)\right) =: q_j(\mathbf{a}_t) \tag{11}$$

where F is the distribution function of the latent errors ξ. Define $\mathbf{q}(\mathbf{a}_t) \equiv \{q_j(\mathbf{a}_t)\}_{j=1}^N$. These conditional choice probabilities (CCPs) are a best response probability to other firms following the strategy σ in state $\mathbf{a}_t$, and they "contain all the information about competitors' strategies that a firm needs to construct its best response" (Aguirregabiria and Vicentini, 2016, p.726). The reason is that the value functions depend on the strategy only through the CCPs that feed into the expectation operator $\mathbb{E}^\sigma$:

$$\begin{aligned} &\mathbb{E}^\sigma\left[\overline{V}_j(a_{jt+1}, \mathbf{a}_{-jt+1})|a_{jt+1}, \mathbf{a}_t\right] = \\ &\underbrace{\sum_{\mathbf{a}_{-jt+1}\in\{0,1\}^{N-1}} \overline{V}_j(a_{jt+1}, \mathbf{a}_{-jt+1}) \prod_{i\neq j} q_i(\mathbf{a}_t)^{a_{it+1}}(1-q_i(\mathbf{a}_t))^{1-a_{it+1}}}_{\equiv \mathbb{E}^{\mathbf{q}}\left[\overline{V}_j(a_{jt+1}, \mathbf{a}_{-jt+1})|a_{jt+1}, \mathbf{a}_t\right]} \end{aligned} \tag{12}$$

Therefore, the problem of finding equilibrium strategies σ is equivalent to determining equilibrium CCPs $\mathbf{q}$ that satisfy the following equations at all states $\mathbf{a}_t$, and for all firms j

[12] Note that the arguments of the integrated value function, a_{jt} and $\mathbf{a}_{-jt}$, are different from the arguments of the choice-specific value functions, a_{jt+1} and $\mathbf{a}_t$.

(Aguirregabiria and Mira, 2007, p.11):

$$
\begin{aligned}
q_j(\mathbf{a}_t) &= F\left(v_j^{\mathbf{q}}(1,\mathbf{a}_t) - v_j^{\mathbf{q}}(0,\mathbf{a}_t)\right), \text{ where} \\
v_j^{\mathbf{q}}(1,\mathbf{a}_t) &= \pi_j(\mathbf{a}_t) - (1-a_{jt})\theta^e + \beta\mathbb{E}^{\mathbf{q}}\left[\overline{V}_j^{\mathbf{q}}(1,\mathbf{a}_{-jt+1})|a_{jt+1}=1,\mathbf{a}_t\right] \\
v_j^{\mathbf{q}}(0,\mathbf{a}_t) &= \pi_j(\mathbf{a}_t) + a_{jt}\theta^x + \beta\mathbb{E}^{\mathbf{q}}\left[\overline{V}_j^{\mathbf{q}}(0,\mathbf{a}_{-jt+1})|a_{jt+1}=0,\mathbf{a}_t\right] \\
\overline{V}_j^{\mathbf{q}}(a_{jt},\mathbf{a}_{-jt}) &= \int \max\left\{a_{jt}\xi + v_j^{\mathbf{q}}(0,\mathbf{a}_t), -(1-a_{jt})\xi + v_j^{\mathbf{q}}(1,\mathbf{a}_t)\right\} \mathrm{d}F(\xi) \qquad (13)
\end{aligned}
$$

The function $q_j(\mathbf{a}_t)$ embodies firm j's best response, given all other firms' CCPs. By Brower's theorem, this system of best response functions is guaranteed to have a fixed point, as it defines a continuous mapping from the compact space $[0,1]^N$ onto itself. This motivates using an iterative procedure to solve for an equilibrium vector of CCPs, as will be outlined in more detail below. However, it must be noted that the above mentioned problem suffers from a "curse of dimensionality" that prevents its computation in all but the simplest problems. This is a common problem encountered in dynamic discrete games, as was outlined in section 3.3. According to Pakes and McGuire (2001), the computational burden of finding an equilibrium in such problems is principally determined by the size of the state space, the time it takes to compute the expectation, and the time to convergence. In the above problem, the computational burden to check whether a given vector $\mathbf{q}$ is in equilibrium grows exponentially in the number of firms.[13] Therefore, without further simplifying assumptions, the model is of little practical use when it comes to examining real-world economies with many firms.

Contrary to many empirical applications, I will not restrict attention to symmetric and anonymous equilibria. An equilibrium is symmetric if the equilibrium strategies are the same for all firms, i.e. $q_j(\mathbf{a}) = q_k(\mathbf{a})$ for every state $\mathbf{a} \in A$ and for all firms j, k, and it is anonymous if the equilibrium strategies are invariant to arbitrary permutations of the vector of its competitors' states $\mathbf{a}_{-j}$ (Doraszelski and Pakes, 2007). While being very convenient from a computational point of view, symmetry is not a good assumption in the context of spatial competition because the payoffs of a certain firm in any given state depend crucially on its location relative to its competitors, i.e. $\pi_j(\mathbf{a})$ is in general different from $\pi_k(\mathbf{a})$ and therefore, the equilibrium CCPs differ too. For the same reason, players' period return functions are in general not anonymous which leads to strategies that are not anonymous. I consider asymmetry and non-anonymity to be crucial characteristics of spatial dynamic interaction processes.

[13] The state space is of size 2^N so that the memory requirements to store CCPs, conditional and unconditional value functions for each firm are of order $4N2^N$. The computational burden of evaluating (13) for a given vector $\mathbf{q}$ is determined by the expectation operator in each of two choice-specific integrated value functions that integrates over the entire state space A_{-j} of size 2^{N-1}, and by evaluating and integrating the distribution function F. Thus, abstracting from the costs of memory look-up operations, the time to compute (13) for all firms and states is proportional to $N \times 2^N \times (2 + 2^N)$, so the computational burden is $\mathcal{O}(N2^{2N})$.

5.2 A spatial oblivious equilibrium model

To obtain a computable equilibrium model while maintaining asymmetry and non-anonymity, I develop a procedure that is close in spirit to the oblivious equilibrium concept of Weintraub et al. (2008), but adapted to fit the spatial, asymmetric structure of my data. My approach can be summarized as follows: firms principally assume that the spatial market structure remains constant, except in a close neighbourhood around their own location. Why firms are restricted in their strategic reasoning in this way is not specified; but it could be a rational decision to do so if planning ahead per se is costly. Indeed, given the sheer size of the unrestricted state space, it would be unreasonable to assume that any firm can accurately form and store expectations for all possible spatial market structures.

To be more concrete, I will restrict the strategy space by assuming that firms follow a time-varying heuristic strategy

$$\tilde{\sigma}_{jt} : (a_{jt}, \tilde{\mathbf{a}}_{-jt}, \xi_{jt}) \mapsto \{0, 1\}$$

where $\tilde{\mathbf{a}}_{jt} = (a_{jt}, \tilde{\mathbf{a}}_{-jt})$ is a member of what I call the "oblivious state space" $\tilde{A}_{jt}$ of firm j at time t that is composed of the observed actual state outside a close neighbourhood around firm j, and all possible market configurations of firms within a neighbourhood around firm j. In what follows, let $\hat{\mathbf{a}}_t$ denote the observed state at time t, and let $\hat{a}_{jt}$ denote the observed status of firm j at time t. Then, the oblivious state space of firm j at time t is defined as

$$\tilde{A}_{jt} \equiv \left\{ \left(a_i : a_i \in \{0, 1\} \text{ if } i \in nn_j^k, \text{ else } a_i = \hat{a}_{it} \right)_{i \in N} \right\}$$

That is, in any given period t, firm j takes the state of its competitors beyond the range of k "strategic nearest neighbours" nn_j^k [14] as given, and heuristically assumes that only its k nearest neighbours will ever change their state. Note that the magnitude of the oblivious state space is only 2^k. Figure 5 illustrates the idea. The model is solved analogously to the full problem described above by finding equilibrium entry probabilities that satisfy (13), but using the restricted state space $\tilde{A}_{jt}$ for all firms and observation periods.

One problem that arises in computing the equilibrium entry probabilities is that the oblivious state spaces of any two firms j and i will often be different, because these two firms have different strategic neighbourhoods, i.e. $\tilde{A}_{jt} \neq \tilde{A}_{it}$. This implies that the expectation in (12) is not well defined: consider firm j and some state $\tilde{\mathbf{a}}_{jt} \in \tilde{A}_{jt}$ such that $\tilde{\mathbf{a}}_{jt} \notin \tilde{A}_{it}$. Since this state is not in firm i's oblivious state space, its strategy $\tilde{\sigma}_{it}$ is not defined at that point, so that firm j cannot form the conditional expectation in

[14] I specify that $j \in nn_j^k$ so that each firm is its own nearest neighbour. But this is only . In principle, one could also define the neighbourhood based on the inter-firm distance, but using a fixed number of k neighbours has the advantage of allowing the usage of equally sized matrices in the computational implementation.

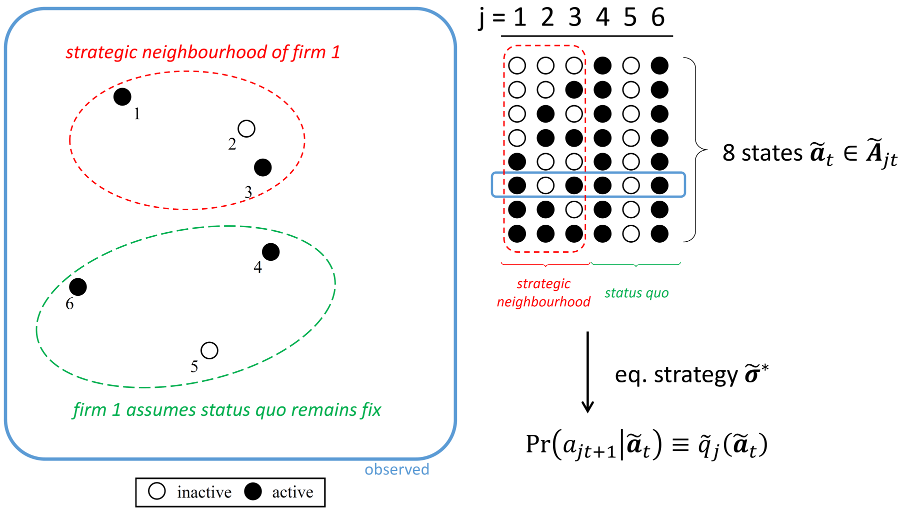


Figure 5: The left side of the figure shows a sample market with six firms, four of which are active (indicated by a solid dot) and two of which are inactive (hollow dot). Firm one assumes that all firms except its two nearest neighbours will remain in their current status quo, and so the oblivious state space of firm two consists of only eight distinct states which are illustrated in the right part of the figure. In contrast, the unrestricted state space encompasses $(2^6 = 64)$ distinct states.

(12). However, an appropriate interpretation of the oblivious state space still allows for a coherent formation of this expectation in the following sense: For any firm i at time t, define the mapping $M_{it} : A \to \tilde{A}_{it}$ as

$$M_{it}(\mathbf{a}) = \left(\tilde{a}_s : \tilde{a}_s = a_s \text{ if } s \in nn_i^k, \text{ else } \tilde{a}_s = \hat{a}_{st}\right) \tag{14}$$

For any state $\mathbf{a} \in A$, this mapping extracts the relevant local state as seen from the perspective of firm i, and uses the actual state $\hat{\mathbf{a}}$ for any firm outside the strategic neighbourhood nn_i^k. This idea is illustrated in figure 6. Using this mapping, I define the conjecture that firm j has about firm i's behaviour as follows:

$$_j\tilde{q}_{it}(\mathbf{a}) \equiv \begin{cases} \tilde{q}_{it}(\mathbf{a}) \text{ if } \mathbf{a} \in \tilde{A}_{it} \\ \tilde{q}_{it}\left(M_{it}(\mathbf{a})\right) \text{ else.} \end{cases} \tag{15}$$

where $\tilde{q}_{it}$ are the CCPs that are implied by firm i's strategy $\tilde{\sigma}_{it}$. Note that $M_{it}(\mathbf{a}_t)$ differs from $\mathbf{a}_t$ only for firms that are outside the strategic neighbourhood of firm i, and so the conjecture about firm i's strategy that other firms may have can be assumed to be reasonably close to the actual strategy of a firm i.

I assume that firms use these conjectures about their competitors' strategies to form approximate expectation over the future states. For a firm j that chooses an action a, this

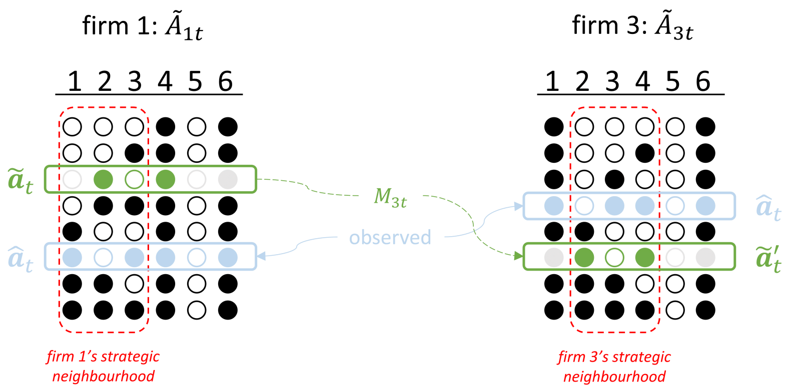


Figure 6: This figure shows the oblivious state spaces of two firms that have only one common neighbour, so that their two oblivious state spaces differ. By construction, the observed state $\hat{a}_t$ (blue) is contained in both oblivious state spaces, but another state $\tilde{a}_t$ is not. Instead, firm 1 maps this state to another similar state $\tilde{a}'_t$ that is identical to $\tilde{a}_t$ for all firms that are contained in firm 3's strategic neighbourhood.

approximate expectation is:

$$\mathcal{E}^{\tilde{\mathbf{q}}}\left[\overline{V}_j(a_{jt+1}, \mathbf{a}_{-jt+1})|a_{jt+1} = a, \mathbf{a}_t\right] = \sum_{\substack{\tilde{\mathbf{a}}_{t+1}\in\tilde{A}_{jt} \\ \tilde{a}_{jt+1}=a}} \overline{V}_j(a, \tilde{\mathbf{a}}_{-jt+1}) \prod_{i\in nn_j^k\setminus\{j\}} {}_j\tilde{q}_{it}(\mathbf{a}_t)^{\tilde{a}_{it+1}}(1 - {}_j\tilde{q}_{it}(\mathbf{a}_t))^{1-\tilde{a}_{it+1}} \tag{16}$$

for all states $\mathbf{a}_t \in \tilde{A}_{jt}$. The above expression differs from that in equation (12) in two important ways: first, firm j assumes that all firms outside of its k-neighbourhood neither enter nor exit, and second, firm j forms a conjecture about the strategies of those firms inside its k-neighbourhood that is consistent with that assumption. Because firm j assumes that the future state will remain in its oblivious state space, which is of magnitude 2^k, the expectation $\mathcal{E}$ can be computed very quickly. Using the above expression (16), I define a spatial oblivious equilibrium to be a vector of CCPs $\tilde{\mathbf{q}}^*$ such that, for all firms j, at each time t, it holds for every state $\tilde{\mathbf{a}}_t \in \tilde{A}_{jt}$ that

$$\begin{aligned}
\tilde{q}_j^*(\tilde{\mathbf{a}}_t) &= F\left(v_j^{\tilde{\mathbf{q}}}(1, \tilde{\mathbf{a}}_t) - v_j^{\tilde{\mathbf{q}}}(0, \tilde{\mathbf{a}}_t)\right), \text{ where} \\
v_j^{\tilde{\mathbf{q}}}(1, \tilde{\mathbf{a}}_t) &= \pi_j(\tilde{\mathbf{a}}_t) - (1 - \tilde{a}_{jt})\theta^e + \beta\mathcal{E}^{\tilde{\mathbf{q}}}\left[\overline{V}_j^{\tilde{\mathbf{q}}}(1, \mathbf{a}_{-jt+1})|a_{jt+1} = 1, \tilde{\mathbf{a}}_t\right] \\
v_j^{\tilde{\mathbf{q}}}(0, \tilde{\mathbf{a}}_t) &= \pi_j(\tilde{\mathbf{a}}_t) + \tilde{a}_{jt}\theta^x + \beta\mathcal{E}^{\tilde{\mathbf{q}}}\left[\overline{V}_j^{\tilde{\mathbf{q}}}(0, \mathbf{a}_{-jt+1})|a_{jt+1} = 0, \tilde{\mathbf{a}}_t\right] \\
\overline{V}_j^{\tilde{\mathbf{q}}}(\tilde{a}_{jt}, \tilde{\mathbf{a}}_{-jt}) &= \int \max\left\{\tilde{a}_{jt}\xi + v_j^{\tilde{\mathbf{q}}}(0, \tilde{\mathbf{a}}_t), -(1 - \tilde{a}_{jt})\xi + v_j^{\tilde{\mathbf{q}}}(1, \tilde{\mathbf{a}}_t)\right\} \mathrm{d}F(\xi)
\end{aligned} \tag{17}$$

Again, Brower's fixed point theorem can be applied so that an equilibrium $\tilde{\mathbf{q}}^*$ is guaranteed to exist.

5.3 Estimation and identification

The structural parameters of the model are estimated using a nested fixed point approach to accommodate the asymmetric and non-anonymous nature of spatial strategic interactions. I assume that the private information shocks ξ_{jt} follow a standard normal distribution Φ so that the conditional choice probabilities in equation (13) can be expressed in convenient form as:

$$\Pr(a_{jt+1} = 1|\tilde{\mathbf{a}}_t) = \tilde{q}_j(\tilde{\mathbf{a}}_t) = \Phi\left(v_j^{\tilde{\mathbf{q}}}(1, \tilde{\mathbf{a}}_t) - v_j^{\tilde{\mathbf{q}}}(0, \tilde{\mathbf{a}}_t)\right) \tag{18}$$

The integrated value function can then be computed as

$$\overline{V}_j^{\tilde{\mathbf{q}}}(a_{jt}, \tilde{\mathbf{a}}_{-jt}) = \phi\left(v_j^{\tilde{\mathbf{q}}}(1, \tilde{\mathbf{a}}_t) - v_j^{\tilde{\mathbf{q}}}(0, \tilde{\mathbf{a}}_t)\right) + (1 - \tilde{q}_j(\tilde{\mathbf{a}}_t)) \cdot v_j^{\tilde{\mathbf{q}}}(0, \tilde{\mathbf{a}}_t) + \tilde{q}_j(\tilde{\mathbf{a}}_t) \cdot v_j^{\tilde{\mathbf{q}}}(1, \tilde{\mathbf{a}}_t) \tag{19}$$

where ϕ is the probability density function of the standard normal distribution.[15] For the empirical application, the reduced form profit equation is parametrized as follows:

$$\pi_j(\mathbf{a}_t) = \begin{cases} \underbrace{\left(\alpha \mathbf{X}_j + \frac{\beta Y_j}{1 + N_{jt}^d}\right)}_{\text{local demand}} \underbrace{\left(1 - \delta N_{jt}^d)\right)}_{\text{local competition}}, \text{ if } a_{jt} = 1 \\ 0 \ \text{ else.} \end{cases} \tag{20}$$

where Y_j is the local population around store j that is divided by the number of active firms in firm j's d-neighbourhood, N_{jt}^d (and including firm j). X_j is a vector of profit shifters of store j that is common knowledge to all players. The first composite term captures local demand at a given location in market state $\mathbf{a}_t$, and the second term captures the market power effect of local competition. The parameter δ measures the relative reduction of a pharmacy's profitability due to the presence of one additional active competitor within a distance d. In order to test the main hypothesis of the paper, namely whether spatial competition has increased after 2004, δ was estimated separately before and after 2004 (δ^{pre} and δ^{post}). The spatial co-variates include measures of the local residential population within a radius x around the firm's location and measures such as the number of nearby supermarkets or doctors. A summary of these variables can be found in table 4. As part of a robustness check, the population variable was scaled with aggregate municipality-level population growth rates, and further time-varying and municipality-level covariates were included. However, for the sake of simplicity this time dependence is not explicitly modelled: in the model, agents act as if all variables are time-constant while they actually change over time. This naturally introduces some error, but I believe that this error is small because the time-varying variables change rather slowly so that the assumption of time-constant co-variates may be a good approximation to actual decision processes.

[15] This follows from the last equation in (17) and from the fact that the expectation of a truncated normally distributed random variable x is given by $\mathbb{E}[x|x \leq y] = \frac{-\phi(y)}{\Phi(y)}$, where Φ is the normal c.d.f. and ϕ is the normal p.d.f..

Using the parametric profit function in (20), the conditional expectation in (16), the conditional choice probabilities (18) and the integrated value function (19), the system of equations in (13) for some market m and time period $t < T$ can be computed as follows:

Procedure 1 (Fixed point algorithm)**.**

0. initialization:

- *(a) set* $k \leftarrow 0$
- *(b) compute* $\pi_j(\mathbf{a})$ *for all* $\mathbf{a} \in \tilde{A}_{jt}$*, and for all firms* $j \in 1, \ldots, N$
- *(c) for all firms* $j = 1, \ldots, N$*, initialize the vectors* $\mathbf{q}_j$*,* $\mathbf{v}_j^0$*,* $\mathbf{v}_j^1$ *and* $\bar{\mathbf{V}}_j$ *of length* 2^k *to zero, representing the corresponding functions* $q_j(\cdot)$*,* $v_j^{\mathbf{q}}(0, \cdot)$*,* $v_j^{\mathbf{q}}(1, \cdot)$ *and* $\overline{V}_j^{\mathbf{q}}(\cdot)$ *evaluated at each state* $\mathbf{a}_{jt} \in \tilde{A}_{jt}$*. Collect all firm-specific vectors into* $\mathbf{q}, \mathbf{v}^0, \mathbf{v}^1$ *and* $\overline{\mathbf{V}}^{\mathbf{q}}$*.*

1. at step k:

- *(a) set* $\Delta \leftarrow 0$*, and for all firms* j *do:*
  - $\mathbf{v}_j^{a_{jt+1}} \leftarrow \left(v_j^{\mathbf{q}}(a_{jt+1}, \tilde{\mathbf{a}})\right)_{\tilde{\mathbf{a}} \in \tilde{A}_{jt}}$ *for* $a_{jt+1} \in \{0, 1\}$ *using* (8)*,* (7)*,* (20) *and* (16)*.*
  - $\bar{\mathbf{V}}_j \leftarrow \left(\overline{V}_j^{\mathbf{q}}(\tilde{\mathbf{a}})\right)_{\tilde{\mathbf{a}} \in \tilde{A}_{jt}}$ *using* (19)
  - $\Delta_j \leftarrow \left\| \mathbf{q}_j - (\tilde{q}_j(\tilde{\mathbf{a}}))_{\tilde{\mathbf{a}} \in \tilde{A}_{jt}} \right\|_\infty$ *and* $\mathbf{q}_j \leftarrow \frac{1}{2}\left(\mathbf{q}_j + (\tilde{q}_j(\tilde{\mathbf{a}}))_{\tilde{\mathbf{a}} \in \tilde{A}_{jt}}\right)$ *using* (18)
  - $\Delta \leftarrow \max\{\Delta, \Delta_j\}$
- *(b) if* $\Delta \geq \epsilon$ *go back to step 1 with* $k \leftarrow k + 1$*, else STOP.*

Technically, this is a Gauss-Seidel algorithm because the updates in step k are always computed using the most recent available conditional choice probabilities from either of steps k or $k-1$. Doraszelski and Pakes (2007) write that this leads to faster convergence in many cases, and I found that this applied also to my setting. The dampening that is introduced in updating the conditional choice probabilities was found to significantly improve convergence speeds, as is also suggested by Doraszelski and Pakes (2007).[16] In my examples, with more than two hundred firms per market, the algorithm usually converged within one hundred iterations to a tolerance of $\epsilon = \sqrt{3 \cdot 10^{-10}}$, irrespective of the starting values. In each market, I computed the equilibrium only up to time period $T - 1$ because the equilibrium in period T makes predictions about transition patterns in period $T + 1$ which are not observed.[17]

[16] I implemented this model in Python (version 3.7) using the Numpy (version 1.15.4), Scipy (version 1.1.0) and Numba (version 0.42.0) libraries. The actual estimation was conducted on a fast compute node of the bwHPC cluster, using the multiprocessing library.

[17] The oblivious state space is of size 2^k so that the memory requirements to store CCPs, conditional and unconditional value functions for each firm in every period are of order $4NT2^k$. The computational burden of evaluating (13) for a given vector $\tilde{\mathbf{q}}$ is determined by the expectation operator $\mathcal{E}$ in each of two

The model's parameters of interest are α, δ, θ^e and θ^x. As outlined above, the spatial interaction parameter δ is estimated separately before and after the reform in 2003. I also estimated θ^e separately, and included a dummy variable for $t \geq 2004$ in the profit equation. I assume that the decision making units do not anticipate this change in parameters, i.e. the parameter change in 2004 comes as a surprise to them, and the market then transitions into a new steady state that is consistent with new parameter values. In Monte Carlo simulations, I found that I could not identify all parameters separately, so I chose to normalize the market exit value to unity, i.e. $\theta^x = 1$.[18] Thus, the parameters of interest can be summarized in a vector $\theta = (\alpha, \delta_{pre}, \delta_{post}, \theta^e_{pre}, \theta^e_{post})$ with $\theta^x = 1$ and α including a pre/post dummy. In order to estimate θ, for each market m, and conditional on parameters θ, the equilibrium $\tilde{\mathbf{q}}^*_{mt}$ is computed for all years $t = 1, \ldots, T-1$. Thus, the log likelihood of the observed market outcomes $\{\mathbf{a}_{mt}\}_{t=2}^{T}$, conditional on the market states $\{\mathbf{a}_{mt}\}_{t=1}^{T-1}$ is computed as follows:

$$ll_m(\theta) = \sum_{t=2}^{T} \sum_{j=1}^{N_m} a_{mjt} \log \tilde{q}^*_{mjt-1} + (1 - a_{mjt}) \log(1 - \tilde{q}^*_{mjt-1})$$

These market likelihoods are then aggregated to form the total log-likelihood

$$ll(\theta) = \sum_{m=1}^{M} ll_m(\theta)$$

The likelihood is optimized with respect to parameters θ using the BFGS algorithm.[19] Standard errors are computed using the estimated Hessian matrix that is returned by the BFGS algorithm.

Economic agents in the model that is described above are heterogeneous with respect to the realization of their private information shocks, and with respect to their spatial configuration relative to each other. As in Seim (2006), the multiplicity of observed outcomes that may arise in a pure strategy equilibrium due to the presence of a spatial interaction effect is circumvented by modelling entry and exit probabilities. Thus, players form their expectations ex ante and they may eventually end up in a state which is not an equilibrium outcome ex post. Yet, Berry and Reiss (2007, p.1878) note that the entry probabilities in such a model may not be unique: as the variance of the unobserved error decreases so that the model approaches one of perfect information, multiple equilibrium entry rates that mirror the multiple equilibria in pure strategies can arise. Thus, for

choice-specific integrated value functions that integrates over the oblivious state space $\tilde{A}_{-jt}$ of size 2^{k-1} in each time period t, and by evaluating and integrating the distribution function F. Thus, abstracting from the costs of memory look-up operations, the time to compute (13) for all firms and states is approximately $\mathcal{O}(NT2^k(2 + 2 \cdot 2^{k-1})) = \mathcal{O}(NT2^k(2 + \cdot 2^k)$. The actual time that it takes to compute an equilibrium will also crucially depend on the number of iterations that it takes to converge to $\tilde{\mathbf{q}}^*$.

[18] This problem was alleviated when payoffs were assumed to depend on market-level variates, and one had many markets. But although my model does include market-level covariates, it is by no means certain that these are the correct ones, so I decided to normalize the scrap values nonetheless.

[19] as implemented in the Scipy (version 1.1.0) library

the model to predict unique equilibrium entry and exit rates it is necessary that the private information shocks, relative to the observed component of the player's payoffs, are sufficiently important. I believe that this is the case in my empirical application, because the Gauss-Seidel algorithm that is described above always converged to the same equilibrium probabilities regardless of the initial conditions.

Given that the conditional entry and exit rates are uniquely determined, the model is primarily identified by matching the predicted transition rates between observed market states to the observed transition rates. Period returns and entry costs are only identified relative to the variance of the errors, which is set to unity. The magnitude of the entry costs is identified by matching the degree of turnover in the data: larger entry costs imply higher persistence, i.e. fewer firms enter and leave the market. Larger exit values have the opposite effect, and this is why I constrain the parameter θ^x to unity so as to circumvent near collinearity issues. The magnitude of the period returns are identified – relative to the logit error scale – by the average number of active firms in the market: Larger period returns alone imply that more firms will be active, on average. The parameters that govern local demand vary across locations, and are thus identified by the spatial variation in entry and exit rates. Finally, the spatial interaction parameter δ is identified through the effect that every additional active firm has on entry and exit rates in nearby locations.

5.4 Remarks

Before proceeding to describe the data, and the estimation results of this paper, I discuss certain aspects of the method and the model by means of illustrative examples. In particular, I will outline why a structural model that incorporates dynamic strategic interactions is needed, rather than a reduced form model.

5.4.1 Why a dynamic model is needed

Reduced form estimates lead to inconsistent results of the interaction parameter because the competitors' actions are endogenous with respect to own actions, which renders reduced form estimators inconsistent. A structural model such as the one put forward in this paper can alleviate this problem by imposing appropriate behavioural assumptions. To explore this issue further, I set up a dynamic entry and exit model with two firms. The notation and timing structure is the same as in the full model above. Their period returns are given by

$$\pi_i(a_{it}, a_{-it}) = \begin{cases} \frac{1}{2} - \delta a_{-it}, \text{ if } a_{it} = 1 \text{ with } \delta \in [0,1] \\ 0, \text{ else} \end{cases}$$

Entry costs are given by $\theta^e = 4$ and scrap values are given by $\theta^x = 1$, and both are subject to a standard normally distributed shock ξ_{it} as in the full model above. The state space of this small illustrative model encompasses only four distinct states so that it can easily be solved exactly. A Markov Perfect Equilibrium (MPE) of this model is a set of conditional choice probabilities (CCPs), denoted by $q_i^*(a_{it}, a_{-it})$, for $i \in \{1,2\}$ and $a_{it}, a_{-it} \in \{0,1\}^2$ such that the system of equations (13) holds. Suppose only the interaction parameter δ is to be estimated from a sequence of observed market states $\{\mathbf{a}_t\}_{t=1}^T$. This can be achieved by choosing δ such that the model-implied CCPs match the observed transition rates as closely as possible. I computed the equilibrium CCPs for a range of parameter values δ, ranging from zero to one. These CCPs are shown in figure 7, in terms of entry and exit probabilities for different states of the competitor (solid and dotted blue lines). Alongside the equilibrium CCPs I also plotted CCPs that are derived non-strategically, i.e. with players that assume that their competitors do not change their state (dashed red lines).

The interaction parameter is identified if there is a unique mapping from entry and exit probabilities to parameter values, and the presence of multiple equilibria may prevent this. Figure 7 shows that the model generates an asymmetric equilibrium (dotted blue lines) for very large values of δ in addition to a symmetric equilibrium (solid blue lines), in line with what Berry and Reiss (2007, p.1878) write. While a multiplicity of equilibria does not necessarily lead to non-identification, in this case it does lead to a non-unique mapping from CCPs to parameter values which can prevent identification. To alleviate this problem, I will assume that the interaction parameter is sufficiently small compared to the period returns so as to admit a unique equilibrium. Figure 7 also shows that an identification of the interaction parameter comes mainly from matching entry and exit rates in the presence of an active competitor (top right and top left panel) because in these cases, the CCPs exhibit monotonicity over a large range of parameters δ.

If agents ignore the strategic reactions of their competitors, their optimal entry and exit decisions will differ from the ones obtained by a model of strategic decision making. This can be seen in the two panels on the right hand side of figure 7. The figure shows that a potential entrant is less likely to enter if it disregards the possibility that the incumbent will leave the market, and that a duopolist is more likely to leave the market if it disregards the reactions of its competitor. Thus, strategic play leads to more entry and delayed exit. This implies that any estimation procedure that attempts to match entry and exit rates without modelling the strategic interaction will underestimate the interaction parameter δ if agents act strategically, and it is the reason why a structural model of dynamic forward-looking decision making is needed. Of course, it could be that agents do not behave in this manner and merely take their competitors' actions as given. This could indeed be a rational strategy to follow if entry and exit rates are rather small, and the costs of strategic planning are large. In markets with more than two firms, intermediate cases of strategic decision making are likely to occur, where decision makers do not pay attention to very distant competitors. This is precisely the idea behind the spatial oblivious equilibrium concept; and my empirical approach will allow me to determine the degree to which strategic dynamic decision making is important.

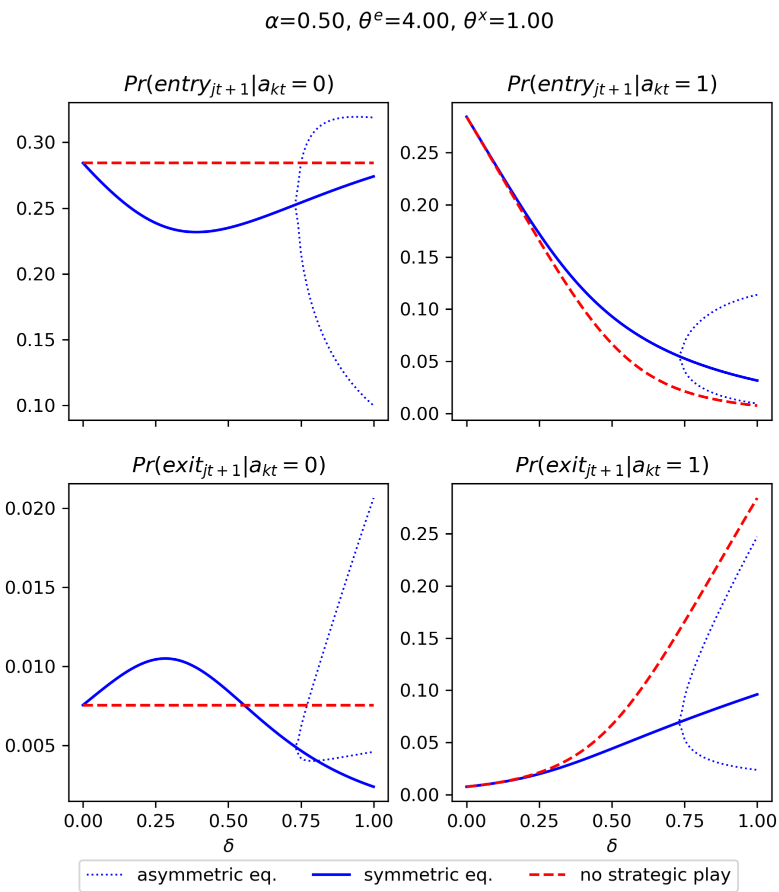
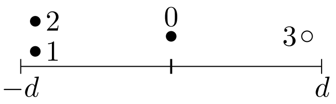
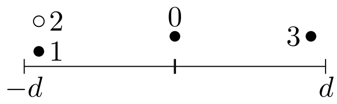


Figure 7: Conditional choice probabilities in a two-firm model of dynamic entry for different interaction parameters. The figure shows the CCPs of firm j conditional on firm k's current status.



(a) $\mathbf{a}_t = (1,1,1,0), q_0^*(\mathbf{a}_t) = 0.46$



(b) $\mathbf{a}_t = (1,0,1,1), q_0^*(\mathbf{a}_t) = 0.59$

Figure 8: Non-anonymity. Solid circle: active firm. Firm zero is less likely to remain active if its two neighbours to the left are active, than if one firm on either side is active. The equilibrium CCPs were computed for $\alpha = 1$, $\delta = \frac{1}{2}$, $\theta^e = 4$ and $\theta^x = 1$.

5.4.2 Why two-step estimators cannot be used

The spatial aspect of the entry game at hand introduces non-anonymity (Doraszelski and Pakes, 2007) in firms' best response functions that render conventional two-step estimators of dynamic games inapplicable. These estimators typically rely on some consistent first-stage estimates of firm's CCPs. However, such estimates are hard to obtain in the current setting because CCPs depend crucially on the precise spatial configuration of firms' competitors: Even if the period return function depends only on the number of active neighbours, but not on their identity or spatial configuration, the same does not hold for firms' CCPs. Therefore, the first stage estimates would have to be estimated conditionally on the spatial configuration. But this configuration is drawn from a high dimensional space, which precludes the usage of simple non-parametric estimators.

This point shall be highlighted in an illustrative example. Consider a linear market of length $2d$ with four firm locations as illustrated in figure 8. Suppose that period returns of an active firm are given by $\pi_{jt} = 1 - \frac{1}{2}N^d_{jt}$ where N^d_j is the number of firm j's active neighbours within a radius d. The remaining structure of the game is as described above, with $\theta^e = 4$ and $\theta^x = 1$, both being subject to privately known random perturbations. I am interested in the equilibrium behaviour of the central firm 0. Note that this firm's profits are negatively affected if any of its three neighbours is active. Conversely, firms 1 and 2 have only two potential direct competitors, and firm 3 has only one such neighbour. This means that firm 3 is a stronger competitor for firm 0 than firms 1 and 2 are. Keeping the number of firm 0's active neighbours fixed at two, firm 0 is more likely to remain active if its weaker competitor 2 is the potential entrant (figure 8b), than if its stronger competitor 3 is a potential entrant (figure 8a). The same mechanisms are at play in spatial entry games more generally, and because of this inherent non-anonymity, it is generally not possible to consistently estimate firms' CCPs conditional on some low-dimensional market characteristic such as the number of active competitors, as would be required for a two-step estimator.

5.4.3 Properties of the oblivious approximation to the MPE

The natural question is how the spatial oblivious equilibrium in (17) relates to the full MPE defined in (13) above. Of course, if the number of strategic nearest neighbours is equal to the total number of firm locations in the market ($k = N$), then the two equilibria are the same but the whole idea of the spatial oblivious equilibrium is that the number of strategic neighbours (k) is smaller than the number of firms (N). Thus, it is interesting to know whether the two quantities become closer as k increases and eventually approaches N. A theoretical answer to this question along the lines of Weintraub et al. (2008)[20] is work to be done in the future. To approach this question from a computational point of view, I created a sample of $N = 10$ firm locations in a square market of length one thousand. The profit of an active firm is given by $\pi_{jt} = 1 - \frac{1}{3}N_j^d$ where N_j^d is the number of firm j's active neighbours within a radius $d = 400$. This radius is chosen such that, on average, five neighbour locations fall within it.[21] Entry costs are given by $\theta^e = 3$, and scrap values are given by $\theta^x = 1$, both being subject to randomly drawn, normally distributed disturbances. Using the model-implied CCPs, the industry's long run distribution across states was computed, and the state with the largest long-run probability of occurrence was selected as the industry's initial state.[22] This market configuration is denoted as $\hat{\mathbf{a}}$ and is shown in figure 9. At this initial industry state, I computed the equilibrium CCPs $\tilde{\mathbf{q}}^{(k)}(\hat{\mathbf{a}})$ that satisfy (17) for different choices of k, ranging from $k = 1$ (no strategic interaction) to $k = 10$ (full strategic interaction; nine strategic nearest neighbours and self). For each value of k, I computed two distance measures of the firms' CCPs between $\tilde{\mathbf{q}}^{(k)}(\hat{\mathbf{a}})$ and $\tilde{\mathbf{q}}^{(10)}(\hat{\mathbf{a}})$: the maximum absolute difference ($|\cdot|_\infty$), and the root of the mean squared difference ($|\cdot|_2$).

The results, presented in table 2, indicate that both distance measures become very small as k increases, while at the same time the computational time increases rapidly. For this particular market, the oblivious MPE for $k = 6$ offers a good approximation of the "true" MPE with $k = N$ at an acceptable computational cost. Of course, this depends crucially on the particular choice of the interaction range d that determines how many of a firms' k nearest neighbours have a direct effect on its period returns. In the extreme, if the interaction is such that every firm is completely isolated, then any choice $k \geq 1$ would obviously lead to the same result, and one did not need to worry about strategic interactions at all. On the other hand, if all firms interacted with every one of their competitors, then any choice of $k < 10$ would be unlikely to produce a correct result. In this case, one could instead directly apply the oblivious equilibrium concept of Weintraub et al. (2008) without any modifications. If the interaction parameter is so large that multiple equilibria occur, it

[20] A direct application of their results is not possible because of the asymmetric structure of the problem at hand.

[21] Since firm locations were generated randomly, the expected number of firms within radius d is $\lambda\pi d^2$, where $\lambda = N/A$ is the density of locations on the area A.

[22] Given the CCPs, one can build the transition matrix Q that determines the probability of transitioning from each market state $\mathbf{a}$ to any other state $\mathbf{a}'$, with $Q(\mathbf{a}', \mathbf{a}) = \Pr(\mathbf{a}'|\mathbf{a})$. Then, the steady state distribution across market states is a vector $\mathbf{p}^*$ that satisfies $Q\mathbf{p}^* = \mathbf{p}^*$ and $\sum_s p_s^* = 1$.

firm j	$\tilde{q}_j^{(1)}$	$\tilde{q}_j^{(2)}$	$\tilde{q}_j^{(3)}$	$\tilde{q}_j^{(4)}$	$\tilde{q}_j^{(5)}$	$\tilde{q}_j^{(6)}$	$\tilde{q}_j^{(7)}$	$\tilde{q}_j^{(8)}$	$\tilde{q}_j^{(9)}$	$\tilde{q}_j^{(10)}$
0	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
1	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
2	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
3	0.07	0.07	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
4	0.69	0.82	0.86	0.83	0.88	0.85	0.85	0.85	0.85	0.85
5	0.69	0.80	0.87	0.93	0.89	0.85	0.85	0.85	0.85	0.85
6	0.69	0.68	0.68	0.70	0.78	0.85	0.85	0.85	0.85	0.85
7	0.69	0.80	0.87	0.82	0.81	0.85	0.85	0.85	0.85	0.85
8	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
9	0.02	0.03	0.03	0.06	0.05	0.09	0.09	0.09	0.09	0.09
$\lvert\tilde{\mathbf{q}}^{(k)} - \tilde{\mathbf{q}}^{(10)}\rvert_\infty$	0.161	0.166	0.168	0.147	0.071	0.000	0.000	0.000	0.000	
$\lvert\tilde{\mathbf{q}}^{(k)} - \tilde{\mathbf{q}}^{(10)}\rvert_2$	0.322	0.192	0.181	0.175	0.103	0.001	0.000	0.000	0.000	
runtime [s]	0.03	0.04	0.04	0.04	0.04	0.07	0.30	0.82	9.24	54.82

Table 2: Convergence of the spatial oblivious equilibrium to the MPE. This table shows the equilibrium CCPs that were derived using different levels of strategic sophistication in a generic market of ten firms, at a particular industry state. See the main text for a description of how the market was constructed, and see figure 9 for a graphical depiction.

could even be that an approximation with $k > 1$ does worse than the myopic MPE with $k = 1$. Furthermore, the quality of the approximation depends crucially on firm turnover in the market: if turnover is very low, then the status quo is a good prediction of the future state, and so a smaller strategic neighbourhood might suffice. In future work, it would thus be desirable to investigate the relationship between the spatial structure of firms' potential locations and the properties of the approximative equilibrium in greater detail, and in more general terms.

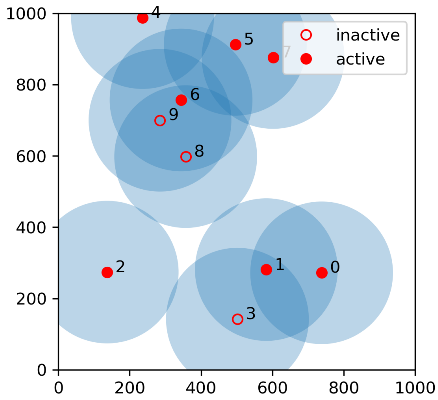


Figure 9: The example market. The blue circles are drawn to represent half the interaction radius. Hence, if the circles around to adjacent locations overlap, these two locations interact directly through the profit equation.

	Germany			80 city sample		
year	*active*	*entries*	*exits*	*active*	*entries*	*exits*
2001	16,286			5,449		
2002	16,272	175	189	5,438	57	68
2003	16,300	120	92	5,442	48	44
2004	16,328	110	82	5,437	25	30
2005	16,184	313	457	5,307	91	221
2006	16,226	1,042	1,000	5,234	334	407
2007	16,307	420	339	5,233	129	130
2008	16,372	409	344	5,229	161	165
2009	16,342	101	131	5,209	33	53
2010	16,273	460	529	5,178	161	192
2011	16,168	266	371	5,126	84	136
2012	16,051	256	373	5,067	96	155
2013	15,845	266	472	4,953	93	207
2014	15,807	54	92	4,933	11	31
2015	15,645	181	343	4,856	62	139
2016	15,519	192	318	4,771	56	141
Total	26,964	4,365	5,132	6,741	1,441	2,119

Table 3: Number of active firms, entries, and exits across years for the entire dataset, and for the sample of eighty large German cities that is used in the subsequent analysis.

6 Data

6.1 Data sources

In order to address the research questions of this paper, extensive data on the German pharmacy market were collected. The addresses of all active pharmacy locations[23] were taken from sixteen editions of the *Bundesapothekenregister* (Deutscher Apotheker Verlag, 2016) and were geocoded.[24] An overview of the resulting panel data set is given in table 3. The number of new establishments and firm exits displays substantial variability over time, which may be due to the fact the the data source is issued quarterly, but it was not always possible to obtain the same issue in each year. Lacking a unique firm identifier, I attempted to identify firms whose location changed from year to year using fuzzy string matching techniques. But because the number of firm re-locations is rather small compared to the number of entries and exits, I decided to abstract from firm re-locations in the empirical model, and these figures are not reported here. Hence, a re-location is treated as simultaneous entry and exit in the same year in two different locations. In total, there are 26,964 distinct locations.

For the empirical analysis, attention is restricted to eighty German cities (excluding Berlin, Hamburg, Munich and Cologne). This set of urban markets was chosen in order to create a homogeneous sample in which the nature of spatial interaction is fairly similar. Rural

[23]For this empirical analysis, a pharmacy is one outlet but may belong to a group of pharmacies

[24]This was done using an academic licence for Bing Spatial Data Services. Care was taken to obtain accurate locations, and the results were double-checked manually where the geocoding API indicated that its result was imprecise.

areas, on the other hand, are likely to exhibit very different spatial interaction mechanisms due to different travel and commuting patterns. Also, the largest German cities are larger by an order of magnitude than the majority of other cities and so they were excluded from the analysis. A list of the eighty sample cities is shown in table 14 in the appendix.

In the base line analysis, I only use locations where an active pharmacy has been observed at some point as potential entry locations. In a robustness check, I extend the set of potential entry locations in two different ways. On the one hand, I use the locations of bakery shops.[25] Since bakery shops and pharmacies have approximately the same size, these locations therefore represent an appropriate set of potential entry locations. Furthermore, they also respect local entry restrictions that may result from zoning laws. As a second alternative, I generated random entry locations within the administrative boundaries of each city. These random entry locations, of course, do not respect zoning laws, and they also probably do not correspond to actual feasible entry locations. Therefore, these results should be interpreted cautiously.

To model pharmacies' variable reduced form profits (see equation (20)), data on local demand and supply conditions was obtained form various sources. First, data from the German census in 2011 (Zensus, 2011) was used which shows the spatial residential population distribution on a fine grid with a spacing of just one hundred metres. This allows me to compute the local residential population, within a radius of 500 metres around each potential entry location. This variable proxies local residential demand at each location and corresponds to the variable Y_j in equation (20). Moreover, the share of people aged 65 and older was computed for every potential entry location.

Second, I obtained the locations and outlines, respectively, of doctors, supermarkets, train stations, pedestrian zones, and main roads from an OpenStreetMap data base (OpenStreetMap contributors, 2017).[26] Using GIS software, the distances to the nearest doctor, supermarket, main road, etc. were computed for each pharmacy location in the sample.[27] The aforementioned variables are specific to each distinct location, but do not vary over time because the census data are available only for 2011, and because I used only a single year of OpenStreetmap data. To capture temporal changes in the profitability of stores, I allow the intercept, entry costs, and the interaction term, to differ before and after the reform period. Table 4 shows summary statistics for these co-variates in the selected sample of cities, and for the three sets of point locations – pharmacies, bake shops, and random dummy locations. The table shows that pharmacy locations, and the bake shop locations are fairly similar in terms of their observable statistics, although a formal t-test rejects the null of equal means for all variables (see table 15). In comparison, the random locations differ substantially in their observable characteristics.

[25] These locations were extracted from OpenStreetMap (OpenStreetMap contributors, 2017).
[26] The data were downloaded from download.geofabrik.de, and processed using the command line tool Osmosis
[27] This was done in the QGIS environment.

		pharmacies ($N = 6,741$)				bake shops ($N = 7,382$)				dummy points ($N = 10,033$)			
Variable	*Explanation*	*mean*	*SD*	*min*	*max*	*mean*	*SD*	*min*	*max*	*mean*	*SD*	*min*	*max*
Local residential population as of 2011 census (Y_i, between variation)													
local population	within 500m radius (in 10k)	0.495	0.269	0.000	1.678	0.467	0.284	0.000	1.809	0.142	0.194	0.000	1.530
elderly share	share over 65 within 500m radius	0.198	0.062	0.000	0.634	0.194	0.066	0.000	1.000	0.171	0.124	0.000	1.000
Local spatial covariates from Open StreetMap (time invariant, between variation)													
pedestrian zone	$\leq 50m$ from pedestrian zone	0.216	0.411	0.000	1.000	0.212	0.408	0.000	1.000	0.008	0.088	0.000	1.000
main road	$\leq 50m$ from main road	0.331	0.471	0.000	1.000	0.263	0.440	0.000	1.000	0.064	0.245	0.000	1.000
doctor nearby	physician within 100m	0.217	0.412	0.000	1.000	0.141	0.348	0.000	1.000	0.006	0.076	0.000	1.000
supermarket	supermarket within 100m	0.231	0.421	0.000	1.000	0.298	0.458	0.000	1.000	0.007	0.086	0.000	1.000
trainstation	trainstation within 250m	0.045	0.208	0.000	1.000	0.061	0.239	0.000	1.000	0.007	0.086	0.000	1.000

Table 4: Summary statistics of variables that determine local demand, data from 80 large German cities (excluding Berlin, Hamburg, Munich, Cologne). Author's own calculations based on data from Zensus (2011), OpenStreetMap contributors (2017), and Deutscher Apotheker Verlag (2016).

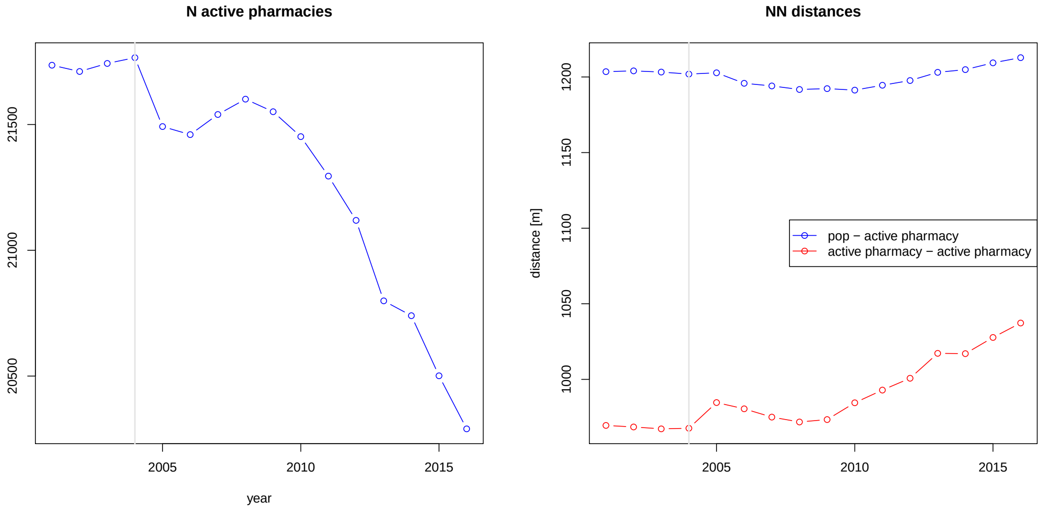
Third, further economic municipality-level co-variates from the German statistical offices (Statistische Ämter des Bundes und der Länder, 2018) were assigned to each location based on municipal boundaries (Bundesamt für Kartographie und Geodäsie, 2018). The local population data were scaled with municipality level population growth rates. As a robustness check, I also estimated the model with unscaled population data. Table 5 shows the summary statistics of these variables across cities, and across observational periods.

6.2 Descriptive analysis

The most interesting information contained in the panel data set are the pharmacies' relative locations, and how they change over time. The analysis of these spatial data is complicated by the fact that individual observations are usually not independent of each other, so that classical statistical concepts cannot be used. For this reason, a specialized branch of statistics has evolved that is concerned with the analysis of such spatial point patterns. Although the methods from spatial point pattern statistics lack a direct economic interpretation, they are nonetheless useful to describe the observed data appropriately. This subsection describes the spatial data set using methods from point pattern statistics. A good introduction to point pattern statistics is Diggle (2014).

First, the data are described in terms of nearest neighbour distances. For each active pharmacy in every year, the distance towards its nearest active competitor was computed. The average nearest competitor distance is plotted in figure 10b along with the average population weighted distance from consumer cells (Zensus, 2011) to closest active pharmacies. That metric can be thought of as a crude welfare measure that can be used to evaluate the importance of changes in the spatial distribution of stores from a consumer perspective. The figure shows that the average nearest pharmacy distance changes very little over time, in the magnitude of only a few metres. On the other hand, there has been a marked increase by 70 metres in the nearest competitor distance since 2004. This change is not a large one in absolute terms, but it is still remarkable because changes in the spatial equilibrium configuration are naturally expected to be a rather slow process.[28] The structural empirical estimation below will use a subset of data from eighty large German cities (see table 14). Figure 11 below shows the development of the number of active pharmacies, as well as the nearest competitor and nearest pharmacy distances over time for this sub-sample of the data. The patterns shown in figures 10 and 11 are qualitatively very similar, although the magnitudes of the nearest neighbour distances are naturally much smaller. The descriptive evidence so far is consistent with the hypothesis of increased competition among nearby competitors as a result of the introduction of price competition to the retail pharmacy market.

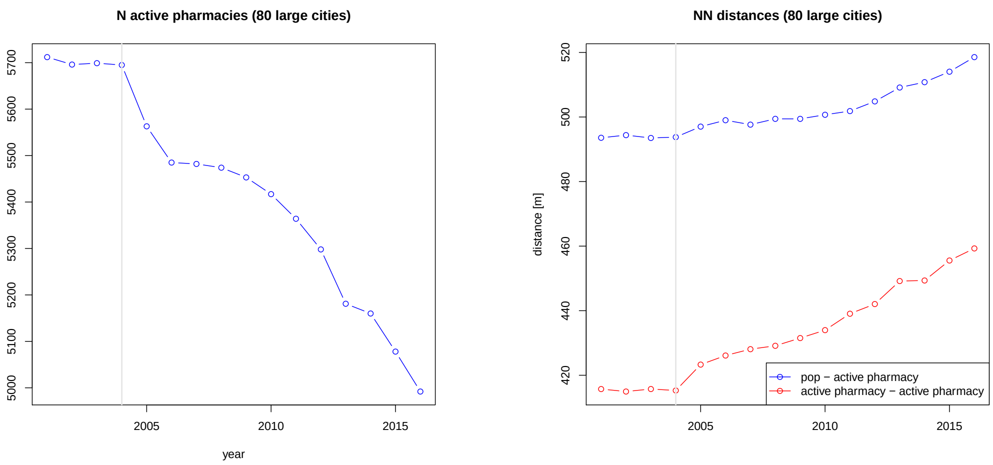
[28]Note that it is not straightforward to test for yoy changes because the data are not independent, and do not converge to a normal distribution. That is why (Diggle, 2014, p.19) suggests using bootstrap tests in spatial point statistics.



(a) No. of active pharmacies

(b) Nearest neighbour metrics

Figure 10: Spatial configuration of pharmacies in Germany



(a) No. of active pharmacies

(b) Nearest neighbour metrics

Figure 11: Spatial configuration of pharmacies in 60 large German cities

Variable	*Explanation*	*Variation*	*mean*	*SD*	*min*	*max*
vacancy rate	among all buildings, (2011)	total	0.043	0.023	0.016	0.136
commuters (in)	share of total population (2012)	total	0.091	0.114	-0.056	0.452
sq. m. price	annual price of construction land	total	0.220	0.155	0.002	1.236
	per square metre, in 1,000€	between		0.140	0.027	0.792
		within		0.067	-0.098	0.793
unemployment	annual unemployment rate	total	0.099	0.035	0.031	0.237
		between		0.029	0.042	0.169
		within		0.019	0.038	0.172
income	annual real disposable income	total	2.069	0.281	1.569	4.337
	per capita, in 10,000€	between		0.270	1.638	3.335
		within		0.082	1.088	3.071
income growth	annual growth rates	total	0.002	0.018	-0.100	0.100
	in per capita units	between		0.004	-0.006	0.020
		within		0.018	-0.109	0.106
population growth	annual population growth	total	0.003	0.008	-0.043	0.058
		between		0.005	-0.008	0.013
		within		0.006	-0.046	0.055

Table 5: Summary statistics of variables that determine demand at the municipal level. Data from 80 large German cities (excluding Berlin, Hamburg, Munich, Cologne). The between and within variations are only computed for variables which actually vary over time. Author's own calculations based on data from Statistische Ämter des Bundes und der Länder (2018).

A key question that is addressed in spatial point pattern statistics is whether the observed events occur independently of each other, or not. In particular, researchers are often interested in whether the data generating process exhibits a tendency to produce clustered or, on the contrary, regular point patterns. As a benchmark hypothesis, it is often assumed that the points are generated by a spatial Poisson point process. Poisson processes generate point patterns that are characterized by complete spatial randomness (CSR). Their theoretical properties are used to construct formal tests against the null hypothesis of CSR. The interpretation of such tests is however complicated by the fact that it is very difficult to formally distinguish whether a point process exhibits inherent clustering, or whether the observed clustering is an artefact of some unobserved spatial heterogeneity (Diggle, 2014, chapters 2 and 4). One frequently used statistic to describe the properties of spatial point processes is the cumulative distribution function of the nearest neighbour distances between points ("events"), called the G-function.[29] It can be used to construct a test against CSR, but also more generally to test whether two different point patterns share the same distributive properties. The tests are usually constructed as exact Monte-Carlo tests (Diggle, 2014, p.19).

The left panel of figure 12 shows the estimated G-functions for all years from 2001 through

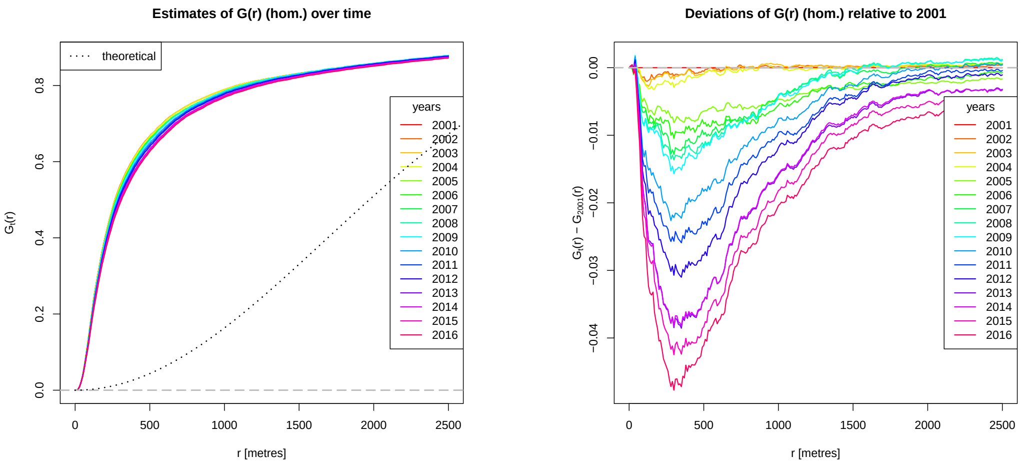
[29] In Diggle (2014), the K-function is discussed as an alternative measure. It has the appealing property that it does not depend on the total number of observations, but is also less intuitive to explain and thus requires a more extensive discussion.

to 2016. The dotted line represents the theoretical G-function under CSR. The figure clearly shows that the empirical G-functions differ from their theoretical counter-part under CSR, which can be formally confirmed by means of a bootstrap Monte Carlo test. But as discussed above, this is does by no means imply that pharmacies have an inherent tendency to cluster together. Instead, it is far more likely that the observed tendency to cluster is the result of spatial heterogeneity in local demand conditions, which can be unobserved (the "attractiveness" of a location) or observed (such as the local residential population).[30] To ascertain whether the spatial pattern of pharmacies indeed exhibits clustering, one would have to control for all factors that affect the probability to open up a pharmacy at a given location. However, since the prime goal of this paper is whether the 2004 health care reform has *changed* the spatial pattern of locations over time, the panel structure of the data allows me to examine this more directly. To make the changes over time more visible, the difference $G_t(d) - G_{2001}(d)$ is shown in the right panel of figure 12. That figure clearly shows that the G-function has decreased over time and moved gradually closer to the theoretical function under CSR. Therefore, the amount of clustering has decreased over time. It seems plausible that this change has occurred as a consequence of price competition among nearby competitors, because the most pronounced changes occur in the range from zero to four hundred metres. In order to test whether the observed changes of the G-function are statistically significant, an exact Monte Carlo test for the equality of the G-function in two subsequent years was constructed. Further, a variation of the test which uses the differences between G_y and G_{2001}, $y = 2002, \ldots, 2016$ was conducted in order to test whether the cumulative changes relative to the base year are statistically significant.[31] The test statistics of these tests are shown in table 6, and the 0.95 Monte Carlo critical value was found to be 0.019. The null hypothesis that two distributions are the same is rejected if the test statistic exceeds the critical value. So the table shows that the year-over-year changes are never statistically significant at the 5% level, but that the cumulative changes relative to 2001 are significant from 2010 onwards.

The statistical analysis in this subsection has shown show that the spatial distribution of pharmacies exhibits pronounced changes over time. The structural model in the next section will explore the causes of this change from an economic perspective, and relate it to the introduction of price competition in the retail pharmacy market.

[30]There are methods to compute the G-function in the presence of spatial heterogeneity, but these methods are highly susceptible to obtaining an initial estimate of the spatial intensity function (Diggle, 2014).

[31]The test was conducted with the methods described in Diggle (2014, p.19), with the exception that the *difference* between the G-functions of two point patterns is used as a test statistic. The distribution of this test statistic under CSR was computed by repeatedly simulating random point patterns.



(a) $G_t(d)$ **(b)** $G_t(d) - G_{2001}(d)$

Figure 12: The distribution of nearest-neighbour distances (G-function) over time

t	Test statistics $G_t - G_{t-1}$	$G_t - G_{2001}$
2002	0.00006	0.00006
2003	0.00001	0.00011
2004	0.00005	0.00023
2005	0.00378	0.00487
2006	0.00035	0.00708
2007	0.00065	0.00752
2008	0.00014	0.00908
2009	0.00007	0.01034
2010	0.00361	0.02543*
2011	0.00138	0.03801*
2012	0.00134	0.05337*
2013	0.00453	0.08719*
2014	0.00001	0.08622*
2015	0.00146	0.10886*
2016	0.00161	0.13525*

H_0: G-functions are the same.
0.95 critical value: $q_{95} = 0.01933$

Table 6: Test statistics for the equality of the distribution of nearest neighbour distances, G, in two subsequent years (first column) and relative to the base year 2001 (second column). The Monte Carlo critical value is based on 199 simulations of two random spatial point patterns.

7 Empirical results

The maximum likelihood estimator presented in section 5.3 is used to estimate the principal structural parameters of the dynamic entry game in a set of large German cities. I am mainly interested in the spatial interaction parameter δ in equation (20) that governs by how much the variable profits of a pharmacy change due to the presence of a nearby competitor. In order to assess the effect of the 2004 reform, this parameter is allowed to differ before and after 2004. Following the discussion about the institutional details of the market, I also allow for the entry costs to differ before and after the regulatory change in 2004. The empirical analysis proceeds as follows. In a first step, the spatial interaction radius d is chosen by means of a simplified model without strategic interaction. Then, the model that allows for strategic interaction at the local level of k nearest neighbours is brought to the data, and an appropriate value for k is chosen. The results of this model are discussed, followed by a model validation exercise. Lastly, I use the estimated model parameters to isolate the effect of more intense local competition on market outcomes, and also perform a counter-factual exercise to assess the effect of a hard geographic entry restriction. As a robustness check, I re-estimate the model with additional potential entry locations and with additional co-variates.

7.1 Specification search

In order to choose an appropriate spatial interaction radius d that determines whether two adjoining pharmacies have a direct effect on each others' profits (c.f. the profit equation (20)), a stripped down version of the model that excludes any strategic interaction is estimated. This model is obtained by setting the number of strategic nearest neighbours to one (so firms assume that no competitor changes its status), and solving the resulting single-agent dynamic decision problem. Pharmacies' profits are given by equation (20), with variables as given in table 4, and their decision was modelled as outlined in section 5.2 with $k = 1$, i.e. no strategic neighbours are considered. Table 7 shows the estimated spatial interaction parameters, and the resulting log-likelihood value for different choices of the interaction parameter. It can be seen that the log-likelihood attains a maximal value for $d = 900$, and I use this value in the subsequent analysis. Also, the table shows that the estimates of the interaction terms δ remain approximately constant as the interaction radius increases further. Since the number of parameters is the same across all specifications, the Akaike information criterion would therefore lead to the same model selection.

Next, I use a similar procedure to determine the number of strategic nearest neighbours that corresponds to the size of the local state space which every firm forms their expectations about. For a spatial interaction radius of nine hundred metres, I estimate the model for $k = 1, 2, \ldots, 6$ and record the maximum likelihood value. Table 8 shows that the maximum likelihood is attained at $k = 5$. The table also shows that there is initially a

$d[m]$	$\hat{\delta}_{pre}$	$\hat{\delta}_{post}$	ll	$d[m]$	$\hat{\delta}_{pre}$	$\hat{\delta}_{post}$	ll
100	0.051	-0.004	-14837.8	1100	0.003	0.009	-14783.7
200	0.023	0.022	-14833.9	1200	0.003	0.009	-14788.2
300	0.018	0.018	-14823.6	1300	0.003	0.009	-14789.8
400	0.011	0.014	-14810.7	1400	0.002	0.009	-14794.3
500	0.008	0.013	-14798.9	1500	0.002	0.009	-14797.4
600	0.005	0.011	-14789.4	1600	0.002	0.009	-14801.4
700	0.004	0.010	-14787.8	1700	0.002	0.009	-14805.6
800	0.003	0.009	-14786.6	1800	0.002	0.009	-14810.0
900	**0.002**	**0.009**	**-14780.3**	1900	0.002	0.009	-14814.4
1000	0.002	0.009	-14780.5	2000	0.002	0.008	-14820.3

Table 7: Estimates of the spatial interaction parameter and the log-likelihood for different values of the spatial interaction radius d, in a simple model without strategic interaction. A maximal log-likelihood is attained at $d = 900m$.

large improvement in the log-likelihood when just one strategic nearest neighbour is added (going from $k = 1$ to $k = 2$). For larger values of k the log-likelihood remains approximately flat, and parameter estimates change only marginally but the computational time increases rapidly. Therefore, I am confident that larger values of k beyond of what is computationally feasible would not lead to great improvements or changes in the model.

The full parameter estimates are shown in table 16 in the appendix. An interesting insight of this table is the apparent invariance of the estimated coefficients with regard to the choice of the parameter k. A formal test of one specification against the other is work to be done in the future[32] but the log-likelihood, and the estimated coefficients are virtually the same for any $k > 1$. The specification without strategic interaction ($k = 1$) attains a somewhat smaller log-likelihood, and estimated parameter values that are different, albeit probably not significantly so. This could indicate that very little strategic interaction takes place among pharmacies and that players only take into account the actions of their immediate nearest neighbouring location. On the other hand, the kind of strategic interaction that is built into the model by means of adding "strategic neighbours" is of anticipatory nature, and so another explanation is that firms do not engage in anticipating their neighbours' actions and instead base their decisions solely on the currently observed market state. This behaviour is already captured by the panel structure of the data.

Does this invalidate the chosen approach of building a dynamic entry model with strategic interaction? The answer is no. For although the result is that anticipatory strategic interactions play a relatively minor role in determining firms' behaviour in the industry under consideration, the answer could be a different one in a different industry. The strength of the approach presented here is that it allows the researcher to test to what degree agents make strategic anticipatory decisions. These insights can also guide modelling approaches in other contexts with regard to how much emphasis is placed on dynamic strategic interactions of agents.

[32]This is complicated by the fact that the models are not nested into each other

k	$\hat{\delta}_{pre}$	$\hat{\delta}_{post}$	ll	runtime [s]
1	0.0024	0.0089	-14780.27	730.00
2	0.0021	0.0087	-14769.41	587.00
3	0.0020	0.0086	-14768.09	1170.00
4	0.0020	0.0087	-14768.42	2186.00
5	**0.0020**	**0.0087**	**-14767.65**	**4067.00**
6	0.0020	0.0088	-14768.27	15673.00

Table 8: Estimates of the spatial interaction parameter and the log-likelihood for different sizes of the strategic neighbours k, at a spatial interaction radius $d = 900m$. A maximal log-likelihood is attained at $k = 5$. The estimation with $k = 1$ had a larger runtime because the parameters were not initialized in that specification.

7.2 Main result

Table 9 below shows the main estimation result that was obtained from a sample of eighty large German cities with more than six thousand pharmacy locations, using $d = 900m$ and $k = 5$ as outlined above. Standard errors were computed using the estimated inverse Hessian matrix that is returned by the BFGS optimization routine. The exit value θ^x was normalized to unity. Further results are deferred to table 17 in appendix B.5.

The estimated spatial interaction parameter δ is smaller and insignificant before the reform, and it is more than four times as large in the post-period, and significantly different from zero. This confirms one key hypothesis of the paper, namely that the introduction of price competition for non-prescription drugs has stiffened competition among nearby pharmacies, and so increased the tendency of firms to locate further away from each other. The estimates imply that one additional active competitor within a radius of 900m reduces profit margins by about 0.9%. The total effect on variable profits is larger than this, because local demand decreases as the number of active neighbours increases. Since the number of active nearest neighbours within that radius can be quite large in urban areas, this implies that competition has now sizeable effects on pharmacies' profitability, whereas it was virtually nil before the reform. Because the estimated interaction parameters are also rather small in comparison to the magnitudes of the other parameters, the model is likely to possess only one single equilibrium, as is also discussed in section 5.3. Entry costs are smaller in the post-reform period, and the post-reform dummy is negative which points to smaller period returns in the post period. Lower entry costs and smaller period returns together imply that there is more turnover. The size of the local population, divided by the number of active stores within the interaction radius has a significantly positive effect on period returns, as well as the local share of the population that is older than 65 (elderly share). The coefficients for proximity to public transport, supermarkets and physicians generally have the anticipated signs, whereas proximity to a main road seems to have a negative effect on profits, albeit insignificant.

Local demand		
intercept	0.2941***	*(0.0092)*
post reform	-0.0324***	*(0.0065)*
local population†	0.1682***	*(0.0260)*
elderly share	0.0968***	*(0.0258)*
pedestrian zone	0.0163***	*(0.0042)*
mainroad	-0.0024	*(0.0032)*
doctor nearby	0.0272***	*(0.0039)*
supermarket nearby	0.0323***	*(0.0038)*
trainstation nearby	0.0187**	*(0.0074)*
Local competition		
δ_{pre}	0.0020	*(0.0025)*
δ_{post}	0.0087***	*(0.0017)*
Entry costs		
θ^e_{pre}	4.9005***	*(0.0393)*
θ^e_{post}	4.3318***	*(0.0179)*
log-likelihood	-14,767.7	
N locations	6,741	
T periods	16	
	* < 0.1; ** < 0.05; *** < 0.01	

Table 9: Estimates of the spatial entry model with a strategic neighbourhood of size five (self and four nearest neighbours), and a spatial interaction radius of nine hundred metres. N=6741 firms, T=16 time periods in 80 large German cities. Exit values are normalized to 1. †local population is the residential population within 500 metres of the store's location, divided by the number of active competitors in the respective time period or future state. Standard errors in parentheses, computed from estimated Hessian matrix.

7.3 Model validation

In order to assess whether the model can replicate key trends that are observed in the data (see figure 10), I simulated a large number of counter-factual market outcomes, starting from the observed market state in the year 2004 and using either the pre-reform estimates (i.e. post reform dummy set to zero, $\delta = \hat{\delta}_{pre}$, and θ^e_{pre}), or the corresponding post-reform estimates. The simulated market outcomes are analysed along three dimensions: (1) number of active stores, (2) average distance to the nearest competitor and (3) average consumer distance to the nearest pharmacy.

The simulation results are shown graphically in figure 13 in appendix B.4. The top panel in figure 13a shows that the model, when set up with the pre-reform parameter values, predicts that the total number of active stores remains approximately constant, as desired. When using the post-reform parameter values, shown in the top panel of figure 13b, this number exhibits a downward sloping trend that does follow the observed number of active stores quite closely. On the other hand, the bottom two panels in figures 13a and 13b show that the simulated average store-to-store distance is smaller, and the average simulated consumer travel distance is larger than what is observed prior to the reform, and after the reform, respectively. Apparently, the model-implied competition among nearby stores is too small to fully replicate the observed behaviour. This could also be due to the linear

	year	Number of stores	distance (metres): pharmacy to nearest competitor	distance (metres): consumer to nearest pharmacy
observed				
	2004	5,437	423	514
	2016	4,770	469	539
	Δ	**-667**	**+45**	**+25**
simulated				
pre-reform parameters	2016	5,466	407	526
post-reform parameters	2016	4,850	441	558
	Δ	**-615**	**+34**	**+32**

Table 10: Comparison of actual changes throughout the post-reform period, and the model-implied differences between the pre- and the post-reform periods.

way in which I modelled the competition among nearby stores, where every store within a radius d has the same negative effect δ on its competitors' profit margins. It seems plausible that stores which are closer also exhibit more competitive pressure, but modelling this in a reduced form manner would require an arbitrary choice of a functional form. Instead, one could integrate a truly spatial demand model in the estimation routine, which would automatically capture such effects.[33] This is work to be done in the future.

Despite the discrepancies between the observed and the model-implied simulation results, I argue that the *difference* between the two simulation results (pre- and post-reform) accurately reflects the changes that have occured due to the reform. This is supported by table (10). This table shows that the model-implied differences between the pre- and the post-reform period are rather close to the observed changes from 2004 to 2016, and it therefore confirms that the changes of the structural parameters, when suitably interpreted, can indeed explain a good part of what was observed in the post reform period.

7.4 Quantifying the effect of price competition

What can be seen in the data as well as in the simulations in figure 13b is the total effect of three changes: first, lower entry costs; second, lower per-period profits; and third, increased local competition due to price competition. To isolate the effect of increased local competition, the idea is to differentiate the model's predictions with respect to the spatial interaction parameter δ. Since no closed form solutions are available, this is done numerically, as outlined in the following. The effect of increased price competition can be evaluated using either the pre-reform parameter estimates as a starting point, or by using the post-reform estimates as a starting point. More precisely, consider a simulated time series of market outcomes that was generated using the parameters $post\_2004 \in \{0, 1\}$, θ^e and denote an arbitrary aggregate statistic that was computed from this simulated data as

[33] On the other hand, such a structural demand model, possibly combined with a price equilibrium, is much harder to interpret than the single interaction parameter δ.

	post2004	entry costs	interaction	outcome of interest
(A) compare	0	$\hat{\theta}^e_{pre}$	$\hat{\delta}_{post}$	$t(0, \theta^e_{pre}, \delta_{post})$
against	0	$\hat{\theta}^e_{pre}$	$\hat{\delta}_{pre}$	$-t(0, \theta^e_{pre}, \delta_{pre})$
				$= \Delta_A t$
(B) compare	1	$\hat{\theta}^e_{post}$	$\hat{\delta}_{post}$	$t(1, \theta^e_{post}, \delta_{post})$
against	1	$\hat{\theta}^e_{post}$	$\hat{\delta}_{pre}$	$-t(1, \theta^e_{post}, \delta_{pre})$
				$\Delta_B t$

Table 11: Counterfactual simulations to quantify the effect of stiffer price competition

$t(post\_2004, \theta^e, \delta)$. Then, the partial effect of changing δ from δ_{pre} to δ_{post} can be computed as either $\Delta_A = t(0, \theta^e_{pre}, \delta_{post}) - t(0, \theta^e_{pre}, \delta_{pre})$ or as $\Delta_B = t(1, \theta^e_{post}, \delta_{post}) - t(1, \theta^e_{post}, \delta_{post})$. These two estimates of the partial effect will in general be different, but it turns out that they are quite close to each other. Table 11 summarizes the procedure.

Table 12 shows the results of this decomposition exercise for the three aggregate statistics that are also shown graphically in figure 13, using simulated data runs from 2004 to 2016. The table shows that increased local competition due to changing the interaction parameter from δ_{pre} to δ_{post} can explain about one third of the decline in the number of pharmacies. The table also shows that about one third of the observed increase in the inter-firm nearest neighbour distance can be attributed to this change of parameters, whereas only one sixth to one seventh of the total increase in consumer travel distances are attributable to this factor.

Thus, from a consumer perspective, while increased price competition has lead to a substantial reduction of the number of pharmacies, it did not lead to much greater travel distances, presumably because it has caused the exit of retail pharmacies that were located very close to another competitor which can offer the same services and products. If the aim of the 2003 health care reform was to reduce the costs of the health care system, introducing a modest degree of price competition into the retail pharmacy sector has thus been a very consumer-friendly way of reducing the number of pharmacies and, thereby, the total fixed costs of the health care system. One should note that a full welfare analysis is not possible due to the lack of detailed price data. However, it seems reasonable to assume that prices did not increase as a result of more intense price competition, and so the cost savings due to the lower number of retail pharmacies probably outweigh the small increase in consumer travel distances.

7.5 Policy experiment: geographical entry restriction

The theoretical model in section 4 has shown that free location choice in the absence of spatial competition leads to inefficient, Hotelling-style clustering, thus inflicting inefficiently large travel costs on consumers. This is precisely the reason why many European countries have or had minimum distance regulations in place whereby a minimum distance $\bar{d}$

		distance (metres)	
	Number of stores	pharmacy to nearest competitor	consumer to nearest pharmacy
Total change 2004-2016			
actual	-667	+45	+25
simulated	-616	+34	+32
of which: competition effect			
(A) $t(0, \theta^e_{pre}, \delta_{post}) - t(0, \theta^e_{pre}, \delta_{pre})$	-224	+15	+4
(B) $t(1, \theta^e_{post}, \delta_{post}) - t(1, \theta^e_{post}, \delta_{post})$	-215	+16	+4

Table 12: The effect of increased price competition on aggregate outcomes in 2016 using model (5) in table 9, average over 100 simulations, 80 large Germany cities.

between any two active pharmacies must be maintained at all times (see section 2.2). The estimated model allows me to evaluate the effect of imposing such a regulation on the German pharmacy market, by changing the period return structure to include a "penalty" parameter p that is subtracted from firms' profits if any one of their active neighbours is closer than the regulated minimum distance. Thus, new period returns are given by

$$\pi_j^{reg} = \begin{cases} \pi_j - p \,, \text{ if } \exists k : d_{jk} \leq \overline{d} \\ \pi_j \,, \text{ else.} \end{cases}$$

where π_j is specified in (4). I chose to set $p = \theta^e$, so that entry is unprofitable already after the first period, as desired. Then, two hundred independent market configurations are simulated, starting from the market configuration in 2004.

The average statistics across two hundred independent simulations for a minimum distance of one hundred metres are shown in figure 15a in appendix B.4. That figure shows that such a regulation would immediately reduce the number of active pharmacies by around six hundred stores, or by around ten percent, followed by a further decline that is due to the changed profit and competition conditions after the 2004 reform. As an immediate consequence, the nearest competitor distance would have instantaneously increased by roughly seventy metres, followed by a further increase. Consumer to nearest pharmacy distances would have increased, too.

To interpret these simulation results, it is important to keep in mind that neither the nearest competitor distance, nor the nearest pharmacy distance, have been used as direct estimation moments. Therefore, the model predictions for these statistics are biased, as was shown in section 7.3. Thus, to assess the effects of a minimum distance regulation it is necessary to determine how these model predictions change as such a policy change is implemented. The idea behind this is to "differentiate" the model predictions with respect to a policy change by means of simulation, akin to the procedure used in the previous section. To this end, I compared the simulated outcomes under the distance regulation to those without such a regulation in table 13. That table shows that the total number of

		distance (metres)	
	Number of stores	pharmacy to nearest competitor	consumer to nearest pharmacy
Total simulated change 2004-2016			
post-reform parameters	–616	+34	+32
post-reform + distance regulation	–1036	+93	+46
distance regulation effect	**–421**	**+60**	**+14**

Table 13: The effect of a minimum distance regulation on key market outcomes. The first line shows the simulated changes from 2004 to 2016, using the post-reform parameter estimates. The second line shows the simulated changes using the post-reform parameter estimates and a minimum distance regulation of 100 metres. The last line denotes the additional simulated effect of a minimum distance regulation. Numbers are averages over 100 simulations.

stores in 2016 would have been smaller by about four hundred stores had such a regulation been in place since 2004. The nearest competitor distance would have been larger by sixty metres, whereas the nearest pharmacy distance would have increased by only fourteen metres. A graphical depiction of the difference between the simulated market outcomes with and without a minimum distance regulation is shown in figure 15b. The top panel of that figure shows that the number of active firms immediately decreases relative to the base line scenario, but then the difference remains relatively constant. Also, the nearest competitor distance remains approximately constant relative to the base line scenario. The most important insight from this analysis is that the nearest pharmacy distances do not increase much more than in the baseline scenario.

One apparent caveat of this exercise lies in the fact that I am only using observed locations, whereas such a drastic regulatory measure may actually lead to new locations becoming feasible. Section B.5.2 in the appendix addresses this concern by including a larger set of potential entry locations. The results however remain qualitatively the same. A second concern is that pharmacies compete along a quality dimension, so such a regulatory scheme could lead to lower service quality because it actually creates local monopolies. More generally speaking, since the period returns of the dynamic entry model are modelled in a reduced form, counter-factual analyses are in principle subject to the Lucas' critique (Lucas, 1976) in that the estimated reduced form coefficients tell us little about the agent's reactions to such a drastic change in the economic environment. But to a lesser extent, this would also be true for a more elaborate model with a "structural" profit equation. Any model, be it reduced form or structural, can only inform us about those aspects of agents' decision making that are built into it: a structural model of price competition can make predictions about price reactions to the ownership structure only if the ownership structure is part of the model. Similarly, a model of dynamic spatial entry can inform us about the responses to minimum distance regulations, but not how pharmacies would change their business model, their opening hours, or their service quality.

8 Conclusion

I have documented pronounced qualitative and quantitative changes in the spatial distribution of pharmacies in Germany over time. Motivated by a simple theoretical model, I developed a structural dynamic entry model and used it to estimate the key parameters that govern the process of spatial entry and exit. These parameter estimates indicate that local competition has indeed increased after 2004, most likely due to a large health care reform that introduced price competition for non-prescription drugs. A simulation exercise shows that increased competition can explain one third of the total change in the number of pharmacies, but only a small share of the increase in consumer's travel distances. This suggests that more price competition can lead to more efficient spatial store configurations in that the total number of stores is reduced, which implies lower fixed costs, while consumers do not have to travel much farther. Thus, even abstracting from the fact that prices are likely to be smaller due to price competition, increased price competition can lead to better market outcomes. I have also examined the likely effects of introducing a geographic entry barrier that prevents stores from locating very close to each other. My results show that the effects of such a regime are similar to those that are generated by the introduction of price competition in that the total number of stores decreases, but consumers' travel costs do not increase very much. But because such a regulatory regime amounts to establishing local monopolies, it probably has detrimental effects on consumer welfare that are not captured in the model. Therefore, the introduction of price competition is the more efficient regulatory measure.

The analysis has a number of shortcomings which are left for future research. First of all, it restricts the analysis to urban markets. An extension of the analysis to rural markets is possible, but because consumers' travel patterns and, in consequence, the range of spatial interaction among pharmacies, are likely to be very different in those markets, this calls for a separate analysis, perhaps using the isolated market paradigm of Bresnahan and Reiss (1991). Second, the reduced form profit equation could be replaced by a structural revenue model with spatial demand and endogenous prices, but this is currently infeasible in the context of a dynamic model due to the large additional computational burden. Yet, my results indicate that the anticipatory strategic component does not play a large role, and so a simpler model of dynamic decision making could well be used to that effect.

On the methodological front, I have established a method to compute and estimate a spatial dynamic entry model with a large number of asymmetric heterogeneous agents. The method has proves to work well with thousands of potential entry locations, and could be extended to include more sophisticated "structural" period return functions. Due to the flexible way in which the size of the strategic neighbourhood is specified, the model can be used to examine in how far strategic anticipatory motives play a role in dynamic decision making. In principle, this model is applicable to a wide range economic questions, but the main application lies in retail markets where spatial interaction and strategic decision making are important factors.

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A Proofs

First, consider the proof of proposition 1, repeated here for convenience:

Proposition. *The symmetric space-then-price equilibrium of the model described above is characterized by location choices $x_a = x^*$ and $x_b = 1 - x^*$ with*

$$x^* = \begin{cases} 0 & \text{if } \alpha \leq \frac{\tau}{3+\tau}, \\ -\frac{1}{4} + \frac{3}{4}\frac{\alpha}{\tau(1-\alpha)} & \text{if } \frac{\tau}{3+\tau} < \alpha < \frac{\tau}{1+\tau}, \\ \frac{1}{2} & \text{if } \alpha \geq \frac{\tau}{1+\tau}, \end{cases}$$

and prices $p_a = p_b = p^*$ with

$$p^* = \begin{cases} \tau & \text{if } \alpha \leq \frac{\tau}{3+\tau}, \\ \frac{3}{2}\left(\tau - \frac{\alpha}{1-\alpha}\right) & \text{if } \frac{\tau}{3+\tau} < \alpha < \frac{\tau}{1+\tau}, \\ 0 & \text{if } \alpha \geq \frac{\tau}{1+\tau}. \end{cases}$$

Proof. With quadratic travel costs, the consumer who is just indifferent between purchasing a price regulated prescription drug from either pharmacy is located at $\bar{\imath} = (x_a + x_b)/2$, and the demand for prescription drugs is hence given by $Q_a^{Rx} = \alpha\bar{\imath}$ and $Q_b^{Rx} = \alpha(1 - \bar{\imath})$. The indifferent consumer who purchases a non-prescription drug is located at

$$\breve{\imath} = \frac{x_a + x_b}{2} + \frac{1}{2\tau}\frac{p_b - p_a}{x_b - x_a}$$

so that demand for non-prescription drugs is similarly given by $Q_a^{OTC} = (1-\alpha)\breve{\imath}$ and $Q_b^{OTC} = (1-\alpha)(1-\breve{\imath})$.

Consider first the price equilibrium, given location choices x_a and x_b. Because there are no complementarities across products, firms will essentially set the price for non-prescription drugs so as to maximize variable profits from that product category. Maximizing the firms' profit equations, and re-arranging the first-order conditions, it is easy to derive the following price equilibrium:

$$\begin{aligned} p_a^* &= \frac{\tau}{3}(x_b - x_a)(2 + x_a + x_b) \\ p_b^* &= \frac{\tau}{3}(x_b - x_a)(4 - x_a - x_b) \end{aligned} \tag{21}$$

Note that, in the symmetric location case where $x_b = 1 - x_a$, I have $p_a^* = p_b^* \equiv p_{symm}^* = \tau(1 - 2x_a)$. The location of firm a is a measure of centrality, and prices are lower when the two firms are located closer to the market centre (and therefore closer to each other).

Next turn to the equilibrium location decisions of both firms. Anticipating the equilibrium effect on prices, firms now choose their locations simultaneously so as to maximize their profits. In doing so, they must trade off the market share effect of being located closer to the market centre against the market power effect of being located more distantly from their competitor:

$$\frac{\mathrm{d}\pi_j}{\mathrm{d}x_j} = \underbrace{\alpha\frac{\partial Q_j^{Rx}}{\partial x_j} + (1-\alpha)p_j\frac{\partial Q_j^{OTC}}{\partial x_j}}_{\text{market share effect}} + \underbrace{(1-\alpha)p_j\frac{\partial Q_j^{OTC}}{\partial p_{-j}}\frac{\mathrm{d}p_{-j}^*}{\mathrm{d}x_j}}_{\text{market power effect}} \tag{22}$$

The equilibrium effect on own prices is cancelled out in equilibrium, so that the market power effect only includes the equilibrium effect of one's re-locations on the prices of other firms. I am looking for a symmetric equilibrium x^* where $x_a = x^*$ and $x_b = 1 - x^*$. The price equilibrium then implies $p_a^* = p_b^* = \tau(1-2x^*)$. Using results from above, equation (22) can be used to compute a candidate equilibrium:

$$\left.\frac{\mathrm{d}\pi_a}{\mathrm{d}x_a}\right|_{x^*} = 0 \Leftrightarrow x^* = -\frac{1}{4} + \frac{3}{4}\frac{\alpha}{\tau(1-\alpha)}$$

With locations restricted to the unit interval, and $x_a \leq x_b$, the locational equilibrium must satisfy $x^* \in \left[0, \frac{1}{2}\right]$. Hence, an equilibrium location is an interior location whenever the share of consumers purchasing price regulated prescription drugs α is sufficiently large, but not too large:

$$x^* = \begin{cases} 0 & \alpha \leq \frac{\tau}{3+\tau} \\ -\frac{1}{4} + \frac{3}{4}\frac{\alpha}{\tau(1-\alpha)} & \frac{\tau}{3+\tau} < \alpha < \frac{\tau}{1+\tau} \\ \frac{1}{2} & \alpha \geq \frac{\tau}{1+\tau} \end{cases} \tag{23}$$

The ensuing price equilibrium is then given by

$$p^* = \begin{cases} \tau & \alpha \leq \frac{\tau}{3+\tau} \\ \frac{3}{2}\left(\tau - \frac{\alpha}{1-\alpha}\right) & \frac{\tau}{3+\tau} < \alpha < \frac{\tau}{1+\tau} \\ 0 & \alpha \geq \frac{\tau}{1+\tau} \end{cases} \tag{24}$$

$\square$

This section continues with the proof for the proposition 2 in section 4, split up into two lemmas for convenience.

Lemma 1. *Suppose that the regulated price of prescription drugs $\bar{p}$ was zero, and that parameters are such that $x^* < \frac{1}{2}$ in the competitive equilibrium. Then, the difference of consumer welfare in the competitive equilibrium relative to the regulatory benchmark increases strictly as the share of prescription consumers α increases ($\frac{\mathrm{d}}{\mathrm{d}\alpha}\Delta W(0) > 0$).*

Proof. One can distinguish two cases here. *Case 1:* Suppose that $\alpha \leq \frac{\tau}{3+\tau}$ so that $x^* = 0$. Then, $\Delta W = (\alpha - 1)\tau < 0$ and the change in consumer welfare is obviously increasing strictly in α, as $\tau > 0$ by assumption. *Case 2:* If $0 < x^* < \frac{1}{2}$ it must hold that $\frac{\tau}{3+\tau} < \alpha < \frac{\tau}{1+\tau}$. Because $0 \leq \tau < 1$, this implies $0 < \alpha < 1$. Note first that the marginal change of the firms' equilibrium locations with respect to α is given by

$$\frac{\mathrm{d}x^*}{\mathrm{d}\alpha} = \frac{3}{4\tau(1-\alpha)^2}$$

Because this expression is increasing strictly in α for any $\alpha \in (0,1)$, and because $\alpha > \frac{\tau}{3+\tau}$ it can be bounded below by the function $f(\tau) = \frac{1}{12}\frac{(3+\tau)^2}{\tau}$. This term, in turn, is strictly decreasing for $\tau \in [0,1]$ and hence, its minimum is attained at $\tau = 1$ with $f(1) = \frac{4}{3}$. Therefore,

$$\frac{\mathrm{d}x^*}{\mathrm{d}\alpha} \geq \frac{4}{3} \tag{25}$$

with a strict inequality if $\tau < 1$. Also, note that $\alpha < \frac{\tau}{1+\tau}$ is equivalent to $\tau(1-\alpha) > \alpha$ which will be convenient below. The change in consumer welfare in (3) can equivalently be written as

$$\Delta W = (\alpha - 1)\tau + \frac{1}{2}\left(5\tau + \alpha(1-5\tau)\right)x^* - (\tau + \alpha(1-\tau))x^{*2}$$

The marginal change of ΔW with respect to changes in α is

$$\frac{\mathrm{d}\Delta W}{\mathrm{d}\alpha} = \tau + \underbrace{\left[\frac{1-5\tau}{2} - (1-\tau)x^*\right]}_{\equiv A} x^* + \underbrace{\left[\frac{1}{2}(\alpha + 5\tau(1-\alpha)) - 2x^*(\alpha + \tau(1-\alpha))\right]}_{\equiv B}\frac{\mathrm{d}x^*}{\mathrm{d}\alpha} \tag{26}$$

First, consider term A. Substituting for the expression of equilibrium location choices, one obtains

$$\begin{aligned}
A &= \frac{1}{2}(1-5\tau) - \left(-\frac{1}{4} + \frac{3}{4}\frac{\alpha}{\tau(1-\alpha)}\right)(1-\tau) \\
&= -\frac{3}{4}\frac{\alpha(1-\tau)}{\tau(1-\alpha)} + \frac{1}{4}(1-\tau) + \frac{1}{2}(1-5\tau) \\
&= -\frac{3}{4}\underbrace{\frac{\alpha(1-\tau)}{\tau(1-\alpha)}}_{<1-\tau} + \frac{3}{4} - \frac{11}{4}\tau \\
&> -\frac{3}{4}(1-\tau) + \frac{3}{4} - \frac{11}{4}\tau = -2\tau.
\end{aligned}$$

Next, consider term B. Because $x^* < \frac{1}{2}$ and with $\tau(1-\alpha) > \alpha$, it can be bounded below as follows:

$$\begin{aligned}
B &> \frac{1}{2}(\alpha + 5\tau(1-\alpha)) - (\alpha + \tau(1-\alpha)) \\
&= -\frac{1}{2}\alpha + \frac{3}{2}\underbrace{\tau(1-\alpha)}_{>\alpha} > \alpha
\end{aligned}$$

Finally, substituting for the lower bounds of A, B, $\frac{\mathrm{d}x^*}{\mathrm{d}\alpha}$, and x^* in (26), one can derive the following inequality

$$\begin{aligned}\frac{\mathrm{d}\Delta W}{\mathrm{d}\alpha} &> \tau + \frac{4}{3}\alpha - 2\tau\left(-\frac{1}{4} + \frac{3}{4}\frac{\alpha}{\tau(1-\alpha)}\right)\\ &= \frac{3}{2}\tau + \frac{4}{3}\alpha - \frac{3}{2}\frac{\alpha}{1-\alpha}\end{aligned}$$

So, a sufficient condition for $\frac{\mathrm{d}\Delta W}{\mathrm{d}\alpha} > 0$ is

$$\begin{aligned}\frac{3}{2}\underbrace{\tau(1-\alpha)}_{>\alpha} + \frac{4}{3}\alpha(1-\alpha) - \frac{3}{2}\alpha \geq 0\\ \Leftarrow \frac{4}{3}\alpha(1-\alpha) \geq 0\end{aligned}$$

which is true for all $\alpha \in [0, 1]$. □

Lemma 2. *Suppose that the regulated price of prescription drugs $\bar{p}$ was zero, and that parameters are such that $x^* < \frac{1}{2}$ in the competitive equilibrium. Then, the difference of consumer welfare in the competitive equilibrium relative to the regulatory benchmark decreases strictly as the share of prescription consumers τ increases ($\frac{\mathrm{d}}{\mathrm{d}\tau}\Delta W(0) < 0$).*

Proof. Case 1: Again, one can first consider the trivial cases where $x^* = 0$ so that $\Delta W = (\alpha - 1)\tau$ which is strictly decreasing in τ since $\alpha < 1$ is implied (see above). *Case 2:* If $0 < x^* < \frac{1}{2}$ it must hold that $\frac{\tau}{3+\tau} < \alpha < \frac{\tau}{1+\tau}$. Note first that the marginal change of the firms' equilibrium locations with respect to τ is given by

$$\frac{\mathrm{d}x^*}{\mathrm{d}\tau} = -\frac{3}{4}\underbrace{\frac{\alpha}{\tau^2(1-\alpha)}}_{>\frac{1}{\tau}} > -\frac{3}{4\tau}$$

The change in welfare (3) compared to the baseline case where prices are regulated can also be written as

$$\Delta W = (\alpha - 1)\tau + \frac{1}{2}\left(\alpha + 5\tau(1-\alpha)\right)x^* - (\alpha + \tau(1-\alpha))x^{*2},$$

the marginal change of which with respect to τ is

$$\frac{\mathrm{d}\Delta W}{\mathrm{d}\tau} = -(1-\alpha) + \underbrace{\left(\frac{5(1-\alpha)}{2} - x^*(1-\alpha)\right)}_{\equiv C}x^* + \underbrace{\left(\frac{1}{2}(\alpha + 5\tau(1-\alpha)) - 2x^*(\alpha + \tau(1-\alpha))\right)}_{\equiv B}\frac{\mathrm{d}x^*}{\mathrm{d}\tau}. \tag{27}$$

Note that term B in the above equation is the same as term B in equation (26), and so I already know that $B > \alpha$. Substituting for x^* in C and observing that $\alpha > \frac{\tau}{1+\tau}$ is equivalent to writing $\alpha/\tau > 1-\alpha$, I obtain

$$\begin{aligned} C &= \frac{5(1-\tau)}{2} - \left(-\frac{1}{4} + \frac{3}{4}\frac{\alpha}{\tau(1-\alpha)}\right)(1-\alpha) \\ &= \frac{11}{4}(1-\alpha) - \frac{3}{4}\underbrace{\frac{\alpha}{\tau}}_{>1-\alpha} < 2(1-\alpha). \end{aligned}$$

Noting that $0 < x^* < \frac{1}{2}$ and putting together the established lower bounds for B, C, and $\frac{\mathrm{d}x^*}{\mathrm{d}\tau}$ I can derive that

$$\frac{\mathrm{d}\Delta W}{\mathrm{d}\tau} < -(1-\alpha) + (1-\alpha) - \frac{3}{4}\frac{\alpha}{\tau} = -\frac{3}{4}\frac{\alpha}{\tau} < 0$$

because $\alpha > 0$ is implied, and $\tau > 0$ by assumption. □

Lemmas 1 and 2 now allow me to prove the validity of proposition 2, repeated below for the reader's convenience:

Proposition. *Suppose that the regulated price of non-prescription drugs, $\bar{p}$, was initially zero. Then:*

1. *if α and τ are such that $x^* = \frac{1}{2}$, consumer welfare is the same in the competitive equilibrium as in the regulatory benchmark ($\Delta W(0) = 0$);*
2. *if α and τ are such that $x^* < \frac{1}{2}$, (a) the difference of consumer welfare in the competitive equilibrium relative to the regulatory benchmark increases strictly in the share of prescription consumers ($\frac{\mathrm{d}}{\mathrm{d}\alpha}\Delta W(0) > 0$), and it decreases strictly in the travel costs of non-prescription consumers ($\frac{\mathrm{d}}{\mathrm{d}\tau}\Delta W(0) < 0$); and (b) consumer welfare is smaller in the competitive equilibrium ($\Delta W(0) < 0$).*

Proof. Point (1) is trivial. Point (2a) follows immediately from lemmas 1 and 2. To see point (2b), pick any point $(\alpha', \tau') \in [0,1]^2$ with $\alpha' < \frac{\tau'}{1+\tau'}$ so that $x^*(\alpha', \tau') < \frac{1}{2}$. Choose a different point (α'', τ'') with $\alpha'' = \frac{\tau''}{1+\tau''}$, $\alpha'' > \alpha'$ and $\tau'' < \tau'$. Such a point, by construction, always exists. Then,

$$\Delta W(0)_{\alpha',\tau'} = \underbrace{\Delta W(0)_{\alpha'',\tau''}}_{=0} + \int_{\alpha''}^{\alpha'} \underbrace{\Delta W(0)_{\alpha,\tau''}\mathrm{d}\alpha}_{>0\,\forall\alpha<\alpha''} + \int_{\tau''}^{\tau'} \underbrace{\Delta W(0)_{\alpha',\tau}\mathrm{d}\tau}_{<0} < 0$$

which concludes the proof (note again that $\alpha'' > \alpha'$ and $\tau'' < \tau'$). □

B Supplementary empirical material

B.1 List of cities

	city	*AGS8*	*N*		*city*	*AGS8*	*N*
1	Düsseldorf	05 111 000	237	41	Oberhausen	05 119 000	66
2	Frankfurt a.M.	06 412 000	236	42	Ludwigshafen	07 314 000	64
3	Hannover	03 241 001	203	43	Hamm	05 915 000	63
4	Essen	05 113 000	200	44	Würzburg	09 663 000	61
5	Stuttgart	08 111 000	199	45	Heidelberg	08 221 000	61
6	Dortmund	05 913 000	197	46	Potsdam	12 054 000	60
7	Nürnberg	09 564 000	190	47	Paderborn	05 774 032	59
8	Bremen	04 011 000	179	48	Mülheim (Ruhr)	05 117 000	59
9	Leipzig	14 713 000	174	49	Darmstadt	06 411 000	57
10	Duisburg	05 112 000	157	50	Herne	05 916 000	54
11	Dresden	14 612 000	146	51	Leverkusen	05 316 000	54
12	Bonn	05 314 000	135	52	Neuss	05 162 024	53
13	Bochum	05 911 000	133	53	Koblenz	07 111 000	53
14	Münster	05 515 000	121	54	Solingen	05 122 000	51
15	Mannheim	08 222 000	118	55	Pforzheim	08 231 000	51
16	Wuppertal	05 124 000	109	56	Trier	07 211 000	50
17	Augsburg	09 761 000	109	57	Göttingen	03 152 012	50
18	Bielefeld	05 711 000	106	58	Ulm	08 421 000	49
19	Halle (Saale)	15 002 000	105	59	Erlangen	09 562 000	48
20	Karlsruhe	08 212 000	102	60	Recklinghausen	05 562 032	46
21	Wiesbaden	06 414 000	102	61	Ingolstadt	09 161 000	45
22	Gelsenkirchen	05 513 000	99	62	Zwickau	14 524 330	45
23	Mönchengladbach	05 116 000	96	63	Kaiserslautern	07 312 000	45
24	Aachen	05 334 002	96	64	Salzgitter	03 102 000	45
25	Braunschweig	03 101 000	93	65	Offenbach	06 413 000	44
26	Kiel	01 002 000	91	66	Heilbronn	08 121 000	44
27	Lübeck	01 003 000	89	67	Bremerhaven	04 012 000	43
28	Freiburg	08 311 000	87	68	Hildesheim	03 254 021	43
29	Krefeld	05 114 000	87	69	Wolfsburg	03 103 000	42
30	Magdeburg	15 003 000	83	70	Fürth	09 563 000	41
31	Mainz	07 315 000	82	71	Bamberg	09 461 000	40
32	Chemnitz	14 511 000	82	72	Flensburg	01 001 000	39
33	Kassel	06 611 000	81	73	Remscheid	05 120 000	39
34	Osnabrück	03 404 000	74	74	Cottbus	12 052 000	39
35	Erfurt	16 051 000	71	75	Gütersloh	05 754 008	39
36	Saarbrücken	10 041 100	70	76	Worms	07 319 000	38
37	Rostock	13 003 000	69	77	Siegen	05 970 040	38
38	Hagen	05 914 000	69	78	Bergisch Gladbach	05 378 004	38
39	Regensburg	09 362 000	68	79	Wilhelmshaven	03 405 000	37
40	Oldenburg i.O.	03 403 000	66	80	Esslingen	08 116 019	37

Table 14: List of eighty large German cities that were used in the empirical application, their unique identifier codes, and the number of unique locations per city, across all years.

B.2 Comparison of pharmacy and bake shop locations

	bake shops	pharmacies	difference
local population	0.467	0.495	0.028^{***}
	(0.284)	(0.269)	(0.005)
elderly share	0.194	0.198	0.004^{***}
	(0.066)	(0.062)	(0.001)
pedestrian zone	0.212	0.216	0.004
	(0.408)	(0.411)	(0.007)
mainroad	0.263	0.331	0.068^{***}
	(0.440)	(0.471)	(0.008)
doctor	0.141	0.217	0.076^{***}
	(0.348)	(0.412)	(0.006)
supermarket	0.298	0.231	-0.068^{***}
	(0.458)	(0.421)	(0.007)
trainstation	0.061	0.045	-0.015^{***}
	(0.239)	(0.208)	(0.004)
Observations	7,382	6,741	14,123

Table 15: Comparison of local spatial co-variates for pharmacy locations, and bake shops.

B.3 Choosing the strategic neighbourhood

The following table shows the estimates that were obtained using different sizes of the strategic neighbourhood in greater detail than table 8 does. Overall, the changes between the different specifications are largest when increasing k from one to two. For greater values of k, the changes become virtually nil.

	(1)	(2)	(3)	(4)	(5)	(6)
Local demand						
intercept	0.298***	0.295***	0.294***	0.294***	0.294***	0.294***
	(0.009)	*(0.009)*	*(0.009)*	*(0.009)*	*(0.009)*	*(0.009)*
post reform	-0.032***	-0.032***	-0.032***	-0.033***	-0.032***	-0.032***
	(0.007)	*(0.006)*	*(0.007)*	*(0.007)*	*(0.007)*	*(0.007)*
local population†	0.134***	0.162***	0.166***	0.167***	0.168***	0.167***
	(0.044)	*(0.026)*	*(0.026)*	*(0.026)*	*(0.026)*	*(0.026)*
elderly share	0.098***	0.096***	0.096***	0.097***	0.097***	0.097***
	(0.021)	*(0.025)*	*(0.026)*	*(0.026)*	*(0.026)*	*(0.025)*
trainstation	0.018**	0.018**	0.019**	0.019**	0.019**	0.019**
	(0.007)	*(0.007)*	*(0.007)*	*(0.007)*	*(0.007)*	*(0.008)*
pedestrian zone	0.015***	0.016***	0.016***	0.016***	0.016***	0.016***
	(0.004)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*
supermarket	0.032***	0.032***	0.032***	0.032***	0.032***	0.032***
	(0.004)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*
mainroad	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.004)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
doctor	0.027***	0.027***	0.027***	0.027***	0.027***	0.027***
	(0.005)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*
Local competition						
δ_{pre}	0.002	0.002	0.002	0.002	0.002	0.002
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
δ_{post}	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*
Entry costs						
θ^e_{pre}	4.908***	4.902***	4.901***	4.901***	4.901***	4.900***
	(0.049)	*(0.039)*	*(0.039)*	*(0.039)*	*(0.039)*	*(0.039)*
θ^e_{post}	4.335***	4.333***	4.332***	4.332***	4.332***	4.332***
	(0.027)	*(0.018)*	*(0.018)*	*(0.018)*	*(0.018)*	*(0.018)*
interaction radius [m]	900	900	900	900	900	900
strategic neighbours§	1	2	3	4	5	6
total entry locations	6,741	6,741	6,741	6,741	6,741	6,741
runtime [s]	730	587	1,170	2,186	4,067	15,673
log-likelihood	-14,780.3	-14,769.4	-14,768.1	-14,768.4	-14,767.7	-14,768.3

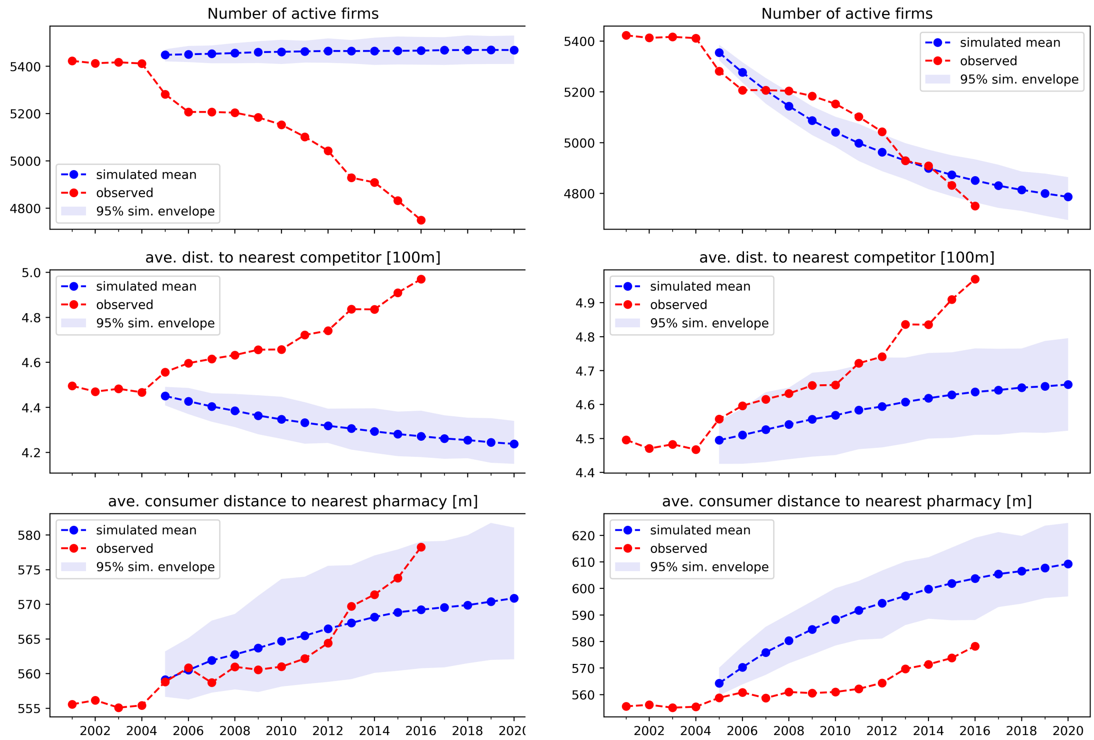
* < 0.1; ** < 0.05; *** < 0.01

†Local residential population ÷ # local active stores

§ Including "self"

Table 16: Estimates of the spatial entry model with various sizes of the strategic neighbourhood (including self). N=6741 firms, T=16 time periods in 80 large German cities. Exit values are normalized to 1. Standard errors in parentheses, computed from estimated Hessian matrix.

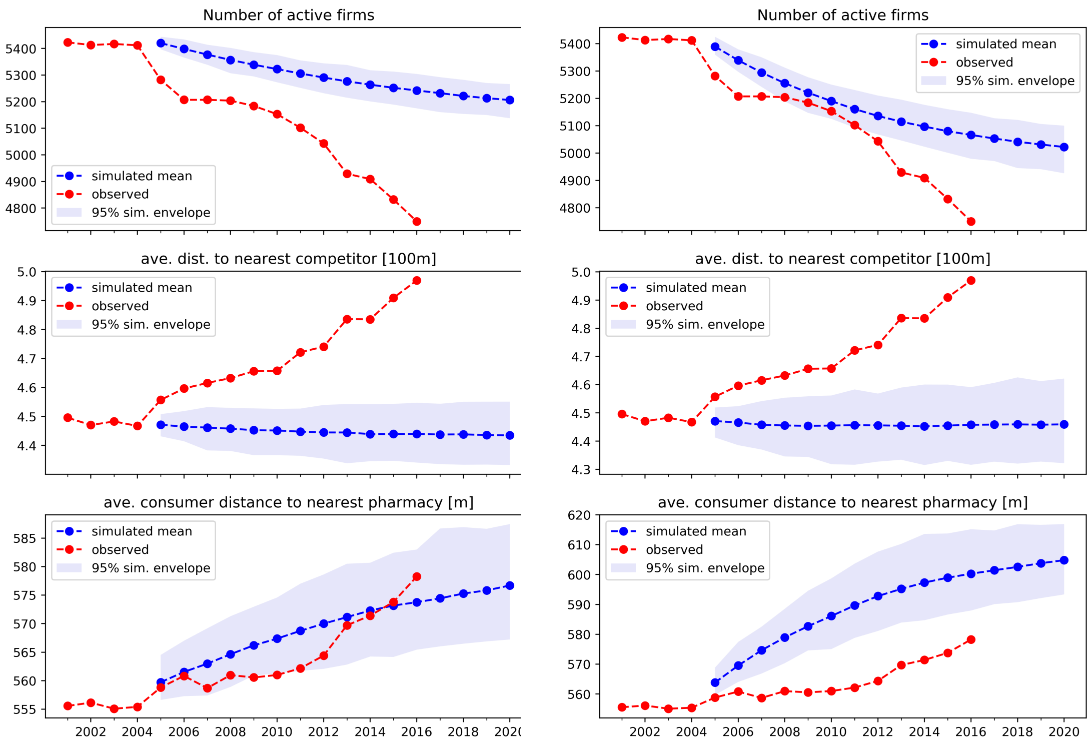
B.4 Simulation results



(a) pre-reform parameters

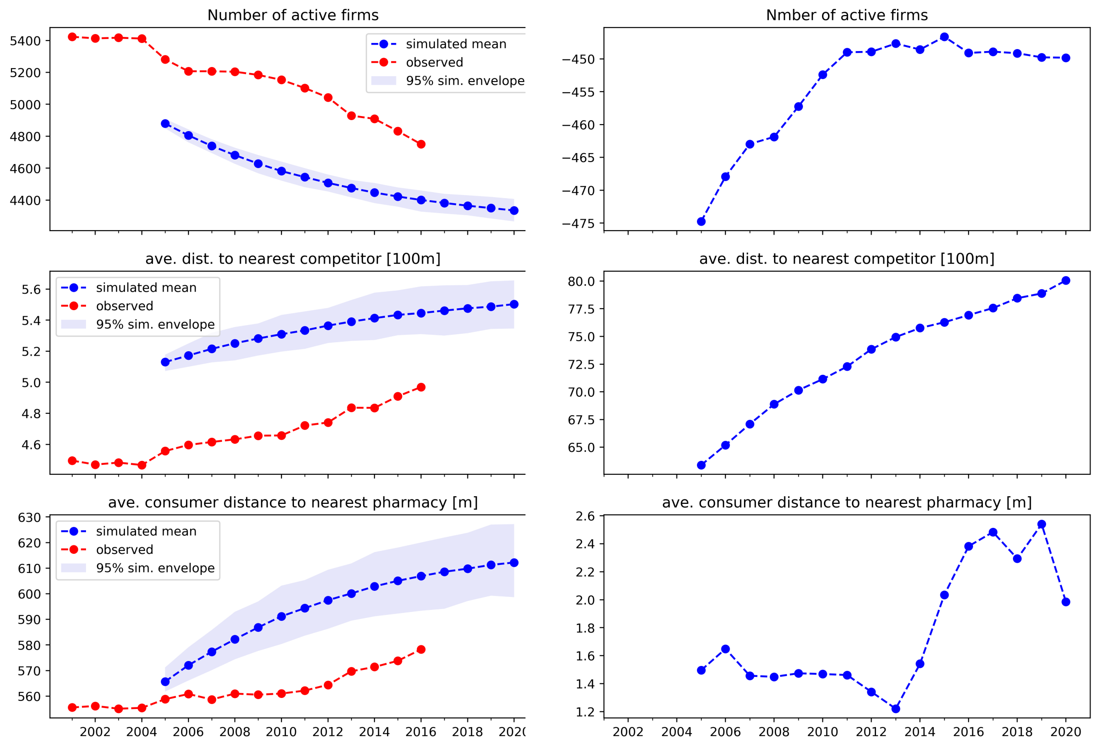
(b) post-reform parameters

Figure 13: Simulation results using the parameters in table 9, starting from the observed market state in 2004 and simulating forward with two hundred parallel samples. The blue shaded areas represents the 95% simulation envelope.



(a) Scenario A **(b)** Scenario B

Figure 14: Incremental effects of increased local competition, model (3) in table 9. See table 11 and section 7.4.



(a) Simulated counter-factual outcomes

(b) Difference to baseline (see figure 14b)

Figure 15: The effects of a mandated 100m minimum distance between store locations, remaining parameters as in model (5) in table 9

B.5 Robustness checks

	$d = 800m$ (1)	$d = 1000m$ (2)	const. pop. (3)	more cov. (4)	bake shops (5)	random loc. (6)
Local demand						
intercept	0.295***	0.295***	0.293***	0.259***	0.293***	0.201***
	(0.009)	*(0.009)*	*(0.010)*	*(0.022)*	*(0.007)*	*(0.006)*
post reform	-0.033***	-0.031***	-0.032***	-0.033***	-0.036***	-0.042***
	(0.007)	*(0.007)*	*(0.007)*	*(0.007)*	*(0.005)*	*(0.004)*
local population†	0.136***	0.180***	0.172***	0.171***	0.066***	0.397***
	(0.021)	*(0.023)*	*(0.032)*	*(0.027)*	*(0.015)*	*(0.017)*
elderly share	0.102***	0.096***	0.098***	0.096***	0.075***	0.116***
	(0.027)	*(0.025)*	*(0.025)*	*(0.026)*	*(0.017)*	*(0.013)*
trainstation	0.018**	0.019**	0.019**	0.019**	0.005	0.022***
	(0.008)	*(0.008)*	*(0.008)*	*(0.008)*	*(0.005)*	*(0.004)*
pedestrian zone	0.017***	0.015***	0.016***	0.016***	0.008***	0.028***
	(0.006)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.003)*	*(0.003)*
supermarket	0.033***	0.032***	0.032***	0.032***	0.011***	0.051***
	(0.004)	*(0.004)*	*(0.005)*	*(0.004)*	*(0.002)*	*(0.003)*
mainroad	-0.003	-0.002	-0.002	-0.003	0.004*	0.020***
	(0.003)	*(0.003)*	*(0.004)*	*(0.003)*	*(0.002)*	*(0.002)*
doctor	0.028***	0.027***	0.027***	0.028***	0.024***	0.042***
	(0.004)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.003)*	*(0.003)*
vacancies				0.048		
				(0.066)		
sq. m. price				-0.014		
				(0.010)		
unemployment				-0.021		
				(0.061)		
income				0.019**		
				(0.008)		
income growth				-0.008		
				(0.090)		
in commuters				-0.005		
				(0.016)		
Local competition						
δ_{pre}	0.003	0.002	0.002	0.002	0.005	-0.021***
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
δ_{post}	0.009***	0.009***	0.009***	0.009***	0.012***	-0.021***
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*
Entry costs						
θ^e_{pre}	4.903***	4.902***	4.900***	4.898***	5.643***	5.435***
	(0.032)	*(0.039)*	*(0.018)*	*(0.040)*	*(0.032)*	*(0.029)*
θ^e_{post}	4.334***	4.332***	4.332***	4.332***	5.106***	4.929***
	(0.018)	*(0.018)*	*(0.019)*	*(0.018)*	*(0.015)*	*(0.016)*
interaction radius	800	1000	900	900	900	900
strategic neighbours§	5	5	5	5	5	5
total entry locations	6,741	6,741	6,741	6,741	14,150	16,728
.. of which pharmacies	6,741	6,741	6,741	6,741	6,741	6,741
runtime [s]	4,800	3,678	4,930	5,188	14,604	13,894
log-likelihood	-14,774.5	-14,768.3	-14,766.7	-14,764.0	-17,374.4	-16,821.8

$^{*} < 0.1$; $^{**} < 0.05$; $^{***} < 0.01$

Table 17: Robustness checks. Exit values are normalized to 1. †local population is the residential population within 500 metres of the store's location, divided by the number of active competitors in the respective time period or future state. Except for columns three, the local residential population was scaled with municipality-level population growth rates. Standard errors in parentheses, computed from estimated Hessian matrix. § The number of strategic nearest neighbours always includes the decision maker.

B.5.1 Model specification

The spatial interaction radius was chosen in a non-strategic version of the model, with $k = 1$. To ensure that the choice of the interaction radius remained optimal after having chosen the size of the strategic neighbourhood, I re-estimated the model with $k = 5$ and for two different interaction radii, eight hundred and one thousand metres. These results are shown in columns one and two of table 17. The table shows that the estimated coefficients are very close to the ones obtained with an interaction radius of nine hundred metres. Also, the log-likelihood in either case is smaller than the one obtained for an interaction radius of nine hundred metres; so the choice of the interaction radius remains optimal.

The population data are derived from the 2011 census and also, the spatial co-variates that are derived from OpenStreetmap reflect only one particular point in time, as the data were downloaded in 2016. Unobserved temporal variation of these co-variates may lead to biased estimates but unfortunately, there are no comparable data sources for earlier years. I controlled for unobserved population growth by scaling the spatial population distribution with observed municipality-level growth rates, but this obviously leaves the spatial variation unchanged. It would be desirable to obtain the spatial population distribution for at least one additional time period, so that a population growth rate could be computed at every given point in space. Currently, such data is unavailable, but a new census is planned for 2021[34] so that this could, in principle, be achieved in the future. For the current analysis, I assessed the robustness of the estimation results only with respect to the temporal aggregate variation of the population data, by re-estimating the model's parameters with the unscaled, constant, local population data. These results are shown in column three of figure 17. That column shows that the estimated population coefficient (0.172) is not statistically different from the coefficient that is derived with the annually scaled population data (0.168, see table 9). Also, the other coefficients remain largely the same.

As a further robustness check, I added municipality level co-variates that are described in table 5 to the model. These results are shown in column four of table 17. The column shows that all added coefficients are insignificant, except for municipality level income per capita. All other coefficients retain their sign, magnitude, and significance. Apparently, city-level heterogeneity is unlikely to have a large effect on the results.

B.5.2 Potential entry locations

The analysis in section 7.2 is based on the assumption that the set of potential entry locations can be approximated well by the set of locations where a pharmacy has been active at least once. In this section, I will assess the robustness of the main result with respect to this assumption by including additional entry locations. As explained in section

[34] See `www.zensus2021.de`, accessed 03/18/2020

6.1, the additional entry locations are generated from two sources: first, I used the locations of bake shops in Germany and second, I generated a set of uniformly distributed random entry locations in all cities of my sample.

Column five in table 17 shows the estimation results with bake shop locations, and column six displays the estimation results with additional random locations. First, consider column five. These results are quantitatively very similar to the main estimation results in table 9. The estimated coefficient for the local population density is substantially smaller than in the base line results, and the estimated entry costs are larger than in the base line case. The spatial interaction coefficients remain about the same, which is also true for the estimated coefficients for the local elderly share, and for the proximity to a physician, a supermarket, a trainstation, a pedestrian zone, or a main road. An explanation for this is that the inclusion of many locations that are not pharmacies has forced the model to attribute a greater weight to locations that are specifically important to pharmacies, as opposed to being just favourable to small retail stores in general. This increases the external validity of the model and therefore it can be a useful tool to conduct out-of-sample predictions and simulations. I repeated the model validation and counterfactual simulations described in section 7, using the additional set of entry locations. These results are shown in table 18. The table shows that the simulated change from 2004 to 2016 does not match the actual change quite as well as does the base line model. The magnitudes of the partial competition effect are comparable to those derived in the base line model, and the effect of a minimum distance regulation is estimated to be larger than under the base line scenario.

The time needed to estimate the parameters increased more than proportionally with respect to the number of entry locations. This could be due to the fact that it takes longer for the Gauss-Seidel algorithm to reach the MPE. Still, the increase in computational time is very modest, and so the oblivious spatial equilibrium has proven to be a viable approach to estimate spatial dynamic entry models with a large number of agents.

Next, consider the results that were obtained by using the random set of dummy locations in column six. The estimated coefficients differ substantially from the base line results. In general, all estimated coefficients that govern local demand, except for the intercept and the post reform dummy, are larger than in the base line result. Moreover, the estimated interaction coefficients are now negative, and do not differ in the pre and post reform periods. This can be explained as follows. Pharmacy locations, and also the locations of bake shops, do exhibit a substantial amount of spatial clustering, as was shown in section 6.2. This is most likely an artefact of unobserved spatial heterogeneity, and not due to an inherent tendency of firms to cluster. On the other hand, the dummy locations were generated at random, and so do not exhibit any spatial clustering; and further, these dummy locations are never “active”. Therefore, it is natural for the model to explain the higher likelihood that a “true” pharmacy location is active relative to a randomly generated dummy location by a positive point-to-point interaction, which is reflected in a

		distance (metres)	
	Number of stores	pharmacy to nearest competitor	consumer to nearest pharmacy
observed outcomes			
2004	5,437	423	514
2016	4,770	469	539
Δ	**-667**	**+45**	**+25**
simulated outcomes			
pre-reform, 2016	5,403	403	536
post-reform, 2016	4,982	423	571
Δ	**–511**	**+20**	**+35**
competition effect			
(A) $t(0, \theta^e_{pre}, \delta_{post}) - t(0, \theta^e_{pre}, \delta_{pre})$	-226	+17	+4
(B) $t(1, \theta^e_{post}, \delta_{post}) - t(1, \theta^e_{post}, \delta_{post})$	-267	+20	+6
minimum distance regulation			
simulated change 2004-2016	–680	+81	+30

Table 18: Comparison of actual changes throughout the post-reform period; incremental effect of increased spatial competition; and the effect of a minimum distance regulation.

negative interaction coefficient (recall that the interaction coefficient denotes by how much variable profits *decrease* due to the presence of a nearby competitor). Another interesting observation is the fact that the interaction coefficient is estimated to be the same in both the pre- and the post-periods. This is rather unintuitive, because the pattern of randomly generated entry locations does not change over time, whereas the pattern of pharmacy locations does (as is reflected in the larger interaction coefficients in column five, and in table 9). The most likely explanation is an inaccuracy of the estimation procedure which prematurely stopped the algorithm before having reached the true global optimum.

How should these two additional results be interpreted, and compared to each other? Many of the randomly generated dummy locations would fall in residential zones, or even in uninhabited areas where it is either not permitted, or not possible to open a store. Thus, these locations can hardly be considered to be "potential entry locations". On the other hand, many bakery shops have a size that is similar to that of a pharmacy, and so their locations can arguably be a potential entry location. At the same time, the underlying behavioural assumption of the dynamic entry model is that each potential entrant plays an entry game (in entry probabilities, essentially) with each of its $k-1$ strategic nearest neighbours. The model therefore presupposes that at every entry locations sits a potential competitor which could conceivably become an active firm. But as discussed above, this is not true for many of the randomly generated locations and so the estimation results obtained with random entry locations may not accurately reflect the true parameters, and should be interpreted cautiously.